Neighbourhood and home environments and adolescent physical activity behaviours:

Longitudinal analyses of the Olympic Regeneration in East London (ORiEL) study

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Declaration

I, Nicolas Berger, confirm that the work presented in this thesis is my own. Where information has been derived from other sources, I confirm that this has been indicated in the thesis.

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Abstract

Context Regular physical activity has been shown to prevent major non-communicable diseases and improve physical and mental health. However, a quarter of adults and the majority of adolescents do not achieve the recommended level of physical activity in England. In recent years, the home and neighbourhood environments as determinants of physical activity have received attention because of their proximal influence on everyday behaviours, especially in young people. The current literature on adolescents is however limited. This thesis aims to investigate whether features of the home and neighbourhood environments – specifically, perceptions of the neighbourhood environment, ethnic density, neighbourhood trust and social support – predict physical activity and its change over time in an ethnically diverse and deprived adolescent population.

Methods Longitudinal data from the Olympic Regeneration in East London (ORiEL) study (2012-2014) are used. Analyses are conducted on four physical activity outcomes, namely, walking to school, walking for leisure, outdoor physical activity, and pay and play physical activity. Models are estimated using generalised estimating equations, and novel methods for handling missing data with multilevel multiple imputation are applied.

Results Analyses show that adolescents' perceptions of their neighbourhood environment (including proximity, aesthetics, street connectivity, traffic safety and personal safety) and their changes over time do not consistently predict the forms of physical activity investigated. School-level ethnic density increases the chance of walking to school in some ethnic groups and decreases it in others; whereas walking for leisure and outdoor physical activity are not consistently associated with ethnic density. Adolescents with higher perceived trust in their neighbours have higher chances of reporting outdoor physical activity, and pay and play physical activity. Finally, general social support from family, friends and significant others is shown to predict walking for leisure and its change over time. In boys only, social support from friends predicts outdoor physical activity.

Discussion This thesis advances the field methodologically and empirically by applying novel analytical approaches to important research questions. Results from this thesis contribute to our understanding of the individual, family, peer, community and neighbourhood influences on physical activity in adolescents. The predictors of physical activity identified in this thesis are mostly modifiable and therefore could be the target of policies and interventions that aim to improve physical activity.

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Acronyms and abbreviations

ACF Autocorrelation Function

ALPHA Assessing Levels of Physical Activity

BMI Body Mass Index

CI Confidence Interval

EM Expectation-Maximisation

FAS Family Affluence Scale

FSM Free School Meal

GEE Generalised Estimating Equations

GLM Generalised Linear Model

GLMM Generalised Linear Mixed Model

LSOA Lower Layer Super Output Area

MAR Missing At Random

MCAR Missing Completely At Random

MCMC Markov Chain Monte Carlo

MESA Multi-Ethnic Study of Atherosclerosis

MSOA Middle Layer Super Output Area

MI Multiple Imputation

MNAR Missing Not At Random

MSPSS Multidimensional Scale of Perceived Social Support

NEWS Neighbourhood Environment Walkability Scale

OR Odds Ratio

ORiEL Olympic Regeneration in East London

SD Standard Deviation

SE Standard Error

UK United Kingdom

US United States

WEMWBS Warwick-Edinburgh Mental Wellbeing Scale

WHO World Health Organization

Y-PAQ Youth Physical Activity Questionnaire

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Chapter 1: Introduction

Lack of physical activity is a global public health threat. Physical inactivity is estimated to cause 6-10% of deaths from the major non-communicable diseases such as coronary heart disease, type 2 diabetes as well as breast and colon cancers (Lee et al. 2012). Whereas regular physical activity has been shown to benefit physical and mental health (Strong et al. 2005, U.S. Department of Health and Human Services 2008), 26% of adults and 87% of adolescents do not achieve the recommended level of physical activity in England (Health and Social Care Information Centre 2017, Scholes 2016).

The characteristics of individuals alone have been shown to be insufficient to explain the variation in the prevalence of physical activity in the population. Following the principles of the socio-ecological model, researchers have investigated the multiple determinants of physical activity (Sallis et al. 2006). Amongst these, the neighbourhood and home environments have been hypothesised to play an important role by creating a context which promotes or demotes energy expenditure (Davison & Birch 2001, Papas et al. 2007). Understanding which features of the neighbourhood and home environments influence physical activity constitutes useful information for the development of public health policies and interventions because these features are potentially modifiable (Sallis et al. 2012). Adolescence appears to be a crucial period during which these determinants of physical activity can be addressed. This is because young adolescents spend most of their free and active time in their local area (Carlson et al. 2016, Pearce et al. 2009), while gradually spending more time without adult supervision (Mackett et al. 2007). It also appears that ethnic minority groups and deprived populations are at greater risk of physical inactivity (Griffiths et al. 2013, Owen et al. 2009, Sport London 2017) and this aspect is worth further exploration. The extent to which the neighbourhood and home environments may differentially affect ethnic minorities and deprived populations in the UK is currently unknown.

In this thesis, I will try to answer why some young people living in deprived and ethnically diverse contexts are and remain physically active during adolescence, while others remain or become inactive. To achieve this, I will attempt to improve the understanding of the determinants of physical activity in adolescents by investigating the role of certain less explored aspects of the neighbourhood and home environments – namely, perceptions of the neighbourhood environment, ethnic density, neighbourhood trust and social support. More specifically, in this thesis I will aim to:

1. Investigate longitudinal associations between perceptions of the neighbourhood environment and three physical activity outcomes;

2. Explore the associations between ethnic density and three physical activity outcomes;

3. Investigate longitudinal associations between neighbourhood trust and four physical activity outcomes;

4. Investigate longitudinal associations between social support and four physical activity outcomes.

To achieve these four aims, I will use longitudinal data from the Olympic Regeneration in East London (ORiEL) study. Recent methods for handling missing data with multilevel multiple imputation will be applied, and longitudinal analyses will be conducted in respect of four physical activity outcomes, namely walking to school, walking for leisure, outdoor physical activity and pay and play physical activity.

This thesis opens with a critical review of literature on the determinants of physical activity. In particular, chapter 2 critically assesses the literature on four potential determinants of physical activity of interest to this thesis: perceptions of the neighbourhood environment, ethnic density, social capital and social support. Chapter 2 ends with the presentation of research aims.

Chapter 3 describes the data used in the analyses of this thesis. More specifically, this chapter briefly describes the scope and design of the ORiEL study, defines the four analytical samples used in this thesis, gives a brief overview of the extent of missing data in the ORiEL study, and finally presents the variables used in the analyses.

Chapter 4 gives a detailed description of the methods used to analyse the data. The first part explains how missing data will be handled in the thesis and details why and how multilevel multiple imputation will be used to account for item non-response. The second part presents the statistical methods used for the main analyses.

Findings of the thesis are described in chapters 5 to 8. Chapter 5 presents exploratory analyses of the associations between measures of perceptions of the neighbourhood and six physical activity outcomes using the baseline ORiEL data.

Chapter 6 assesses longitudinal associations between perceptions of the neighbourhood and three physical activity outcomes: walking to school, walking for leisure and outdoor physical activity (aim 1). From a methodological perspective, chapter 6 determines the feasibility of multilevel multiple imputation to handle missing data in this thesis.

Chapter 7 presents findings on the associations between ethnic density and three physical activity outcomes (aim 2). Results from the imputation analyses specific to this chapter are briefly reported.

Chapter 8 examines the associations between neighbourhood trust and social support and four physical activity outcomes: walking to school, walking for leisure, outdoor physical activity and pay and play physical activity (aims 3 and 4). Results from the imputation analyses specific to this chapter are also briefly reported.

This thesis concludes with chapter 9, which provides a summary and discussion of study findings, a description of the study strengths and limitations, and recommendations for future research.

Chapter 2: Background

2.1. Introduction

This thesis aims to improve understanding of the determinants of physical activity in adolescents by investigating the role of features of the neighbourhood and home environments which have received relatively less attention in the literature. First though, a critical engagement with the existing literature is required. This chapter provides an overview of previously conducted work on the determinants of physical activity. It provides a summary of the epidemiological state of the science on physical activity, presents the socio-ecological approach to physical activity and summarises the available evidence on multilevel determinants. Accordingly, the main objective of this review is to critically assess the literature on perceptions of the neighbourhood environment, ethnic density, social capital and social support and identify important gaps in knowledge. The research aims of this thesis are then presented at the end of the chapter.

2.2. Physical activity

Physical activity is defined as 'any bodily movement produced by skeletal muscles that requires energy expenditure' (Caspersen et al. 1985). Physical activity can be subdivided into four domains, which correspond to how people spend their time. These are exercise, leisure and recreational activities; occupational or school activities; transportation or utilitarian activities; and household activities (Sallis et al. 2012). For many children and young adolescents, physical activity is a central part of daily routine. It is incorporated in playing and interacting with family and friends and does not generally entail a conscious decision to exercise (Koplan et al. 2005). Free play time, school physical activity, organised sport and transport to school are the main domains of physical activity in young people.

In a seminal paper, Morris et al. (1953) reported that bus conductors and postmen, who were more physically active at work, had lower rates of cardiovascular mortality than bus drivers and government clerks, who were less active. The evidence on the benefits of physical activity has since accumulated and been synthesised in landmark official documents (Strong et al. 2005; U.S. Department of Health and Human Services 1996, 2008). Participation in regular physical activity reduces the risk of premature death, coronary heart diseases, stroke, hypertension, type 2 diabetes, colon cancer and breast cancer. It further improves cardiorespiratory and muscular fitness, prevents falls and reduces depression. In children and adolescents, there is strong evidence that regular physical activity benefits cardiovascular health, musculoskeletal health, and reduces hypertension. Evidence also suggests positive effects on mental, psychological and emotional health (Koplan et al. 2005, Strong et al. 2005). Physical activity is also a key determinant of energy expenditure and therefore contributes to energy balance and the prevention of weight gain in both adults and young people (World Health Organization 2004). In recent years, many studies have investigated the independent effect of sedentary behaviour on health. Current evidence suggests that it is prudent to recommend to minimise sedentary time; however, optimal recommendation levels of sedentary behaviour are currently unknown (Katzmarzyk 2010). The focus of this thesis is on physical activity, which in comparison to sedentary behaviour, has a stronger supporting evidence base, and well established recommendations for minimum activity levels.

Globally, the WHO recommends that 'adults should do at least 150 minutes of moderate-intensity aerobic physical activity throughout the week or do at least 75 minutes of vigorous-intensity aerobic physical activity throughout the week or an equivalent combination of moderate- and vigorous-intensity activity'. Current recommendations for children and adolescents are to accumulate a minimum of 60 minutes of moderate to vigorous physical activity each day (World Health Organization 2010). In the UK, guidelines additionally target the minimisation of sedentary behaviour, without further specification. Recommendations from the Chief Medical Office are as follows (Bull & Expert Working Groups 2010):

1. All children and young people should engage in moderate to vigorous intensity physical activity for at least 60 minutes and up to several hours every day.

2. Vigorous intensity activities, including those that strengthen muscle and bone, should be incorporated at least three days a week.

3. All children and young people should minimise the amount of time spent being sedentary (sitting) for extended periods.

The data available indicate that about one-quarter of the adult population is not sufficiently physically active worldwide (Sallis et al. 2016). The proportion of inactivity is estimated to range from 15% in Southeast Asia to about 38% in the Eastern Mediterranean (Sallis et al. 2016). Globally, only one-quarter of adolescents (aged 11-17 years) meet public health recommendations on daily physical activity (Sallis et al. 2016), which partly reflects a decline in physical activity commonly observed between childhood and adolescence (Koplan et al. 2005). Overall, women and girls are less active than men and boys (Hallal et al. 2012). In

England, 27% of adult women and 24% of men were considered not sufficiently active in 2015/6; 79% of children aged 5-15 were not active for at least 60 minutes a day; and 87% of adolescents aged 13-15 did not reach daily recommended physical activity (Health and Social Care Information Centre 2017, Scholes 2016).

Available data from various high-income countries, including England, seem to indicate two opposing trends in adults' activity patterns over past decades: a promising upward trend in leisure-time physical activity is observed, but concurrently, occupational and transportation-related physical activity are falling (Knuth & Hallal 2009, Stamatakis et al. 2007). Physical activity trends in young people are less clear than in adults. Physical activity seems to have decreased at school since the 1990s and there is some evidence that active transportation has decreased in high-income countries over the last 40 years (Knuth & Hallal 2009). A few recent studies have used objective measures to evaluate trends in physical activity, but no global picture has emerged and standardised accelerometer methods are still needed (Hallal et al. 2012, Sallis et al. 2016). Recent data from the UK indicate a decrease from 28% in 2008 to 23% in 2015 in the proportion of boys aged 5-15 meeting the recommendations of physical activity, while the figure remained stable for girls (NatCen Social Research 2016).

In summary, lack of physical activity is an important global public health threat. Physical inactivity has been estimated to cause 6-10% of death from the major non-communicable diseases such as coronary heart disease, type 2 diabetes and breast and colon cancers. If physical inactivity were eliminated, life expectancy would be expected to increase by 0.68 years globally (Lee et al. 2012). Ding et al. (2016) further estimated that physical inactivity cost health-care systems 53.8 billion international dollars worldwide in 2013. Understanding the determinants of physical activity is therefore essential to public health.

2.3. Multilevel determinants of physical activity

The previous section presented the health benefits of physical activity and some key physical activity figures which indicate that a great proportion of adolescents do not meet current recommendations. Since Morris et al.'s (1953) paper on occupational differences in physical activity, researchers have documented various predictors of physical activity. The current literature goes beyond the once dominant focus on individual determinants including personal characteristics, choices and behaviours (Diez-Roux 1998). In contrast, current research incorporates socio-ecological perspectives to the determinants of physical activity. It is currently established that a better understanding of the multilevel determinants of physical activity, that is the intrapersonal, interpersonal, organisational, community, and macro levels of influence, can help designing public health policies and interventions to improve active living (Sallis et al. 2012).

2.3.1. A socio-ecological approach to the determinants of physical activity

In the past decades, it has been recognised that policies and interventions aiming to improve health and health behaviours such as physical activity should not solely target individual risk factors, but also consider influences that are located outside the person (Egger & Swinburn 1997, Hill & Peters 1998, Plotnikoff et al. 2013). Drawing on the early work of the Chicago School of Sociology (Park 1915, Sampson 2012) and Bronfenbrenner's ecological systems theory (1979), socio-ecological models were proposed to conceptualise the multilevel determinants of health and to help develop policies and interventions (Flay & Petraitis 1994, McLeroy et al. 1988, Stokols 1992). These models distinguish between intrapersonal, interpersonal, organisational, community, and public policy levels of influence (Sallis et al. 2008). In the UK, the socio-ecological framework proposed by Dahlgren and Whitehead (1991) has been particularly popular and its 'rainbow' diagram (Figure 2.1) has helped researchers to construct hypotheses about the multiple determinants of health and how they interact across different levels. The main determinants of health in Dahlgren and Whitehead's diagram include: age, sex and constitutional factors; lifestyle factors; social and community networks; living and working conditions; and general socioeconomic, cultural and environmental conditions.

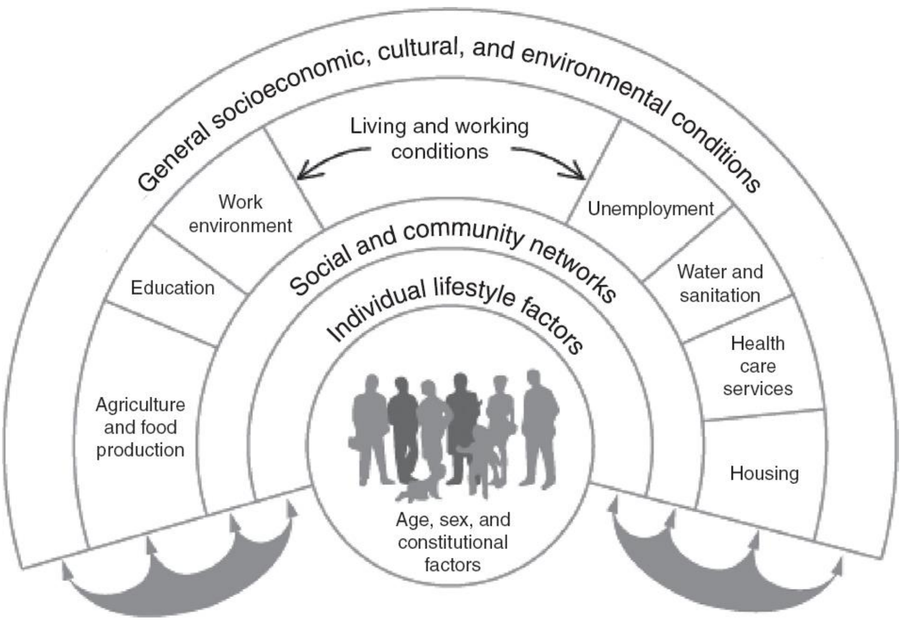

Figure 2.1 The main determinants of health **(Dahlgren & Whitehead 1991)**

Socio-ecological models are expected to be particularly useful when they are tailored to a specific health status or health behaviour (McLeroy et al. 1988, Sallis et al. 2008). As a result several socio-ecological models for the study of the wider determinants of obesity and physical activity are currently available (Bauman et al. 2012, Booth et al. 2001, Egger & Swinburn 1997, Koplan et al. 2005, Kremers et al. 2006, Lakerveld et al. 2012, Sallis et al. 1998, 2006, Swinburn et al. 1999, 2011; World Health Organization 2004). The model proposed by Sallis et al. (2006) recognises the importance of identifying specific environmental and intra-individual influences for each domain of physical activity, i.e. active recreation, active transport, household activities, and occupational activities. Giles-Corti et al. (2005) further suggest developing conceptual models which account for the particular setting in which each type of physical activity takes place (e.g. in neighbourhoods, school, homes) because environmental determinants are likely to be specific to activity context.

Amongst the many models available, the ANGELO framework (ANalysis Grid for Environments Linked to Obesity) proposed by Swinburn et al. (1999) has proven to be useful for conceptualising environmental influences on physical activity and dietary behaviours and has guided the development of subsequent models (e.g. Koplan et al. (2005) and Kremers et al. (2006)). This framework classifies environmental determinants according to two dimensions: i) the level of influence: micro-environmental settings (e.g. neighbourhood, home, school) vs. macro-environmental sectors (e.g. transport, health system); and, ii) the type of influence: physical, economic, politic and socio-cultural. In a more recent model, Bauman et al. (2012) differentiate five levels of determinants of physical activity: individual (psychological, biological), interpersonal (e.g. social support, cultural norms), environmental (social, built and natural environments), regional or national policy (e.g. transport systems, education, health), and global influences (e.g. economic development, urbanisation, global marketing).

Other models have elaborated how the environment, intra-individual characteristics and health behaviours are linked together (Bauman et al. 2002, Pikora et al. 2002). In the environmental research framework for weight gain prevention (EnRG), Kremers et al. (2006) have argued that the environment may have a direct influence on health behaviours. Yet, its impact may also be mediated and moderated by various intra-individual characteristics. Mediators include various cognitive processes, such as attitudes, subjective norms and perceived behavioural controls which are assumed to influence behavioural intention, as conceptualised by the theory of planned behaviour. Lakerveld et al. (2012) have further described the psychological mediators and differentiated motivational meditators from self-regulatory skills and perceptions of the environment. Moderators of the associations between different environmental factors and health/health behaviour include socio-demographic characteristics, awareness of the features of the environment, health literacy and physiological factors.

Another useful perspective on the multiple determinants of physical activity and obesity was proposed by Swinburn et al. (2011). Their model emphasises the differential population effects and the implementation difficulties of interventions targeting different levels of 'drivers' of obesity. 'Systemic drivers', such as policy and economic systems, which enable and promote growth and consumption, are expected to have the greater population effect, while being the most difficult to modify. 'Environmental drivers' are located at an intermediate level and include aspects such as the marketing environment. 'Environmental moderators' encompass more proximal socio-cultural and economic attributes of the environment, and are expected to amplify or attenuate the 'systemic drivers'. According to Swinburn et al., 'environmental moderators' are more amenable to change and often the target of health promotion programmes.

In summary, the literature on socio-ecological models for obesity and physical activity has acknowledged the multiple and multilevel determinants of physical activity. In addition, the specific domain of activity and the setting in which an activity is taking place are expected to have different determinants. The influence of the environment is expected to be moderated by individual factors, such as socio-demographics, and mediators have been suggested to explain the associations between the environment and physical activity. In particular, perceptions of the environment are expected to both mediate these associations and have their own independent effect. Finally, more proximal aspects of the environment such as features of the neighbourhood environment are more amenable to change and therefore could be straightforward targets for promotion programmes and interventions aiming to improve physical activity. The next section outlines the main evidence on the associations between physical activity and its multilevel predictors.

2.3.2. Overview of the multiple predictors of physical activity globally and in the UK

Studies have examined potential determinants of physical activity at different levels, including socio-demographic, psychological, biological, interpersonal, community and macro-level factors. The global evidence has recently been reviewed in two *Lancet* series on physical activity (Bauman et al. 2012, Sallis et al. 2016).

In high-income countries, self-efficacy (i.e. confidence in your ability to achieve an objective in a specific situation) is the most consistent correlate of physical activity in adults and young people. Health status is another consistent individual-level correlate, and so is previous physical activity (Bauman et al. 2012). Sex is recognised as a determinant of physical activity in children aged 4-9 years and as a correlate in older age groups (Bauman et al. 2012)[1]. In adults, education, ethnicity and social support are consistent correlates. Family social support is an important correlate in children and adolescents (Sallis et al. 2016), whereas the evidence is mixed with respect to the association with both ethnicity and socio-economic status (Bauman et al. 2012). Amongst characteristics of the neighbourhood environment, proximity to destinations, neighbourhood aesthetics, and access to open space are the most consistent correlates of higher physical activity in both adults and young people (Sallis et al. 2016).

Some of the evidence on the predictors of physical activity is specific to the national and local context. In the UK, differences in physical activity prevalence are reported at national, regional and local levels. These are likely to reflect the influence of general socio-economic, cultural and environmental conditions (Dahlgren & Whitehead 1991). Data from the latest Health Survey for England (British Heart Foundation 2017) indicate that South East England has the greatest proportion of adults achieving the recommended levels of physical activity (66%) and North West England the lowest (53%). Similar patterns are reported in children, with London and South East England being the regions with the highest levels of children physically active (Townsend et al. 2015). Data from the Active People Survey 2016 indicate important differences between local authorities within regions. East London, which is characterised by an ethnically diverse population and high levels of social, economic and environmental deprivation (McLennan et al. 2011, Office for National Statistics 2013a), has a lower proportion of adults reporting being physically active, compared to boroughs of central and South London (Sport London 2017). In Barking & Dagenham, one of the Boroughs of East London, 57% of adults reported being physically active in that study, compared to 72% in Richmond upon Thames. In a 2001 study of adolescents, Stansfeld (2003) confirmed the lower level of reported exercise in East London compared to the rest of England.

Physical activity in the UK is also patterned according to individual- and household-level socio-demographics. The evidence in adults indicates that the higher the household income, the higher the probability of reaching recommended level of physical activity (Townsend et al.

[1] The distinction between correlate and determinant used by Bauman et al. (2012) reflects whether the evidence comes from cross-sectional or longitudinal data.

2015). The evidence regarding household socio-economic differences in children and adolescents is less consistent however (Brodersen et al. 2007, King et al. 2011, Townsend et al. 2015).

Ethnic differences in health and health behaviours are well documented in the UK (Nazroo 2001). Studies consistently showed that the non-White groups are at higher risk of poor health compared with the White groups (Nazroo 2014). Physical inactivity also appears to differ as a function of ethnicity (Williams et al. 2011). Early evidence in children and adolescents showed differences in self-reported physical activity (Fischbacher et al. 2004, Rogers et al. 1997). This was confirmed by an accelerometer-based study from Owen et al. (2009) showing that South Asian children (aged 9-10 year-old) were less active than the European White and Black African-Caribbean children. Results from the Millennium Cohort Study, confirmed these patterns in 8 year-olds (Griffiths et al. 2013). Owen et al. (2012) further indicate that the White European children were more likely to walk or cycle to school, the Black African-Caribbean children to travel by public transport, and the South Asian children to travel by car. Those travelling by car had significantly lower level of objectively measured physical activity during the commute but also in their everyday life.

2.3.3. Conclusion

This section on the multilevel determinants of physical activity has indicated that the predictors of physical activity go beyond intrapersonal characteristics, and include a series of environmental factors ranging from the interpersonal environment to the macro environment. Some of these predictors are consistent across high-income countries, while others are specific to the UK. Amongst the multiple levels of hypothesised determinants, those located in the proximal environment, such as the neighbourhood environment, are more amenable to change and public health interventions (Swinburn et al. 2011), and are therefore relevant focus of inquiry. In particular, younger adolescents who are at high risk of physical inactivity, are likely to be affected by the neighbourhood and home environments because this is where they spend most of their free time (Carlson et al. 2016, Jones et al. 2009, Pearce et al. 2009)[2].

In the UK, the evidence has indicated that ethnic minorities and deprived populations are at higher risk of physical inactivity. These populations, who may spend a greater proportion of

[2] The school is another proximal environment where adolescents are physically active.

their time in their local environment (Perchoux et al. 2013), are also expected to be more affected by some of the negative components of their neighbourhood environment, such as crime and disorder (Lovasi et al. 2009, McNeill et al. 2006, Suglia et al. 2016). Adolescents from deprived populations are therefore a relevant population target in order to study the influence of the local environment on physical activity, although few prior studies having focused on them specifically.

Accordingly, this thesis will investigate aspects of the neighbourhood and home environments likely to affect adolescent physical activity behaviours, focusing on a deprived population. The remaining of this chapter will therefore critically review the related literature.

2.4. The neighbourhood and home environments and physical activity behaviours

Amongst the features of the neighbourhood and home environments, the built environment around home and school neighbourhoods has received a lot of attention in the literature (Harris et al. 2013). It has been suggested however that less intensively studied aspects of the neighbourhood and home environments could be equally relevant determinants of physical activity. These aspects fall into two broad and partly overlapping categories: the social environment and perceptions of the neighbourhood environment.

Barnett and Casper (2001) have defined the social environment as 'the immediate physical surroundings, social relationships, and cultural milieus within which defined groups of people function and interact'. Although there is no universal agreement on that specific definition, it is generally accepted that there are various mechanisms by which aspects of the social environment affect health and health behaviours by shaping norms, enforcing social control, enabling or constraining action, affecting stress and constraining choices. In a review, McNeill and colleagues (2006) identified three overarching categories commonly studied that represent five social environmental dimensions that are likely to influence health behaviours. According to the authors, *interpersonal characteristics* are captured by the study of (1) social support and social networks; *social inequalities* include (2) socioeconomic position and income inequality, and (3) racial discrimination; and *neighbourhood and community characteristics* are mostly studied through (4) neighbourhood factors, and (5) social cohesion and social capital. Suglia et al. (2016) have recently suggested that the neighbourhood social environment, which is less studied than the neighbourhood built environment, might be as relevant – if not more relevant – to explain differences in physical activity behaviours and obesity. The most commonly studied aspects of the neighbourhood social environment are social cohesion, social capital, collective efficacy, social norms, neighbourhood crime and safety, aesthetics, poverty and segregation (Suglia et al. 2016). At the interpersonal level, social support from family and from peers are identified as an important aspect of the social environment and also deserve investigation (Mendonça et al. 2014).

Other hypothesised determinants of physical activity in the local environment that have been less intensively studied than the objective built environment include perceptions of the neighbourhood environment. Perceptions usually target either i) aspects of the social environment, such as aesthetics and safety; or ii) aspects of the built environment, such as perceived proximity of destinations. In the recent literature, the latter have been recognised for being more than proxies for objective measures of the built environment (Orstad et al. 2017) and there is a growing recognition that perceptions of the neighbourhood environment might be important predictors of physical activity and health more generally (Kent et al. 2017).

The next sections review the evidence between physical activity and four aspects of the neighbourhood and home environments – namely, perceptions of the neighbourhood, ethnic density, social capital and social support. The specific constructs were selected because they are hypothesised to impact physical activity in young people and they have not been extensively studied in the literature. The focus of the review is on the evidence available in young people and in the UK.

2.4.1. Perceptions of the neighbourhood environment

In the neighbourhoods and health literature, researchers have used several methods to operationalise characteristics of the neighbourhood environment. Self-reported instruments assess individual’s perceptions of his/her neighbourhood conditions (Brownson et al. 2009). These have historically been referred to as ‘subjective’ measures and are currently labelled as ‘perceptions’ in the literature. Alternatively, ‘objective’ assessment of neighbourhood features are usually computed on the basis of routine administrative data and are also sometimes obtained from direct observation or virtual audits (Mooney et al. 2017). A greater use of Geographical Information Systems (GIS) has been observed in recent years which has allowed more sophisticated representations of how individuals are exposed to their neighbourhood environment (Brownson et al. 2009, Thornton et al. 2011).

Over the last decade, perceptions of attributes of the neighbourhood environment have received a renewed attention (Maddison et al. 2009, Nasar 2008). Instead of considering perceptions as proxies for more objective measures, researchers have acknowledged differences between the two types of approaches (Orstad et al. 2017). As an illustration, Sallis et al. (2006) distinguished between perceptions and objective measures by placing them at different levels of influence within their ecological model (section 2.3.1.). Empirical research that targeted the same feature of the environment, such as walkability, using objective and subjective measures has often reported low agreement between the two (Gebel et al. 2011). It has been recognised that perceptions are the product of ongoing social, cognitive and affective processes. Perceptions are indeed expected to be affected by physical characteristics of the surroundings, but also by a variety of personal characteristics such as values or gender, and social characteristics, such as socio-economic circumstances, cultural influences and social norms (Orstad et al. 2017). Therefore, it has been suggested that perceptions of the neighbourhood may be more proximal to health behaviour than objective measures, and mediate some of its influence (Lakerveld et al. 2012). Measures of perceptions often target features of the neighbourhood that are intrinsically qualitative – such as fear of crime, aesthetics or quality of local infrastructure (e.g. parks) – and are therefore difficult to capture using objective measures. As a result, the recent literature has indicated that objective measures and perceptions of the neighbourhood environment are complementary predictors of physical activity behaviours (Orstad et al. 2017). Whereas objective measures are more likely to capture the direct influence of neighbourhood physical characteristics, perceptions are the results of a complex interplay between the physical environment, social and intra-individual processes.

In an early paper, Pikora et al. (2003) distinguished between four dimensions of the neighbourhood environment: functionality, accessibility, aesthetics and safety. These dimensions have often served to conceptualise the influences of neighbourhood perceptions on physical activity (Brownson et al. 2009), and still form the basis of questionnaires used in major cross-national studies such as the NEWS (Neighbourhood Environment Walkability Scale) and ALPHA (Assessing Levels of PHysical Activity) questionnaires (Kerr et al. 2016, Saelens et al. 2003a, Spittaels et al. 2010). Functionality reflects the structural aspects of the local environment. It refers to characteristics of the streets and paths within a neighbourhood. Common measures of functionality include street connectivity, walkability, urban sprawl and the availability of pavement and cycling paths. Accessibility relates to the availability of commercial and community destinations in the neighbourhood such as local stores, recreational facilities and green spaces. Aesthetics refers to the overall attractiveness of the neighbourhood. It includes aspects such as architecture and maintenance. Safety encompasses both crime- and traffic-related safety and refers to the extent to which the neighbourhood offers a context in which physical activity is constrained by (fear of) crime or dangerous traffic.

Perceptions of the neighbourhood environment commonly discussed in the literature are reviewed in the following sections and include: perceived street connectivity (one of the aspects of functionality), perceived accessibility of destinations, perceived aesthetics, and perceived safety which includes crime-related and traffic-related safety.

2.4.1.1. Perceived street connectivity

Street connectivity refers to the density of street connections and the directness of distances to local destinations. It is generally hypothesised that neighbourhoods with high connectivity or perceived connectivity, often measured by the number of intersections, have a better accessibility of destinations and are therefore likely to favour walking and cycling in the neighbourhood (Thornton et al. 2011). In parallel, the presence of cul-de-sacs in residential areas might favour physical activity in the neighbourhood because of reduced traffic volume, although it can be a barrier to active transportation.

In adults, there is consistent evidence from cross-sectional and longitudinal studies that objectively measured street connectivity is positively associated with utilitarian walking, especially in Australia and in the US (Grasser et al. 2013, Hirsch et al. 2014, Knuiman et al. 2014, Sugiyama et al. 2012). Similar associations have also been reported in adults using perceived street connectivity, especially in Europe (Sugiyama et al. 2012, Van Holle et al. 2012). An Australian study has further indicated that in low-connectivity neighbourhoods, having a perception of better connectivity increased the chance of utilitarian walking (Koohsari et al. 2015a). Using data from the IPEN cross-national study, Sugiyama et al. (2014) found that the presence of cul-de-sacs, which is one of the indicators of low street connectivity, was also related with more recreational walking. These results suggest that the perception of the presence of cul-de-sacs is an indication of residential areas which are more pleasant for walking. In a qualitative study conducted in Australia, the presence of cul-de-sacs has also been associated with children outdoor play and independent mobility, which is parental permission to wander freely in the neighbourhood without adult supervision (Veitch et al. 2006).

In adolescents, the evidence base on the association between perceived street connectivity and physical activity is more restricted, and there is little consensus on what aspects of physical activity are associated with perceptions of street connectivity (Davison & Lawson 2006, Ding et al. 2011). A few cross-sectional studies indicate that adolescent's perceived street connectivity could be positively associated with walking and cycling to school (De Meester et al. 2013) and with non-organised leisure physical activity in adolescent girls (Mota et al. 2009). No evidence of an association was however found with total physical activity (Mota et al. 2005), which could suggest, according to some authors, that adolescents are unable to meaningfully assess the connectivity of their environment (Davison & Lawson 2006).

2.4.1.2. Perceived accessibility of destinations

The accessibility of local amenities and services such as shops, schools, leisure facilities and green spaces can encourage active transportation to destinations and leisure physical activity at the destination itself, including sports, walking and cycling (Thornton et al. 2011). Perceived access to destinations might reflect residents' awareness of their neighbourhood environment and therefore has the potential to better predict activity behaviour compared to objective measures. Perceptions may also capture dimensions of accessibility and of the broader local environment which are not captured by objective measures, such as quality, aesthetics or opening-time (Bedimo-Rung et al. 2005, Koohsari et al. 2015b, Papas et al. 2007). The three most common measures of perceived accessibility are access to local destinations, access to recreational facilities and access to parks.

Accessibility and perceived accessibility of a variety of local destinations, including land use mix, are consistently positively associated with utilitarian walking (Sugiyama et al. 2012, 2014) and other physical activity in adults (Ding et al. 2013, Saelens et al. 2003b); yet, results from analyses of perceptions conducted in young people (which are cross-sectional for the most part) are mixed and more robust evidence is needed (Davison & Lawson 2006, Ding et al. 2011).

The perception of access to recreational facilities as well as objective measures are associated with leisure-time physical activity both in adults and in young people, although some studies found non-significant associations (Davison & Lawson 2006, Ding et al. 2011, Van Holle et al. 2012). In longitudinal studies, both adolescents' perceptions and parents' perceptions have been shown to be associated with physical activity in young people. In the Netherlands, a longitudinal study of 5 year olds showed that parents' perceived accessibility of physical activity facilities was associated with more minutes of outside play over the follow-up period of two years, independently of parenting influences and social capital (Remmers et al. 2014). In Hong Kong, a large study of adolescents' physical activity revealed that perceived availability of sport facilities was longitudinally associated with leisure-time physical activity (Wong et al. 2014). The baseline level of physical activity also appeared to be an effect modifier: a significant effect of perception was observed only in adolescents who had initially reported a higher level of physical activity.

The significance of green spaces and parks for physical activity has been widely investigated. Quantitative studies examining the association between perceived and objectively measured accessibility of green spaces and physical activity have shown mixed results, both in adults and young people (Davison & Lawson 2006, Ding et al. 2011, McCormack et al. 2004). A proposed explanation is that proximity to green spaces may be over-ridden by other attributes of green spaces such as safety, aesthetics or quality, which are usually not captured by survey instruments (McCormack et al. 2010). This interpretation is corroborated by the RECORD study of adults living in Paris (Chaix et al. 2014) which indicates that aggregated perceived quality of green spaces is associated with recreational walking in the neighbourhood. This suggests that the perceived quality of green spaces is an important dimension.

Many studies have revealed inconsistencies between perceived and objectively measured accessibility with respect to green spaces, leisure facilities and other destinations (Lackey & Kaczynski 2009, Leslie et al. 2010, Macdonald et al. 2013, Macintyre et al. 2008, McCormack et al. 2008, Prins et al. 2009, Wang et al. 2015). In these studies, perceptions of accessibility were often better predictors of physical activity than objective measures. For example, the Australian longitudinal RESIDE study (Knuiman et al. 2014) confirmed the association between perceived access to various destinations and utilitarian walking in adults and provides evidence that perception of access to destinations may be a stronger predictor of utilitarian walking than objective measures. Furthermore, RESIDE participants who were relocated to a different neighbourhood appeared to increase their minutes of recreational and transport walking if they perceived their new neighbourhood as being more attractive, including in terms of land use mix, independently of objective measures of destinations (Giles-Corti et al. 2013).

Final noteworthy findings are differences in perceived accessibility according to socio-economic position (Lovasi et al. 2009, Orstad et al. 2017). In the US for example, Brownson et al. (2001) indicated that low income groups tend to report worse perception of accessibility to indoor and outdoor places to exercise. It should be noted however that there is mixed evidence in the UK as to whether deprived populations have lower objectively measured access to physical activity destinations (Hillsdon et al. 2007, Macintyre 2007, Molaodi et al. 2012).

2.4.1.3. Perceived aesthetics

Areas which are considered pleasant, have lots of greenery and lower levels of graffiti and litter might encourage people to be physically active (Ellaway et al. 2005). Research on neighbourhood physical disorder (Mooney et al. 2017) – visual indications that the neighbourhood is being neglected or deteriorated – also suggests that signs of disorder can discourage physical activity, possibly by the mediation of increase in crime and fear of crime (Lorenc et al. 2013). Asking residents about how they perceive various aspects of their neighbourhood aesthetics and attractiveness is a common approach to assessing aesthetics (Brownson et al. 2009).

The small body of literature relating aesthetics perceptions and physical activity – mainly walking – has been mixed and almost exclusively cross-sectional. Studies conducted in Australian adults indicate consistent positive associations between walking and measures of neighbourhood friendliness, attractiveness and pleasance (Ball et al. 2001, Giles-Corti & Donovan 2002, Humpel et al. 2004). In Europe, including in the UK, however, such findings were rarely corroborated (Foster et al. 2004, Van Holle et al. 2012). Some research has indicated that low-income and minority population tended to live in neighbourhoods that are perceived as less attractive and less safe (Giles-Corti & Donovan 2002, Lovasi et al. 2009, Sallis et al. 2011). There is however little evidence that aesthetics are associated with physical activity in those populations in the UK (Mason et al. 2011).

Very few studies have investigated the associations between aesthetics and physical activity in young people (Davison & Lawson 2006, Ding et al. 2011). A cross-sectional study of Portuguese adolescents has indicated that adolescents who reported interesting things to look at while walking in their neighbourhood, had higher chances of being more physically active (Mota et al. 2005). Further investigations are needed to confirm whether these associations hold true in different contexts, for other measures of aesthetics, and to assess whether change in aesthetics perceptions could bring about change in physical activity.

2.4.1.4. Perceived safety

Safety is a widely studied aspect of the neighbourhood social environment in relationship to physical activity and obesity (Suglia et al. 2016). It is a complex concept and includes diverse components such as harm from strangers (‘stranger danger’), personal injury, bullying and road safety (Carver et al. 2008). In practice, quantitative studies usually distinguish between crime-related safety and traffic-related safety (Panter et al. 2008).

In young people, the study of perceived safety and physical activity is closely related to the concept of independent mobility, which is parental permission to wander freely in the neighbourhood without adult supervision. Studies on independent mobility indicate that children who have the freedom to play outdoors and travel actively without adult supervision accumulate more physical activity than those who do not (Schoeppe et al. 2013). However, independent mobility has declined over recent generations in many developed countries (Foster et al. 2014b). Such a decline is commonly attributed to heightened parental concern about neighbourhood safety, both from crime and traffic, so that low parental perception of safety is expected to be related to lower levels of physical activity in children (Carver et al. 2008). Mobility restrictions resulting from parental safety concerns are furthermore expected to be more salient in girls (Carver et al. 2008).

As children grow up, they spend progressively less time with parents and family and more time with their friends (Larson et al. 1996) and gradually gain more independent mobility from their parents (Mackett et al. 2007). As a result, both adolescents' and parents' perceptions of safety might have an influence on physical activity. The following review summarises the extent to which physical activity is associated with crime-related safety and traffic-related safety in young people.

Crime-related safety

Amongst the various measures of crime-related safety, it is generally hypothesised that fear of crime, stranger danger and personal safety – all three involving emotion and anxiety – are strong predictors of physical activity, including walking (Foster & Giles-Corti 2008). These associations have been confirmed in qualitative studies in relation to outdoor physical activity, including in the UK (Lorenc et al. 2013), and are expected to be particularly relevant in deprived populations which are more at risk of crime-related safety issues (Lovasi et al. 2009).

Results from quantitative studies, including more recent longitudinal studies have been mixed however (An et al. 2017, Carver et al. 2008, Davison & Lawson 2006, Panter et al. 2008). A few studies have nevertheless reported expected associations. For example, Alton et al. (2007) provided some evidence that pre-adolescents who reported that their parent worried little about stranger danger were more likely to walk more regularly. A Belgian study indicated weak evidence of cross-sectional association between a general measure of crime-related safety and active transport to school (De Meester et al. 2013). With respect to outdoor physical activity, a longitudinal study conducted in the US indicated that personal safety increased the chance of doing outdoor physical activity at follow-up, in particular in girls (Gómez et al. 2004). However, many other studies have found null results (An et al. 2017, Carver et al. 2008, Davison & Lawson 2006). Differences in the outcome measurements, exposure measurements (parental vs. adolescent perception), study design (longitudinal vs. cross-sectional), or study setting do not appear to explain these inconsistencies in the quantitative evidence. A recent cross-sectional investigation has nevertheless suggested that the lack of consistency in the findings might be related to the lack of specificity of the physical activity measures. Comparing fear of stranger danger in adolescents and their parents, Esteban-Cornejo (2016) showed that parental perceptions were significantly associated with adolescent active transport but not with physical activity around the neighbourhood. Adolescents perceptions of safety were significantly higher than those of their parents, which had been previously documented (Carver et al. 2008). These results suggest that parental perceptions might still matter more than those of adolescents, despite the increase in independent mobility. Further research is needed to confirm these results.

Traffic-related safety

Similar to crime-related safety, there is limited evidence of a consistent association between perceived traffic-related safety and physical activity, including walking (An et al. 2017, Davison & Lawson 2006, Panter et al. 2008). For example, some cross-sectional evidence from Australia has indicated that parents tended to restrict children's outdoor mobility if they perceived traffic safety to be an issue (Carver et al. 2005, Timperio et al. 2004). However, results from the longitudinal CLAN study did not confirm these associations using an objective measure of physical activity (Crawford et al. 2010). A study by Esteban-Cornejo et al. (2016) suggested that parental perceptions of traffic safety are related to physical activity in the neighbourhood and active transport, whereas adolescents' perceptions were not. More studies on the role of adolescent perception of traffic safety are needed to confirm these results in European settings.

The study of the influence of traffic-related safety on physical activity in adolescents might be complicated by the possibility that physical activity also influences perception of safety. In fact, Ogilvie et al. (2008) reported a negative correlation between active transportation and perceived traffic safety in adults. The authors suggested that the association might reflect a greater awareness of the actual dangers of walking or cycling amongst the more frequent active commuters whose higher level of physical activity could be influenced by other personal or motivational factors. If also present in young people, this might therefore hamper the ability to detect whether perceived safety also positively influences physical activity using observational longitudinal studies in the absence of objective change in traffic safety.

2.4.1.5. Summary and limitations

I have shown that some perceptions of the neighbourhood environment are correlated with several domains of physical activity, despite the diversity of measures and approaches used. The most consistent association appears to be between perceived access to destinations and walking and physical activity in adults, and perceived access to recreational facilities in both adults and young people. Reasonably consistent associations were also found between perceived connectivity and walking in adults. Other perceptions of the neighbourhood have shown mixed results in adults and young people, and most perceptions were understudied in young people.

In addition to gaining more evidence on young people in general, it is important to understand whether adolescents own perceptions of their neighbourhood environment, as opposed to those of their parents, are relevant to predicting their physical activity behaviours. Other limitations have been identified in the literature. First, few studies have examined potential moderators of the relationship between perceptions of the neighbourhood environment and physical activity. In particular, gender differences have not been systematically documented despite well-established differences in the amount and types of physical activity between boys and girls. Second, most of the literature is based on small cross-sectional studies, which limits the effect size it is possible to detect and restricts conclusions about causality. Third, the current literature is dominated by North American and Australian investigations. More research is needed in the UK in order to corroborate results obtained in other settings and to explore potentially important contextual differences. Fourth, deprived and ethnic minority populations have been little studied, despite the fact that they are generally at greater risk of physical inactivity and are more likely to be more exposed to less supportive neighbourhood environments.

2.4.2. Ethnic density

In this section, I present the literature on a potential determinant of physical activity from the local environment that has received very little attention, namely ethnic density. In the 'ethnic density effect' literature, it is hypothesised that people from ethnic minority groups could benefit from being surrounded by people of their own ethnic group in their local environment (Pickett & Wilkinson 2008). The association with ethnic density has been documented for mental health outcomes (Shaw et al. 2012), and some recent investigations have indicated that own-group ethnic density could also be relevant for health behaviours, such as smoking and drinking. By extension, it is expected that differences in ethnic density could also explain differences in physical activity behaviour, although the literature on the topic is rare. This section summarises the conceptual literature on ethnic density, explains how ethnic density is expected to influence physical activity and reviews the evidence on the association between ethnic density and health behaviours.

2.4.2.1. Ethnic density hypothesis

Differences in health and health behaviours across ethnic groups have been well documented in the UK (Nazroo 2001, Owen et al. 2009, Whincup et al. 2010). Common explanations for these differences include genetic and biologic differences, migration effect, cultural differences in lifestyles, experiences of discrimination and racism and broader socio-economic inequalities (Nazroo 2014). In spite of these ethnic inequalities, some studies have indicated that, after adjusting for the concentration of deprivation and neighbourhood poverty, ethnic minorities who lived in ethnically dense areas had better mental health, and sometimes better physical health outcomes compared with those living in less ethnically dense areas (Bécares et al. 2012b, Shaw et al. 2012). This observation has been referred to as 'the ethnic density effect' in the literature and has led to the formulation of the 'ethnic density hypothesis', which is expected to apply to mental health, physical health and health behaviour outcomes (Bécares et al. 2011, Karlsen et al. 2002). Three main theoretical pathways – civic participation, social capital and social support, and exposure to racism and discrimination – are proposed to explain how ethnic density could influence health and health behaviours (Bécares & Nazroo 2013, Shaw et al. 2012). The focus is on those relevant to physical activity, as summarised in Figure 2.2.

First, higher ethnic density may enable greater civic engagement and political mobilisation (Karlsen et al. 2002) which might translate into improved services and infrastructures for the community, such as physical activity services and infrastructures, that are particularly relevant for the dominant ethnic groups in the local area (Whitley et al. 2006). Greater access to services might in turn favour health behaviours such as physical activity. To date, this hypothesised pathway has received little empirical investigation and support (Bécares 2009). Nonetheless Molaodi et al. (2012) showed that, in the UK, a higher ethnic concentration is associated with a greater density of physical activity facilities in the local environment for some ethnic minority groups (e.g. the Indian group), and a lower density for other groups (e.g. the Black Caribbean group).

Second, ethnic density is hypothesised to increase social capital and social support (Bécares & Nazroo 2013, Halpern & Nazroo 2000, Karlsen et al. 2002, Pickett & Wilkinson 2008). Higher own-group ethnic density is expected to be associated with a greater sense of community, a greater sense of belonging to an area and increased opportunity to build social networks. As shown in sections 2.4.3. and 2.4.4., mechanisms by which social capital and social support affect health and health behaviours (including physical activity) are well grounded in theory and have received empirical support.

Third, ethnic density is expected to influence health and health behaviours by a reduction in exposure to racism and discrimination (Pickett & Wilkinson 2008, Whitley et al. 2006). Experienced racism is hypothesised to have a negative effect on perceived personal safety and has the potential to increase fear of crime and the perception of stranger danger, which are expected to have negative impacts on health and health behaviours (Karlsen et al. 2012, Lorenc et al. 2013, Rawlins et al. 2013). Ethnic density might protect against some of these negative effects. Indeed, a greater number of ethnic minority residents in a local environment is expected to reduce the number of potential crime offenders, to improve racism-related social norms and to lower tolerance against racist victimisation (Pickett & Wilkinson 2008, Whitley et al. 2006). In turn, these are hypothesised to translate into greater informal social control against interpersonal racial harassment. With respect to physical activity, it is expected that a higher ethnic density could provide more opportunities for physical activity by means of a reduction in fear of crime and an increase in perceived safety. Empirically, some studies have shown that experienced racism is lower in places with higher ethnic density, which results in a weaker association between racism and health (Bécares et al. 2012b). In addition, ethnic density might have a 'buffering effect' that moderates the negative impacts of racism on health (Das-Munshi et al. 2010). The increased social capital and social support brought about by ethnic density could provide additional resources to better cope with experiences of racism and discrimination, so that they would not translate into a reduction in health or a change in health behaviours (Bécares et al. 2009).

These three theoretical pathways alone cannot explain why the empirical literature on the ethnic density effect in the UK has indicated contradictory ethnic density effects for different ethnic groups (Das-Munshi et al. 2010). In this thesis, I hypothesise that ethnic differences in ethnic density effects on health behaviours can be explained by differences in cultural identities and cultural norms across ethnic groups (Bécares et al. 2011). Indeed, different ethnic groups might have different norms with respect to what socially acceptable behaviours are, such as smoking, drinking, walking to school, and playing outside. I expect that, depending on the underlying norms or cultural identities of an ethnic group, the benefits of greater ethnic density might be moderated (which is expressed by interactions in Figure 2.2).

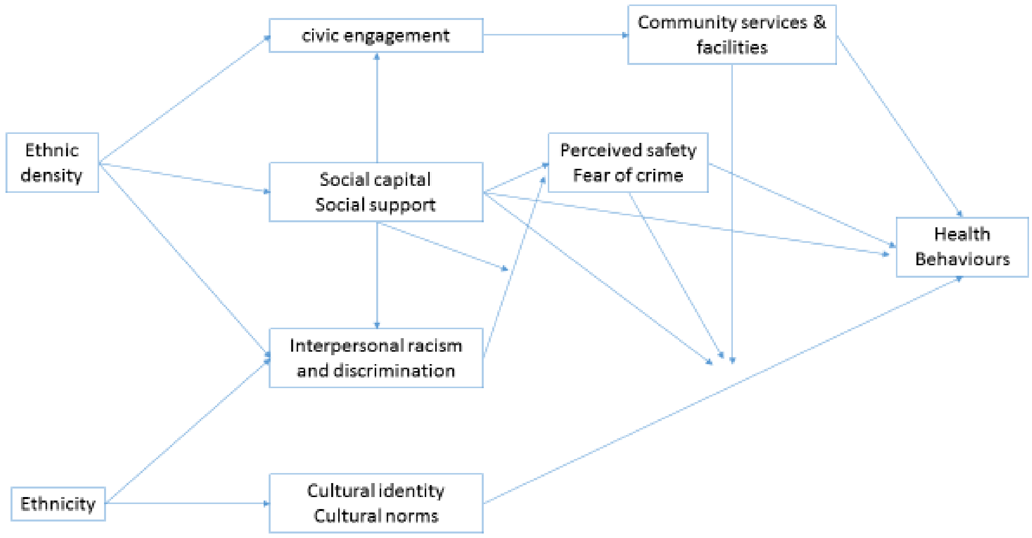

Figure 2.2 Conceptual model for the relationship between ethnicity, ethnic density and health behaviours

2.4.2.2. Evidence supporting the ethnic density hypothesis

Most of the literature on ethnic density was conducted in the US (Bécares et al. 2012b). Given the differences in migration history and socio-demographics dynamics of ethnic minorities between countries (Bécares et al. 2012a), the focus of this review is on the growing body of evidence coming from the UK. In the absence of evidence in physical activity, this section reviews a broader range of health behaviours and some health outcomes to give an overview of the extent to which the ethnic density hypothesis is supported by the current literature.

Two published systematic reviews reported mixed results of an ethnic density hypothesis for mental health (Shaw et al. 2012), physical health and health behaviours (Bécares et al. 2012b). It appears, however, that – for at least some ethnic groups – an ethnic density effect was observed in most of the studies. In practice, ethnic density studies generally combine health survey data with available statistics on the ethnic composition of the residential area of survey participants. Studies to date are heterogeneous in terms of outcomes, ethnic groups, local area definitions, and overall research settings, which means that the distribution of the ethnic density variables varies greatly across studies.

Measures of ethnic density are usually derived from population census data, where information on ethnicity is collected using self-classification and then aggregated to some geographic unit. Another way of assessing ethnic density is to directly ask survey participants what proportion of residents is of the same ethnic group in their area. Such a measure of perceived ethnic density may reflect a person's experience of frequency and intensity of contact with co-ethnics. It is hypothesised that similar processes link objective and perceived measures of ethnic density to health and health behaviours but that perceived ethnic density captures the processes more precisely. This is because perceptions are not prescribed to administrative boundaries used in objective measures, and residents' experience of neighbours and neighbourhood social interactions may be captured more effectively by the perceived ethnic density measure (Stafford et al. 2009).

Convincing evidence for the ethnic density hypothesis was provided in relation to the mental health of adults living in England. Das-Munshi et al. (2010) used a large cross-sectional survey of Irish, Black Caribbean, Indian, Pakistani, Bangladeshi, and White British ethnic groups and measured ethnic density at middle layer super output area (MSOA) level. In their fully adjusted multilevel models, the researchers found a protective ethnic density effect for Irish and Bangladeshi groups and for all ethnic minority groups combined. Their study also indicated that living in areas of higher own-group density was associated with higher social support and less discrimination for some groups, although the measures of social support and experiences of discrimination used in the study did not seem to mediate the observed ethnic density effects.

Only a handful of studies have investigated the association between ethnic density and health behaviours in the UK, and only a few more were identified in the US literature (Bécares et al. 2012b). Bécares et al. (2011) examined the ethnic density hypothesis for alcohol consumption in adults among Black Caribbean, Black African, Indian, Pakistani, and Bangladeshi people using the 1999 and 2004 Health Survey for England. Ethnicity was defined at MSOA level in two ways: as one's own ethnic density and as a typology of neighbourhoods based on their ethnic minority compositions. The results indicated a protective ethnic density effect for alcohol consumption among all ethnic minorities. However, ethnic density associations for adherence to sensible drinking were only found among Black African people living in areas of high own ethnic density. Overall, this study offers some insight into the relevance of social norms as plausible pathways by which ethnic density might influence health behaviours.

Some recent studies have examined the association between smoking and ethnic density in adults. Uphoff et al. (2016) indicated that a higher South Asian density was associated with a lower probability of smoking during pregnancy among Pakistani women in a deprived context. The same pattern of association was not as clear for the White British women. These findings, combined with the fact that smoking was not as well accepted amongst the Pakistani women, suggests that social norms might be responsible for the density effect observed. The second study on smoking behaviour was conducted in the London Boroughs of Hackney, Lambeth, Newham and Tower Hamlets using electronic health records of almost 700,000 patients (Mathur et al. 2017). The analysis was restricted to the majority ethnic group of White British/Irish, and six ethnic minority groups. Ethnic density was defined as own-group ethnic density at lower layer super output area (LSOA) level. Although the results might be subject to residual confounding due to the absence of individual-level socio-economic variables, the results indicate that a 10% increase in own-group ethnic density was associated with a 2–43% reduction in the odds of being a current smoker for all ethnic groups except for the Black Caribbean women, an ethnic group with much lower ethnic density distribution. Analysis of the shape of the associations indicate potential non-linear effects that differed by ethnic group and gender. Positive ethnic density associations were also found for the White British/Irish group and other White group, although the non-linear models indicated that the effect was only protective in very high-density neighbourhoods, whereas a reversed association was observed for mid-level ethnic densities. The effect of density was also much smaller in Indian and Bangladeshi men, two groups with high smoking prevalence. This study therefore seems to indicate that there might be a greater ethnic density effect in ethnic groups where smoking is least socially accepted, reinforcing the hypothesis that ethnic density effect might influence behaviours differently, depending on ethnic-specific norms.

The vast majority of studies on ethnic density were conducted in adults. An exception is Astell-Burt et al.'s (2012) study which investigated psychological well-being in adolescents aged 11-16 years from 51 London schools, by combining two waves of the longitudinal DASH study. The study found little evidence of association with ethnic density, as opposed to a previous study conducted on adults (Shaw et al. 2012). An interesting aspect of the study is that the authors used both school and the residential neighbourhood to compute own-group ethnic density variables.

2.4.2.3. Summary and limitations

The literature on the association between ethnic density and health in the UK indicates mixed results. Most studies have found some form of ethnic density associations but these associations were not consistent across all ethnic groups and all outcomes investigated. In contrast, the few studies that investigated the association between health behaviours and ethnic density were more consistent. A protective effect on alcohol consumption was found for all ethnic minorities, and smoking appeared to be less likely for most ethnic minorities as ethnic density increased. Taken together, these result offer some insight into the relevance of social norms as a plausible mechanism by which ethnic density might influence health behaviours. This suggests that, depending on the social norms associated with a health behaviour within an ethnic group, an ethnic density effect might plausibly be observed.

The 'ethnic density effect' sub-field is still growing. Over recent years, there have been a series of methodological improvements over earlier literature. Further, conceptually more homogeneous ethnic groupings have been used, such as the acknowledgment that Bangladeshi, Pakistani and Indian groups should not simply be classified as 'South Asian'. Most recent studies tend to account for the structure of the data, although few accounted for potential bias due to missing data. More appropriate geographical scales are being used, with more and more neighbourhood data computed at LSOA level, as compared to MSOA, the latter being questioned as a relevant scale of contextual analysis (Stafford et al. 2009).

Despite these improvements, limitations remain. The way ethnic density is operationalised still greatly varies from study to study, making it difficult to detect potential thresholds (Pickett et al. 2009) or non-linearity in the effect. Most studies indicate low average ethnic density values, which seem to be associated with an absence of effect (Mathur et al. 2017). Teasing out the relative influences of neighbourhood deprivation and ethnic density remains an issue, given the correlation between the processes of ethnic and economic segregation (Karlsen & Nazroo 2002). Focusing on homogeneously deprived areas might therefore help better test the ethnic density hypothesis even though results might not be generalisable to the general population (Uphoff et al. 2016). A further limitation of the current literature is its restricted ability to draw conclusions about causality because most of the literature relies on cross-sectional data. Finally, there is a need for more evidence in young people and for other health behaviours, including physical activity.

2.4.3. Social capital, social cohesion, and neighbourhood trust

Social capital, social cohesion and neighbourhood trust are important components of the neighbourhood social environment (Suglia et al. 2016). Although these concepts are connected to some of components of neighbourhood perceptions reviewed in section 2.4.1., in particular crime-related safety, they are usually studied separately and are not included in neighbourhood perceptions instruments such as ALPHA (Spittaels et al. 2010) and NEWS (Saelens et al. 2003a). This section reviews the conceptual and empirical literature on the role of social capital, social cohesion and neighbourhood trust to explain differences in health behaviours in general, and physical activity in particular.

2.4.3.1. Potential mechanisms relating social capital to physical activity

Social capital designates the resources that are accessed by individuals through their membership to a group or a network, including trust, norms of reciprocity and the ability to undertake collective action (Kawachi & Berkman 2014, Putnam 1993). It is a complex construct that has received contributions from numerous authors and disciplines across the social sciences (Coleman 1988, Portes 1998, Putnam 1995) and has been operationalised in different fashions (Kawachi & Berkman 2014, Szreter & Woolcock 2004).

Social capital can be analysed at both the individual and group-level (Kawachi & Berkman 2014). At the individual-level, it refers to resources that are available through the ego-centred network. Under this perspective, social capital is very close to the concept of social support (see section 2.4.4.), the difference being that social capital provides resources not only from close, strong ties (as social support does), but also from weak ties that bridge relationships across groups (Granovetter 1973). At the group-level, social capital is conceptualised as the collective characteristics through which individuals in a community, or living in a particular area, share norms and behaviours. Kawachi and Berkman (2014) identified three main mechanisms through which social capital can be potentially relevant to health outcomes and health behaviours, namely social contagion, collective efficacy and informal social control.

Social contagion refers to the notion that behaviours tend to spread more quickly in a cohesive social network. Although the behaviours that spread via the group can sometimes be deleterious to health, it is hypothesised that parental involvement with their children, as well as their level of cohesion with other parents in the neighbourhood, may improve the ability of a community to adopt healthy norms. For example, a greater communication between neighbours may lead to a quicker diffusion and adoption of healthy behaviours because members of the community are in frequent contact and trust one-another (Kawachi et al. 1999). Close ties between neighbours might also increase awareness about programmes and activities for young people available in the neighbourhood, which are likely to lead to healthy behaviours.

Collective efficacy is the group-level equivalent of the notion of self-efficacy (Sampson 2012). It indicates the capacity and willingness of a group to intervene for a common goal. It results from the combination of social cohesion or mutual trust and shared expectation for social control (e.g. threat of sanction by other member of the group). Resulting collective actions can lead to an improvement of health-promoting resources such as better access for physical activity facilities, construction of bicycle paths or better maintenance of public spaces and parks.

Informal social control indicates the ability of a community to maintain social order and to intervene when deviant behaviours are witnessed (Kawachi & Berkman 2014). Social control operated by cohesive communities was shown to be effective to prevent juvenile delinquency and to improve the perception of safety in the neighbourhood (Sampson 2012). It is therefore expected to have potential benefits for physical activity in the neighbourhood, especially in young people.

These three mechanisms – social contagion, collective efficacy, and informal social control – are thus likely to provide physical activity benefits to individuals through their connection to a group. It is expected that young people will benefit from their own peer connections but also from those of their parents and wider family. It should be added that social capital can have effects beyond the connected members of a group and have benefits for neighbours that did not contribute to it (Kawachi & Berkman 2014). For example, all neighbours can benefit from collective action of a restricted group to improve physical activity resources.

2.4.3.2. Measurement of social capital

There is currently no consensus on the operational definition and measurement of social capital (Kawachi & Berkman 2014, Lindström 2008, Ueshima et al. 2010). The two main measurement approaches are the network-based perspective and the social cohesion-based perspective (Kawachi & Berkman 2014, Legh-Jones & Moore 2012). In the network-based perspective, the investigator attempts to study social connections of the respondents and their significance. This approach has some degree of overlap with social support instruments (see section 2.4.4.), and is therefore less commonly employed in health surveys which often already measure social support (Kawachi & Berkman 2014). The social cohesion-based perspective is more common in population health surveys. Instruments usually either assess individual perceptions of social cohesion (e.g. perception of trust of other), which is sometimes called *cognitive social capital,* or measure the actual behaviour (e.g. participation in social organisations), which is known as *structural social capital*. The individual responses are studied either at the individual level, or as property of a group, such as the neighbourhood, using 'ecometric' methods (Raudenbush & Sampson 1999). There are currently debates on whether trust is actually part of social capital or is a prerequisite for it (Kawachi & Berkman 2014). Trust being a perceptual measure, it is also argued that individual-level measures of trust may sometimes poorly capture social capital and instead reflect individual-specific variations in cynical hostility, which is a general tendency to mistrust interpersonal relationships (Kawachi & Berkman 2014). In the US, the tools for measuring collective efficacy have gained some popularity following the work of Sampson and colleagues (see Sampson (2012) for an overview), but the collective efficacy approach remains uncommon in Europe.

2.4.3.3. Empirical evidence on the association between social capital and physical activity

Social capital, social cohesion and collective efficacy were shown to be associated with a broad range of health behaviours, including alcohol consumption, drug abuse, juvenile delinquency and physical activity (Lindström 2008, McNeill et al. 2006). Most of the evidence in relation to physical activity comes from measures of social cohesion and trust and concerns the adult population. Evidence from the US indicates consistent association between social cohesion and total physical activity, based on both individual-level and group-level measures (Lindström 2008). Outside the US, associations between individual trust and leisure-time or total physical activity have been established in various countries, including Sweden (Lindström 2011) and Japan (Ueshima et al. 2010). However, studies using neighbourhood-level measures of social capital have not always found associations with physical activity outcomes, as exemplified by a study in older adults from China (Gao et al. 2015). A large scale study from Canada has recently found that both individual-level and neighbourhood-level social cohesion were associated with physical activity in adults (Yip et al. 2016). However, results from the European SPOTLIGHT project (Mackenbach et al. 2016), which includes neighbourhoods from London, indicate little evidence of an association between adult leisure-time physical activity and neighbourhood-level social cohesion, and an inverse association was found with transport-related physical activity. The SPOTLIGHT study further indicated that the use of 'ecometric' methods as opposed to simple mean aggregates to obtain neighbourhood-level measures did not have practical advantages.

Some recent studies have compared aspects of social capital. A Japanese study (Ueshima et al. 2010) for example showed that neighbourhood trust or cognitive social capital was more important for physical activity than structural social capital measured by way of social participation. The results might, however, be specific to Japanese society, as suggested by the authors. In Montreal, a study based on various measures of social capital, including network-based measures, concluded that, unlike trust, network diversity was associated with physical inactivity (Legh-Jones & Moore 2012).

There is limited evidence of an association between social capital and physical activity in children and adolescents, and most of it comes from the US. Carroll-Scott and colleagues' study (2013) of a multi-ethnic population indicated that adolescents were likely to report more days of exercise if they also reported greater presence of social ties with friends and neighbours. In Chicago, Cradock et al. (2009) also indicated that adolescents from diverse neighbourhoods were more likely to participate in sports activity and to report physical activity at follow-up if they were living in a neighbourhood that had higher baseline level of social cohesion. In various American cities, Franzini et al. (2009) found that parent-reported collective efficacy, collective socialisation of children, exchange and social ties among neighbours were positively correlated with self-reported physical activity. Kimbro et al. (2011) also reported a small but positive association between collective efficacy and physical activity in young children, as reported by their mothers. Finally, a recent cross-national study showed that, in most high-income countries studied, collective efficacy was associated with objectively-measured total physical activity in 9-11 year old children (Sullivan et al. 2017), suggesting that the results documented in the US might generalise to other contexts. These results still need to be confirmed in Europe, including in the UK.

2.4.3.4. Summary and limitations

This review showed that social capital and related constructs were consistently associated with leisure-time physical activity and total physical activity in the US and in other high-income countries, both in adults and adolescents. Some of the evidence in Europe has, however, indicated an absence of association in adults, and there is currently little information available in young people in Europe. The current literature is also limited in the sense that most of the evidence comes from cross-sectional studies, which restricts the opportunity to draw conclusions about causality. Finally, most of the literature captures total physical activity or leisure-based physical activity and does not explore how social capital could differently affect different forms or domains of physical activity.

2.4.4. Social support

Social support is another important aspect of the social environment which has the potential to influence physical activity (McNeill et al. 2006). The notion of social support is close to the concept of social network introduced in the previous section on social capital (cf. network-based measures discussed in section 2.4.3.3.). The main difference between social support and social network is that the former usually refers to the benefits of close relationships such as families and friends, whereas the latter also includes resources provided by weaker connections (Kawachi & Berkman 2014). This section reviews the literature on the social support and physical activity. The focus is on young people, for whom specific theoretical hypotheses have been proposed, and a sizeable empirical literature exists.

2.4.4.1. The relevance of social support for adolescent physical activity

The evidence that social support is beneficial to physical and mental health is now considerable (Stansfeld 2006). In addition, there is a growing literature on the benefits of social support for health behaviours. The literature on physical activity has even identified social support as one of the most consistent correlates of physical activity in young people (Sallis et al. 2000, 2016). Social support describes resources provided from interpersonal relationships that can influence health and behaviours such as physical activity. These resources are diverse and include: psychological/emotional support (e.g. encouragement, praise), instrumental support (e.g. equipment, transport to a physical activity facility), co-participation (e.g. performing the activity with the adolescent), informational support (e.g. providing advice or instructions about an activity), and support as a role model (Langford et al. 1997). Parents, family members, and friends constitute the main sources of social support for physical activity (Mendonça et al. 2014).

During pre-adolescent years, parental support for physical activity is expected to play an integral role in establishing physical activity in children's free-time play outside of school. Multiple forms of parental support are expected to influence physical activity, including parental modelling of physical activity, encouragement and instrument support, such as providing transport to a physical activity facility. As children grow up, they spend progressively less time with parents and family and more time with their friends (Larson et al. 1996). A well-established finding is that both adolescents' feelings of support, closeness, and intimacy and objectively observed assessments of warmth and cohesion in adolescent-parent relationships decline during adolescence (Smetana et al. 2006). As a result, social support from friends is expected to emerge as a major source of influence on physical activity behaviours (Yao & Rhodes 2015). Over time, parent-child coactivity is likely to decrease, the influence of parental modelling is expected to decline, but instrumental support from parents is still expected to be an important resource for physical activity. It has been suggested that peers could have a powerful influence on physical activity levels by providing various forms of support, in particular as positive communication through social norms and encouragements, co-participation and role modelling (Maturo & Cunningham 2013).

Another important theoretical consideration is that different types of physical activity (e.g. organised sports, active commuting) might be influenced by different aspects of social support and by different providers of such resources. For example, organised physical activity may require more parental support in the form of transport, equipment and enrolment than unstructured leisure-time physical activity (Edwardson & Gorely 2010). Friends, by contrast, are expected to provide more support to engage in more vigorous physical activities and competitive sports (Mendonça et al. 2014).

2.4.4.2. Measuring social support relevant to physical activity

Like many of the exposure variables reviewed in this thesis, social support has been assessed using a variety of survey instruments in the literature, and no gold standard has emerged to date (Yao & Rhodes 2015). It is mainly measured using parental- or self-reported questionnaires. Most questionnaires tap into one or more forms of support (emotional, instrumental, modelling or co-participation) and specify the source or provider of support, usually friends, family or parents (Mendonça et al. 2014). Unlike general social support scales such as the Multidimensional Scale of Perceived Social Support (MSPSS; (Zimet et al. 1990)), most instruments used in the field are specifically designed to capture social support for physical activity, using a generic reference to physical activity in the survey question (e.g. Activity Support Scale (Davison & Jago 2009))[3]. In practice, total support for physical activity by provider of support is the most common measure used (Laird et al. 2016).

2.4.4.3. Empirical evidence on the association between physical activity and social support

Whereas most studies are cross-sectional and based on very small samples, larger cross-sectional studies and longitudinal investigations have emerged in recent years. Three literature reviews have attempted to quantify the overall associations between social support

[3] Given the expectation that the relationships between social support and physical activity might depend on the type of physical activity, some authors have further suggested the use of questionnaires with more specific references to diverse physical activities (Beets et al. 2010).

and physical activity in young people using meta-analyses (Laird et al. 2016, Pugliese & Tinsley 2007, Yao & Rhodes 2015), in spite of the heterogeneity of exposure and outcome measures (including in the person who is reporting social support). Overall, findings indicate consistent yet moderate associations between physical activity and social support from parents (Beets et al. 2010, Edwardson & Gorely 2010, Laird et al. 2016, Pugliese & Tinsley 2007, Yao & Rhodes 2015), family (Laird et al. 2016, Mendonça et al. 2014) and friends (Laird et al. 2016, Maturo & Cunningham 2013, Mendonça et al. 2014). In what follows, the evidence is presented separately for social support from parents and family, and for social support from friends.

Social support from parents and family

Family and parental support have been widely studied. Whereas many studies include family as a general source of support and include parents and siblings, other have investigated the specific influences of parents, or even father/mother. Results are similar for parental and family sources of supports (Laird et al. 2016, Mendonça et al. 2014) and are presented together in this section.

Total parental and family social support were shown to be associated with various physical activity measures in children and adolescents (Beets et al. 2010, Laird et al. 2016). The associations only explain a small amount of the variance in physical activity behaviour (Laird et al. 2016, Yao & Rhodes 2015). There is some indication that the associations might be of a smaller magnitude when physical activity is objectively measured (Maturo & Cunningham 2013, Yao & Rhodes 2015). No gender differences are observed (Yao & Rhodes 2015).

Amongst the various types of social support investigated, analyses indicate that family and parental encouragements are the most consistent correlates of physical activity (Beets et al. 2010, Yao & Rhodes 2015). Transportation is shown to be an important factor too because access to places (e.g. parks, playgrounds, sport facilities) is a major barrier to participation to sport/exercise in young people (Beets et al. 2010, Mendonça et al. 2014). For example, Jago et al. (2011) showed that parental logistic support was positively associated with objectively-measured total physical activity in 10-11 years olds in the UK.

Associations have been shown to hold as children grow up (Laird et al. 2016). Evidence indicates that as children reach their teenage years, they may still benefit from family and parental resources that help them to be physically active. Most relevant types of support during adolescence include transportation, encouragement and role modelling (Edwardson & Gorely 2010, Laird et al. 2016, Yao & Rhodes 2015). For example, Dowda et al. (2007) found that an increase in self-reported physical activity was predicted by an increase in family support in girls between age 13 and 17. Zook et al. (2014) reported similar results using objectively measured physical activity. In a small longitudinal study, Davison and Jago (2009) showed that parental support and peer support had a role in helping girls to maintain recommended level of physical activity between ages 9 and 15. As girls grew up, however, peer social support and parental logistic support appeared to become more important whereas parental modelling support started losing its influence. Using a large Canadian longitudinal study over a 3-year period, Lau et al. (2016) confirmed these trends. They found that adolescents perceived receiving less parental encouragement and instrumental support as they grew up. Their longitudinal model nevertheless indicates that an increase in encouragement and parental instrumental support is associated with an increase in moderate-to-vigorous physical activity. These results suggest that parental support might still be important during adolescence, although its prominence might gradually decrease over time.

Results relating to different forms and intensities of physical activity and social support are difficult to interpret given the diversity of physical activity and social support measures used. There is some indication that parental social support matters in particular for leisure-time and organised physical activity (Edwardson & Gorely 2010, Mendonça et al. 2014). Panter et al. (2010) found that parental encouragement was associated with active commuting in 9-10 years old in south-east England. Deforche (2010) also indicated that modelling support from family and social support from family and friends were positively associated with active transportation in Belgium.

Social support from friends

Overall measures of support indicate consistent positive associations between social support from friends and physical activity (Laird et al. 2016, Mendonça et al. 2014). A meta-analysis has estimated that effect sizes were similar in magnitude for parental and friendship sources of total social support in adolescent girls. This result was a surprise given that adolescents gradually spend more time with friends as they grow up. However, parents and friends are shown to provide different resources. In particular, encouragement and co-participation in activities appear to be the most salient aspects of support from friends (Maturo & Cunningham 2013).

In the aforementioned study by Davison and Jago (2009), results indicate a growing influence of peer social support on physical activity as adolescents grow up. Other longitudinal studies have confirmed the relevance of social support from friends. Lau et al. (2016) indicated that the number of physically active friends was a longitudinal predictor of physical activity in Canadian adolescents. Zook et al. (2014) also indicate a longitudinal association between physical activity and friends' overall support for physical activity in adolescent girls.

Beyond total physical activity, associations were observed for leisure-time and commuting physical activity and social support provided by friends (Mendonça et al. 2014). As for parental social support, too few studies were conducted in order to draw conclusions on the associations between aspects of peer social support and forms or types of physical activity.

2.4.4.4. Summary and limitations

Overall, there are consistent associations between social support and physical activity in young people. Both parents/family and friends appear to provide important resources for physical activity, as illustrated by consistent associations observed with total social support. Yet, the types of resources provided by parents/family and friends appear to differ, and the importance of social support from friends seems to gradually increase over time. Most of the literature has been cross-sectional to date, which provides little evidence on the extent to which change in social support can impact physical activity. Again, the majority of the literature comes from the US, although results appear to be consistent across high-income countries (Laird et al. 2016, Mendonça et al. 2014, Yao & Rhodes 2015). Whether these results hold in deprived and ethnic minority populations remains to be explored. More studies exploring the impact of social support on different types or forms of physical activity are needed.

2.5. Conclusions and research aims

This review of the literature has outlined a wealth of interesting research on the associations between features of the neighbourhood and home environments and physical activity. The focus of this thesis is on perceptions of the neighbourhood environment, ethnic density, social capital and social support and these have all been shown to be associated with forms of physical activity. However, the majority of the studies reviewed were cross-sectional, which reduces the ability to make causal inference about the associations observed, and limits understanding of *how* physical activity could vary over-time as a response to changes in exposure.

Another important limitation of the current literature is that the vast majority of studies were conducted on adults. It therefore remains essential to gain a better understanding of the determinants of physical activity in young people who are at higher risk of physical inactivity. Adolescence appears to be an important period of the life course on which to focus because it marks a transition during which life-long health behaviours, including physical activity, start forming (Papas et al. 2007). It is also a period during which adolescents gradually gain more independent mobility. As a result, adolescents' perceptions of their neighbourhood might become more important determinants of physical activity than those of their parents' and the role of parental social support might gradually become less prominent than that of friends. While some evidence exists on the associations between physical activity and social support, the three aspects of the local environment reviewed – perceptions of the neighbourhood, ethnic density and social capital – have been rarely studied in relation to physical activity in adolescents. Gaining a better understanding on how these factors affect physical activity might be valuable knowledge for designing health promotion interventions.

This review has also indicated that ethnic minorities and deprived populations are at risk of physical inactivity. These populations tend to be more exposed to unsupportive environments and the features of the neighbourhood and home environments might affect them more strongly. As for young people, the evidence base to date regarding deprived and ethnically diverse populations is even more limited. Even the better documented associations, such as those between social support and physical activity, give no indication as to whether the current findings equally apply to disadvantaged populations.

Despite the growing recognition that different features of the environment affect different domains or forms of physical activity (Sallis et al. 2006), few empirical studies have *systematically* investigated the associations between features of the neighbourhood and home environments and domains or forms of physical activity such as walking to school, walking for leisure and leisure sport activities. As a result, the current literature still lacks robust understanding of what specific aspects of physical activity are influenced by what aspects of the environment. Such information would be very valuable for health promotion policies.

Finally, the current literature on the neighbourhood and home environments and physical activity is mostly dominated by North American and Australian investigations. More research is needed in the UK in order to corroborate results obtained in other settings.

From a methodological point of view, the field of the determinants of physical activity seems to lag behind in terms of the adoption and understanding of advanced statistical methods. In particular, potential problems related to missing data have been overlooked in the literature. The common practice is still to drop cases with missing data without acknowledging the potential for bias caused by missing data and the decrease in precision of the model estimates that it implies. This contrasts with the growing statistical literature on methods to handle missing data and the recognition in the medical and epidemiological literature that missing data can no longer be ignored (Sterne et al. 2009).

This thesis will address these gaps. The overall aim of this thesis is to explore how features of the neighbourhood and home environments explain physical activity behaviours in a multi-ethnic and deprived adolescent population. Rather than relying on cross-sectional data this study will use longitudinal data from a cohort study conducted on adolescents in East London, known as the Olympic Regeneration in East London (ORiEL) study. Where possible, different hypotheses will be tested on the nature of the longitudinal associations between exposure and outcome variables. This thesis will account for missing data using multilevel multiple imputation and apply relevant statistical methods for longitudinal data. The dataset used will allow for differentiation between four forms of physical activity – walking to school, walking for leisure, outdoor physical activity and pay and play physical activity – and enable the exploration of associations between features of the environment and each form of physical activity. Where possible, the associations between the exposure and the outcome will be investigated by gender.

Specifically, the four aims of this thesis are as follows:

1. Investigate longitudinal associations between perceptions of the neighbourhood environment and three physical activity outcomes;
2. Explore the associations between ethnic density and three physical activity outcomes;
3. Investigate longitudinal associations between neighbourhood trust and four physical activity outcomes;
4. Investigate longitudinal associations between social support and four physical activity outcomes.

Before addressing these research aims and their associated research questions that are spelt out in each results chapter (chapters 5-8), it is necessary to describe the data and methods used in this thesis.

Chapter 3: Data

3.1. Introduction

In the previous chapter, I have reviewed the literature on the determinants of physical activity and have focused on four aspects of the neighbourhood and home environments – perceptions of the neighbourhood, ethnic density, social capital and social cohesion – which will be investigated in this thesis. This data chapter gives an overview of the Olympic Regeneration in East London (ORiEL) study, the data source for the analyses conducted in this thesis. A methods chapter (chapter 4) complements this data chapter and will present and justify the analytical methods used throughout this thesis to handle missing data and answer the research questions. In this chapter, I briefly describe the scope and design of ORiEL, define the four analytical samples used in this thesis, and give a brief overview of the extent of missing data in ORiEL. I also define the primary physical activity outcomes for the presented analyses, exposure variables, and define and justify the hypothesised confounders and moderators.

3.2. The ORiEL study

The ORiEL study is a prospective cohort study that aimed to assess the health impact of large-scale urban regeneration associated with the London 2012 Olympic and Paralympic Games on a cohort of young people and their families (Cummins et al. 2017, Smith et al. 2012). Data were collected from 3,106 adolescents at baseline across 25 schools in the boroughs of Newham (n=6), Tower Hamlets (n=7), Hackney (n=6) and Barking & Dagenham (n=6). The boroughs have highly ethnically diverse populations and higher levels of social, economic and environmental deprivation than the English and the London averages (McLennan et al. 2011, Office for National Statistics 2013a). Schools were selected using simple randomisation within each borough. The sample frame did not include special needs-schools and pupil referral units. Refusals were replaced by eligible schools within the same borough until a minimum of six schools per borough were recruited. Participants completed paper-based surveys in school settings at three time points. Baseline data were collected in 2012 (January to July) when the students were in Year 7 of secondary school (aged 11-12). Follow-up data were collected approximately 12 months (2013) and 24 months (2014) later[4]. Questionnaire items relevant to this thesis are provided in Appendix A.

Survey data entry was performed by an external agency with extensive experience in generating data files for longitudinal cohort studies. Variable names and coding structures were devised by the ORiEL research team and were implemented by the data entry contractor. Questionnaire data were double-punched and cleaned using range, consistency and logic checks. In a limited number of cases the data were manually cleaned by ORiEL research staff where it was unclear to the third party what the correct coding should be.

Participants were allocated a unique identifier to allow tracking cohort members across waves without directly identifying individuals. Adolescent and parent/carer names and addresses were stored separately from each other on encrypted USB drives. These were accessible by a single data custodian and were linked only temporarily by a unique identification number in order to produce lists of participants who were eligible for follow-up.

3.3. Defining the analytical samples

To account for differences in the research questions, methodological concerns, and availability of the variables, I defined a separate analytical sample for each set of analyses. A flowchart defining the analytical samples is presented in Figure 3.1.

In total, 9,423 adolescent interviews were conducted across three waves (W1 n=3,106; W2 n=3,228; W3 n=3,089). Of these 81 refused to co-operate during the interview or were reported to have 'cheated or chatted' (i.e. when fieldworkers identified instances of copying and/or talking about answers while administering questionnaires) resulting in the exclusion of these (semi-)completed questionnaires (W1 n=18 (0.6%); W2 n=15 (0.5%); W3 n=48 (1.6%)). The available sample is made of 3,088 adolescents at wave 1, 3,213 at wave 2 and 3,041 at wave 3.

Not all baseline participants participated in each of the three survey waves. Table 3.1 indicates that amongst the 3,088 adolescents present at baseline, 7% dropped out after wave 1, 14.4%

[4] The field work was fairly well distributed over 6 month periods, with 6 months of break between the waves. The average time lapse between repeated measurements on the same individual was about 1 year, but varied from person to person. The presence of extreme values for the time lapse indicates that the same adolescents were interviewed at different seasons at follow-up. At wave 2, 80% of adolescents were interviewed between 309 and 403 days after baseline (approximately 10-14 months). The same interval measured at wave 3 was slightly higher (315-462 days).

after wave 2, and 5.4% had intermittent missingness. The 3-wave balanced panel is therefore composed of 2,260 participants. Adolescents also joined the study at wave 2 (n=507) and at wave 3 (n=231), allowing to define a wave 2-3 panel. The analysis of the wave 2-3 panel (Table 3.2) shows that amongst the 2,767 adolescents present at wave 2, 4.5% did not take part to wave 3.

Table 3.1 Types of participation in the 3-wave ORiEL panel

Participation	**Freq.**	**Percent**
Wave 1 only	216	7.0
Wave 1, wave 2 only	446	14.4
Wave 1, wave 2, wave 3 (balanced panel)	2,260	73.2
Wave 1, wave 3 only	166	5.4
Total	3,088	100.0

Table 3.2 Types of participation in the wave 2-3 ORiEL panel

Participation	**Freq.**	**Percent**
Wave 2 only	123	4.5
Wave 2, wave 3 (balanced panel)	2,644	95.6
Total	2,767	100.0

In line with the first aim of this thesis to investigate longitudinal associations between perceptions of the neighbourhood environment and physical activity, I conducted preliminary baseline analyses of the 3-wave balanced panel (chapter 5), followed by longitudinal work (chapter 6). Therefore, chapter 5 uses the same balanced panel as in chapter 6, but restricts data analysed to wave 1 only. Chapter 6 investigates longitudinal associations for the whole ORiEL sample, using measures of exposure and outcome available at all three waves. Chapter 6 uses the 3-wave balanced panel (n=2,260).

The second aim is to explore the associations between ethnic density and physical activity outcomes. Information about ethnic density are obtained from secondary data external to the ORiEL study, which does not restrict the analytical sample of the analyses compared to the first aim (chapter 7). However, due to the interest in ethnic-specific associations between the exposure and outcome variables, analyses had to be restricted to the main ethnic groups, resulting in a balanced panel of 1,160 adolescents.

The third and fourth aims are addressed in chapter 8 which examines the extent of longitudinal associations between physical activity and both neighbourhood trust and social support. Neither neighbourhood trust, nor social support are available at baseline. Chapter 8 is therefore restricted to the waves 2-3 balanced panel (n=2,644). Results of chapter 8 are also reproduced using the 3-wave balanced panel (n=2,260) restricted to wave 2 and wave 3, to ensure that the change in the sample definition did not alter the results.

Figure 3.1 shows the definition of the samples used in this thesis. The potential impact of attrition on the validity of the analyses is discussed in section 4.2.2. of chapter 4[5]. The next section provides an overview of the extent of item missingness in the ORiEL study.

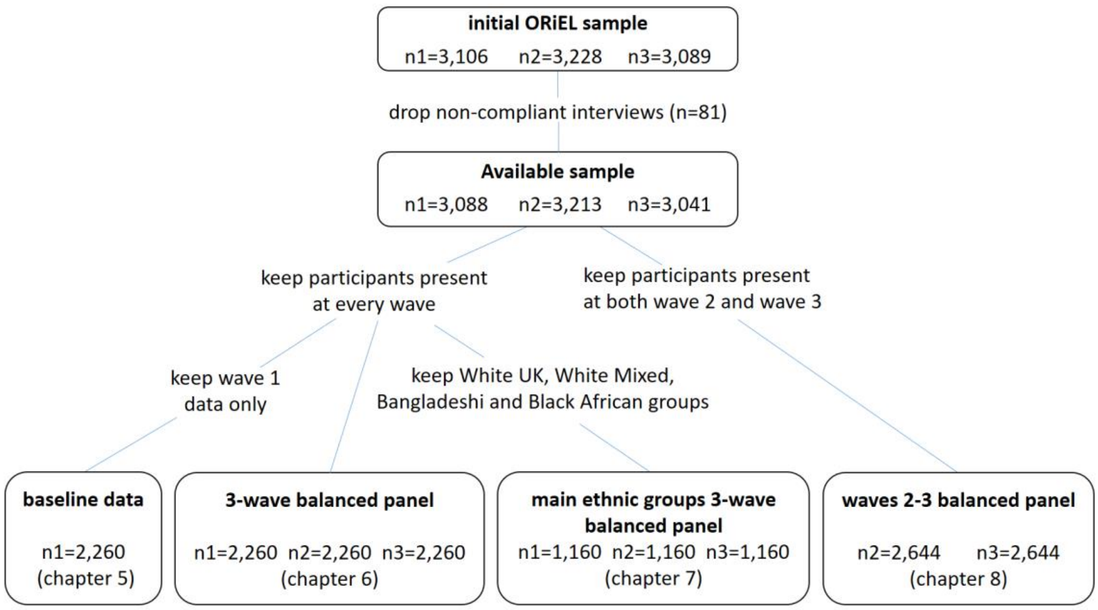

Figure 3.1 Flowchart of the definition of the analytical sample for each chapter of the thesis, based on the ORiEL study.

3.4. Extent of item missingness in the ORiEL study

In addition to attrition, item non-response (or item missingness) was present across the completed questionnaires. Full questionnaire completion at wave 1 was 50%, rising to 60% at wave 2, increasing further to 80% at wave 3. Reasons for non-completion include: unexpectedly short or interrupted questionnaire sessions; inclusion of lower ability groups;

[5] As explained more extensively in the methods chapter (section 4.2.2), the extent of bias due to attrition is not clear in the context of this thesis. ORiEL is an area-based study and the data do not allow for the determination of whether adolescents with attrition had left the study area, in which case, they might differ from the target population. Accounting for attrition in those adolescents might then generate bias, which is why unit-non response is not handled in this thesis and inference is restricted to adolescents who lived within the study area over the study period.

higher levels of special educational needs; and lower than anticipated levels of literacy or English language skills (Cummins et al. 2017).

Item non-response rates increased gradually over the questionnaire at each wave. The decrease was pronounced and continuous after the physical activity instrument (which was situated in the middle of the questionnaire), especially at wave 1 and wave 2. Questions on exposures were situated after the physical activity instrument, and were therefore more prone to item non-response. The main potential confounders were placed towards the beginning of the questionnaire.

For each specific longitudinal analysis conducted in this thesis the extent of item non-response is described in relevant results chapters (chapters 6-8). The potential impact of missingness on bias is also assessed and a general strategy to handle missing data is fully described in the methods chapter (section 4.2.3.).

Having provided a general introduction to the ORiEL study and the way it will be used in this thesis, I now turn to the description of the specific variables employed.

3.5. Variables and descriptive analysis

In this section, I describe the variables used in the main analyses of the thesis and how they were operationalised. I provide basic cross-sectional and longitudinal descriptive statistics, using complete cases from the baseline data and from the 3-wave balanced panel (see section 3.3.). Descriptive analyses were conducted using Stata versions 14 and 15 (StataCorp 2015, 2017).

Longitudinal descriptions include repeated cross-sectional information as well as statistics that depict within individual changes over time. For the main discrete variables I used the 'xttab' Stata command, which decomposes the descriptive statistics into 'overall', 'between' and 'within' categories (Rabe-Hesketh & Skrondal 2012). The overall category describes the data in terms of the total number of observations in the data, regardless of clustering at individual level. The 'between' category describes how different individuals vary from one another, whilst the 'within' category describes how individuals change over time. Table 3.3 offers a detailed interpretation of the descriptive statistics displayed by the 'xttab' Stata command.

Table 3.3 Interpretation of longitudinal descriptive statistics of discrete variables provided by the 'xttab' Stata command

variable	Overall Freq.	 Percent	'Between' individuals Freq.	 Percent	'Within' individual over time Percent
0	Total number with response '0'	Proportion of N response '0'	Number of individuals who *ever* responded '0'	Proportion of individuals who *ever* responded '0'	Conditional on an individual *ever* responding '0', proportion of his/her other obs. that are also '0'
1	Total number with response '1'	Proportion of N response '1'	Number of individuals who *ever* responded '1'	Proportion of individuals who *ever* responded '1'	Conditional on an individual *ever* responding '0', proportion of his/her other obs. that are also '0'
Total	Total number of observations (N)	100	≥ n (number of individuals)	≥ 100	Normalized between-weighted average of the 'within percents' (summarises the stability of the variable)

3.5.1. Outcome variables

Physical activity was measured using the self-administered Youth Physical Activity Questionnaire (Y-PAQ), an instrument developed and validated by the MRC Epidemiology Unit in Cambridge (Corder et al. 2009). The questionnaire assesses the accumulated time spent both physically active and in sedentary behaviours over the previous seven days, using detailed questions on the type of activity. The questionnaire was designed to compute the total time (in minutes) spent on activities over the past week. Whereas objective measures using accelerometers and GPS are more precise and avoid recall bias, they are difficult to implement in large studies and they do not (yet) support the classification of particular activities, which is one of the strengths of the Y-PAQ. Unfortunately, a limitation of the Y-PAQ is that it uses ordinal response categories (i.e. didn't do/ once / 2-3 times / 4 or more times) which prohibits computing the number of days a participant took part in an activity.

Six measures of physical activity were constructed to assess the associations with the various aspects of the neighbourhood and home environments studied in this thesis. In addition to general measures of total and daily recommended physical activity, I took advantage of the detail of the Y-PAQ questionnaire to calculate indicators of four forms of physical activity, which are expected to be differentially associated with the exposure variables. These are walking to school, walking for leisure, outdoor physical activity, and 'pay and play' physical activity. The latter two indicators are composite measures that respectively capture activities usually performed outdoor in the neighbourhood, and more structured activities usually conducted in dedicated sport or leisure centres often incurring an access fee. Owing to their non-normal distributions and to the fact that no adequate transformation could be found, the four variables measuring forms of physical activity were used as binary outcomes throughout the thesis (e.g. activity reported at least once vs. not).

Other discrete physical activity variables were also considered but could not be studied on their own, owing to their low prevalence (especially at follow-up). For example, given the availability of neighbourhood perceptions related to cycling, I originally envisaged using cycling as an outcome. Unfortunately, only 8.6% reported cycling to school at baseline, and 4.3% at wave 3, while girls almost never reported cycling to school. Conventional estimation methods such as logistic regression models suffer from bias with rare events (King & Zeng 2001). In this case, the general rule of thumb that 10 events are needed per variable in logistic regression models for valid inference would not be achieved in fully adjusted models (Vittinghoff & McCulloch 2007)[6]. The six measures of physical activity used in the thesis are described in turn.

3.5.1.1. Total Physical activity

Following the Y-PAQ guidelines (Corder et al. 2009), the total time spent in physical activity during the week preceding the interview was calculated. The variable 'total physical activity' includes the time spent physically active in recreational games and sports outside of school as well as travel to school i.e. walking, cycling or travel by car/bus[7].

At each wave, the total physical activity variable has a non-normal distribution. This would likely cause a violation of the normality assumption of the error terms if conventional models for continuous variables were used. To overcome potential problems, a log-transformation (natural log) of the variable is used for the analyses. A small scaling value is added to all observations to avoid missing values for the log of 0 minutes of physical activity. The distribution of the variable is approximately log-normal (i.e. approximately normal on the log

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[6] Note that cycling for leisure was not included in the Y-PAQ questionnaire.
[7] The questionnaire does not differentiate travel by car from bus and both travel times are considered as physical activity in the Y-PAQ guidelines.

scale) although it has a kurtosis value above 3 (kurtosis=4.9 at baseline) and a normal probability plot slightly deviant in small and large values (Figure 3.2). Linear models on the log scale give geometric means as opposed to arithmetic means, which slightly changes the interpretation of the parameters. When the variable is log-normal, the geometric mean equals the median, which eases interpretation.

Note that the log-transformation reduces the impact of participants who reported unrealistic physical activity time (i.e. those reporting more than 75 hours of activity (including sedentary activities)). The transformation therefore allows outlying participants to be retained, while effectively considering them as simply having a high level of physical activity.

At baseline, the median total physical activity was 15.8 hours. It decreased to 13.9 hours at wave 2 and 11.5 hours at wave 3. Figure 3.3 shows the general decrease in log of total physical activity over time (thick dashed line), and further indicates an overall shift in the distribution towards lower values. There are nevertheless substantial individual variations around those means, as illustrated by twelve randomly selected trajectories (thin solid lines): some adolescents' total physical activity values remained constant, some decreased, other increased and other were more volatile. Some individuals also remain systematically higher than others despite the diversity of patterns evident.

At baseline, reported total physical activity was higher in boys (median=17.1 in boys and 13.6 in girls); higher amongst the Indian, White Mixed, and Black African groups compared to other ethnic groups (median=18.8, 17.5 and 17.4 respectively); and higher in more affluent adolescents (median=11.6, 15.0 and 18.9 respectively for low, moderate and high family affluence). School-level correlation implied by the study design is low: intra-class correlation is estimated to be 0.091 at wave 1; 0.016 at wave 2; and 0.011 at wave 3[8].

3.5.1.2. Daily recommended physical activity

An alternative measure to the log of total physical activity was also created. Time spent physically active was categorised as either 'active' or 'inactive' based on whether adolescents met the current recommendation of 60 minutes physical activity per day (Chief Medical Office 2011, World Health Organization 2010).

[8] Intra class-correlation estimated using a random effect linear model.

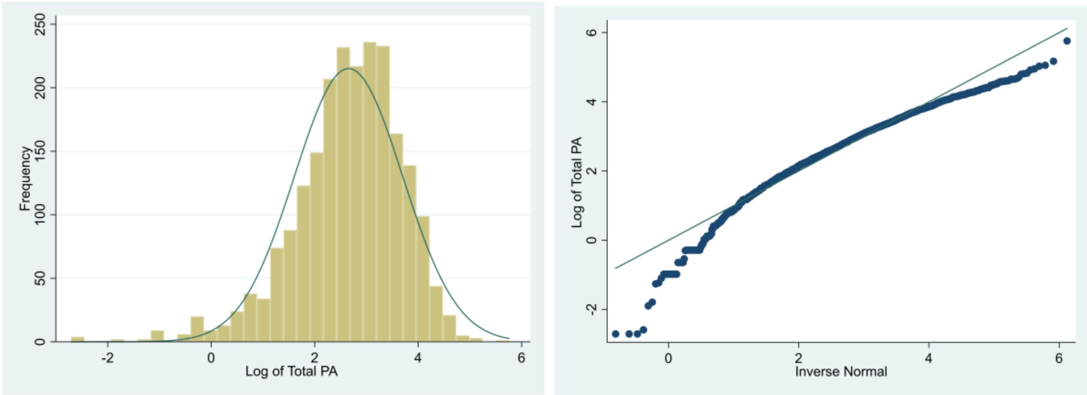

Figure 3.2 Distribution of the log of total physical activity at baseline (left) and standardised normal probability plot of the variable (right)

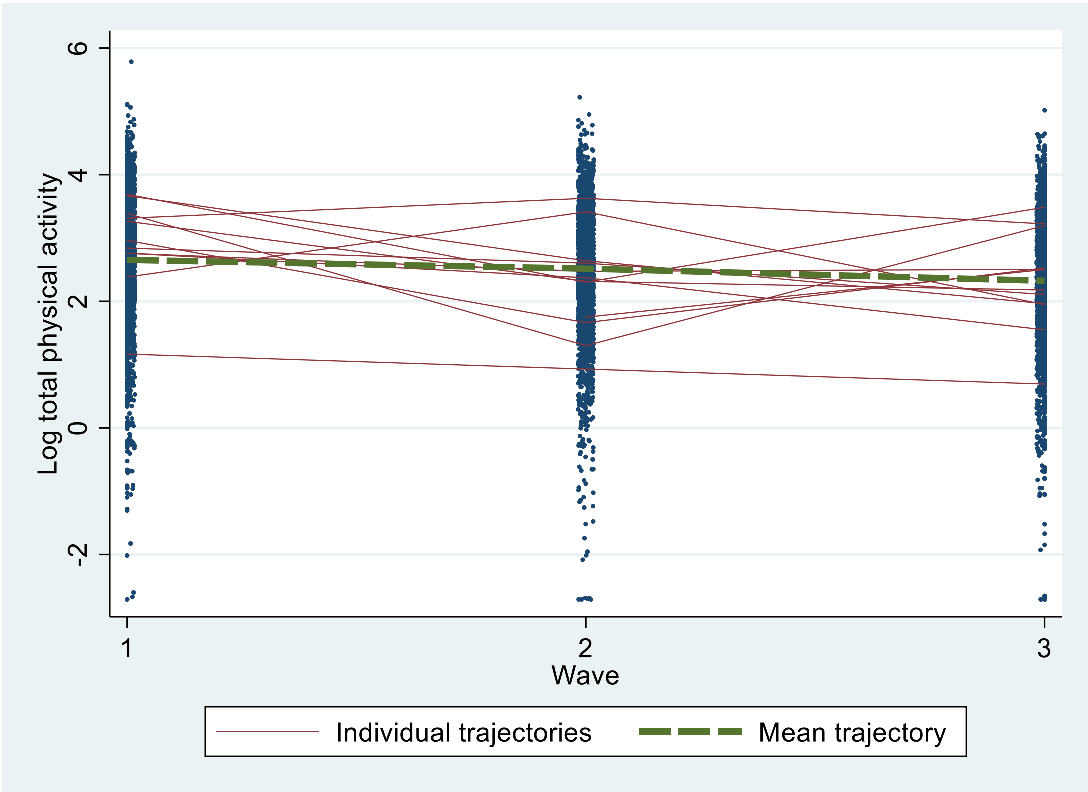

Figure 3.3 Scatterplot of the log of total physical activity versus occasions ; individual trajectories for 12 randomly chosen adolescents (thin solid lines) and mean trajectory (thick dashed line).

Adolescents reporting less than 7 hours of physical activity weekly (outside of school) were recoded as 'did not meet recommendations', andthose reporting 7 hours or more were recoded as 'met recommendations'. As with the use of logarithms, this recoding also retains adolescents with unrealistically high values of physical activity, treating them as 'met recommendations'.

Over one-fifth (20.1%) of the sample reported not meeting physical activity recommendations at baseline and this increased at each subsequent wave (wave 2=24.5%; wave 3=31.0%).

Patterns of associations with socio-demographic variables are similar to those of total physical activity.

3.5.1.3. Walking to school

Walking to school was reported in the Y-PAQ, and the total walking time to school was computed. Owing to its peculiar distribution (Figure 3.4), the continuous form of the variable could not be used for modelling purposes. I therefore created a binary variable, distinguishing those who reported at least some walking to school from those who did not. The use of the intrinsic dichotomy 'participation vs. not' was preferred over the use of arbitrary cut-off(s). The binary variable has a clear interpretation in terms of how the neighbourhood and home environments might affect the decision to participate in a form of physical activity.

In addition, I created a measure of within individual change in the binary walking to school variable between wave 2 and wave 3 (chapter 8). This results in ordinal variables with 3 responses categories (0= stopped reporting walking to school at wave 3; 1= no change; 2= started reporting walking to school at wave 3).

22.1% of the sample did not report walking to school at least once at baseline and this slightly increased at each subsequent wave (wave 2=23.2%; wave 3=23.7%). At baseline, no gender differences were observed. The Indian and Bangladeshi groups reported the highest prevalence of walking, and the Black Caribbean participants the lowest. Detailed description of associations between socio-demographic variables and walking to school are presented in section 6.4.2.1. of chapter 6 and section 8.4.2.1. of chapter 8.

Table 3.4 describes the longitudinal distribution of the binary walking to school variable across the dataset, using the complete cases in the 3-wave balanced panel. Overall, walking to school was reported in 77.0% of measurement occasions. 89.4% of adolescents reported walking to school at least once during their participation in the survey. The 'within' column describes the fraction of time an individual has reported walking to school or not. Conditional on an individual having reported walking to school at least once, 85.3% of their other responses in other waves were also likely to be similar.

3.5.1.4. Walking for leisure

The information provided by the Y-PAQ on walking for leisure combines walking for exercise and/or walking the dog. As with walking to school, I used a binary outcome variable (walked at least once vs. not) due to the distribution of variable (not presented).

Table 3.4 Longitudinal descriptive analysis of walking to school (n=2,260)

Walking to school	**Overall**		**Between**		**Within**
	Freq.	**Percent**	**Freq.**	**Percent**	**Percent**
never	1483	23.0	873	38.6	61.4
1+	4963	77.0	2021	89.4	85.3
Total	6446	100.0	2894	128.0	78.1

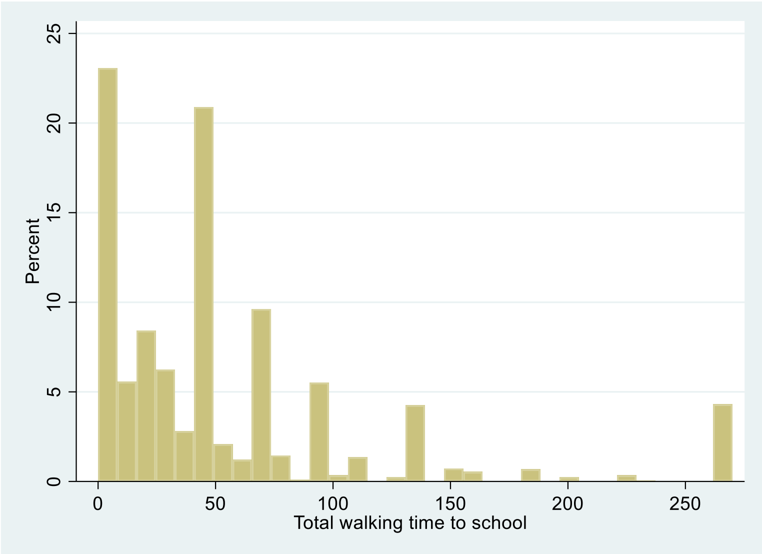

Figure 3.4 Distribution of total walking time to school at baseline (in minutes)

I also created a measure of within individual change in walking for leisure between wave 2 and wave 3 (cf. chapter 8). This results in ordinal variables with three responses categories (0=stopped reporting walking for leisure at wave 3; 1=no change; 2=started reporting walking for leisure at wave 3).

59.1% of the sample did not report walking for leisure at least once at baseline and this increased by five percentage points at each subsequent wave (wave 2=65.2%; wave 3=70.0%). At baseline, girls were more likely to report walking for leisure than boys (respectively 47.1% and 36.1%); and, the prevalence of walking for leisure was highest in the White UK and White mixed groups (respectively 52.7% and 50.7%) compared to other ethnic groups. Associations with other socio-demographic variables are presented in section 6.4.2.2. of chapter 6 and section 8.4.2.2. of chapter 8.

Table 3.5 describes the longitudinal distribution of the binary walking for leisure variable across the dataset, using the complete cases of the 3-wave balanced panel. Overall, walking for leisure was reported in 35.0% of measurement occasions. 57.6% of adolescents reported walking for leisure at least once during their participation in the survey. The 'within' column describes the fraction of time an individual has reported walking for leisure or not. Conditional on an individual having reported walking for leisure at least once, 59.5% of their other responses in other waves were also likely to be similar.

Table 3.5 Longitudinal descriptive analysis of walking for leisure (n=2,252)

Walking for leisure	Overall		Between		Within
	Freq.	**Percent**	**Freq.**	**Percent**	**Percent**
never	3967	65.0	1950	86.6	75.9
1+	2135	35.0	1297	57.6	59.5
Total	6102	100.0	3247	144.2	69.4

3.5.1.5. Outdoor physical activity

Because it was not possible to study each activity separately (in part due to low prevalence), I created two summary scores to reflect forms of physical activity that are hypothesised to be affected by exposure to the neighbourhood and home environments. The first of the composite variables is outdoor physical activity. The variable aims to group physical activities that are mainly performed in open recreation areas such as parks, sport fields and other open spaces, which are usually located in the residential neighbourhood of the adolescents (D'Haese et al. 2015, Esteban-Cornejo et al. 2016). Outdoor physical activity combines basketball/volleyball (with the expectation that basketball is mainly reported in an outdoor court), blading, cricket, football, rounders, rugby and roller skating (7 variables). Running was not included due to its over-reporting which reflects that the activity was likely to be understood as 'running around' by adolescents and could therefore be part of any sport activity.

I created two variables for outdoor physical activity: i) the total time spent in outdoor physical activity; and ii) a binary outdoor physical activity variable, similar to the one used for walking outcomes (i.e. participation in at least one of the seven activities vs. none). Again, the continuous variable has a non-normal distribution which could not be transformed to a known distribution. This arose from the fact that many adolescents reported none of the activities, which resulted in a peak in the distribution at 0 hours (not presented). The logarithmic transformation of the variable (to which a small scaling value is added to avoid missing values at log 0) did not lead to a normal distribution, as indicated by Figure 3.5. To account for this boundary at zero, econometric models such as hurdle models were considered (Wooldridge 2010). However, the distributional restrictions imposed for the handling of missing data (see section 4.3.3.2. of chapter 4) restrict the usefulness of such models in the longitudinal analyses of the thesis. Analyses reported are therefore limited to the binary outdoor physical activity variable.

In addition, I created a measure of within individual change in the binary outdoor physical activity variable between wave 2 and wave 3 (cf. chapter 8). This results in ordinal variables with 3 response categories (0= stopped reporting outdoor physical activity at wave 3; 1= no change; 2= started reporting outdoor physical activity at wave 3).

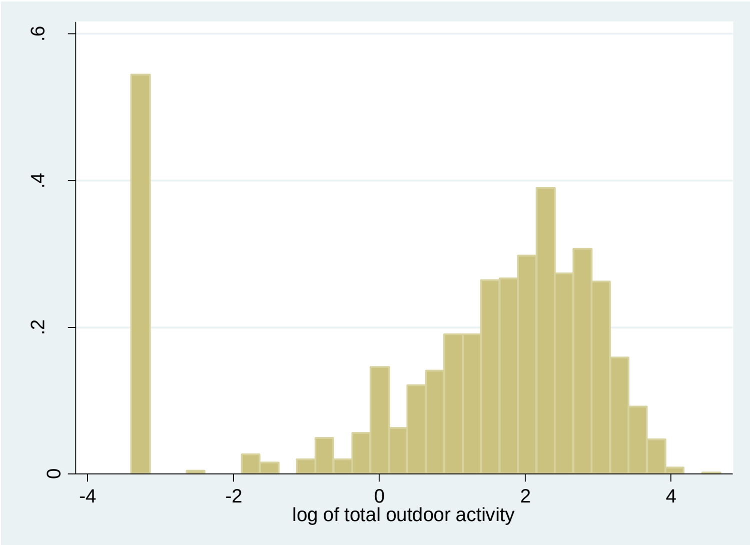

Figure 3.5 Distribution of the log of total outdoor physical activity at baseline

80.1% of the sample reported participating in outdoor physical activity at least once at baseline, but this decreased by five percentage points at each subsequent wave (wave 2=75.8%; wave 3=69.7%). At baseline, boys were much more likely to report outdoor physical activity than girls (respectively 88.6% and 69.0%); and the prevalence of outdoor physical activity was lowest in the Black Caribbean, White UK and Bangladeshi groups (respectively 72.9%, 76.8% and 77.5%). Associations with other socio-demographic variables are presented in section 6.4.2.3. of chapter 6 and section 8.4.2.3. of chapter 8.

Table 3.6 Longitudinal descriptive analysis of outdoor physical activity (n=2,240)

Outdoor physical activity	Overall		Between		Within
	Freq.	Percent	Freq.	Percent	Percent
never	1453	25.1	903	40.3	61.0
1+	4345	74.9	2009	89.7	84.1
Total	5798	100.0	2912	130.0	76.9

Table 3.6 describes the longitudinal distribution of outdoor physical activity binary variable across the dataset, using the complete cases of the 3-wave balanced panel. Overall, outdoor physical activity was reported in 75.9% of measurement occasions. 89.7% of adolescents reported outdoor physical activity at least once during their participation in the survey. The 'within' column describes the fraction of time an individual has reported outdoor physical activity or not. Conditional on an individual having reported outdoor physical activity at least once, 84.1% of their other responses in other waves were also likely to be similar.

3.5.1.6. Pay and play physical activity

The other composite measure used was labelled 'pay and play physical activity'. This variable attempts to capture scheduled formal physical activity, usually performed in sport or leisure centres and for which adolescents might need to pay in order to participate. Pay and play physical activity combines aerobics, climbing, swimming, gymnastics, hockey, martial arts, netball, and tennis. A binary variable was created to measure whether adolescents reported participating in at least one activity vs. not at all. As with outdoor physical activity, the continuous variable capturing the total time spent on pay and play activities could not be used, owing to its non-normal distribution and to the fact that no adequate transformation could be found (not presented). I also created a measure of change in pay and play physical activity between wave 2 and wave 3 (cf. chapter 8). This results in ordinal variables with 3 response categories (0= stopped reporting pay and play physical activity at wave 3; 1= no change; 2= started reporting pay and play physical activity at wave 3).

73.2% of the sample reported participating in pay and play physical activity at least once at baseline and this decreased by approximately ten percentage points at each subsequent wave (wave 2=64.2%; wave 3=51.2%). At baseline, boys and girls reported pay and play physical activity equally (respectively 72.7% and 73.8%); while the prevalence of pay and play physical activity was lower in the Bangladeshi and White UK groups (respectively 65.0% and 71.1%) compared to other ethnic groups. Associations with other socio-demographic variables are presented in section 8.4.2.4. of chapter 8.

Table 3.7 describes the longitudinal distribution of the pay and play binary variable across the dataset, using the complete cases of the 3-wave balanced panel. Overall, pay and play physical activity was reported in 62.4% of measurement occasions. 85.0% of adolescents reported pay and play physical activity at least once during their participation in the survey. The 'within' column describes the fraction of time an individual has reported pay and play physical activity or not. Conditional on an individual having reported pay and play physical activity at least once, 73.8% of their other responses in other waves were also likely to be similar.

Table 3.7 Longitudinal descriptive analysis of pay and play physical activity (n=2,243)

Pay and play physical activity	Overall		Between		Within
	Freq.	**Percent**	**Freq.**	**Percent**	**Percent**
never	2231	37.6	1376	61.4	60.7
1+	3695	62.4	1907	85.0	73.8
Total	5926	100.0	3283	146.4	68.3

3.5.2. Exposure variables

To answer the research questions, I used four sets of exposure variables, each capturing different aspects of the neighbourhood and home environments. These are perceptions of the neighbourhood environment (chapters 5 and 6), own-group ethnic density (chapter 7), neighbourhood trust (chapter 8), and social support (chapter 8). The items on perceptions of the neighbourhood environment are presented in more detail because there is no established procedure for selecting relevant survey items and combining them into meaningful measures.

3.5.2.1. Perceptions of the neighbourhood environment

Adolescents were asked questions related to perceptions of their local environment on selected domains, using an adapted, age-appropriate version of the ALPHA (Assessing Levels of Physical Activity and Fitness) questionnaire (Spittaels et al. 2010). The ALPHA questionnaire has been used in multiple European countries and its validity and reliability assessed in European adult populations (Adams et al. 2013, Bucksch & Spittaels 2011, Eichinger et al. 2015, Spittaels et al. 2010). The adult version of the questionnaire was adapted by the ORiEL research team to make it relevant to adolescents (i.e. the item regarding pubs and bars was removed). As a result of piloting, the wording of some of the questions was changed to improve adolescent comprehension (i.e. the word “pleasant” was replaced by “nice”). A comparable locally adapted adolescent-specific version of the ALPHA questionnaire was shown to have good reliability elsewhere (Garcia-Cervantes et al. 2014). The dimensions of perceptions of the neighbourhood environment captured by the ALPHA questions used in the ORiEL study (including proximity, crime-related safety, traffic-related safety, and aesthetics) are in line with those used in other instruments measuring perceptions of the neighbourhood environment in young people, such as the adolescent version of the NEWS questionnaire (Rosenberg et al. 2009). The local environment was defined as an area within a 15 minute walk from his/her house and most of the questions were specifically targeting walking and cycling behaviours. I used statements about perceptions of traffic safety, aesthetics and street connectivity that were rated by adolescents on a four-point scale (strongly agree; slightly agree; slightly disagree; strongly disagree). I also used variables on reported distance from eight types of facilities and services, and three questions on crime-related safety, which originate from the Multi-Ethnic Study of Atherosclerosis (MESA) study (Mujahid et al. 2007). The MESA questions were preferred over the ALPHA questions on crime-related safety because the MESA instrument was shown to be associated with some physical activity and BMI outcomes (Evenson et al. 2012, Powell-Wiley et al. 2017). The MESA instrument also includes an item which is the best proxy available for fear of crime, which is expected to be associated with physical activity (Foster et al. 2014a). The items are described in Table 3.8 and their baseline distribution is provided in Table 3.9.

I created summary scores to capture separate aspects of neighbourhood perceptions, namely proximity, traffic safety, street connectivity, aesthetics and crime-related safety. I summed numeric values (i.e. ‘strongly disagree’=1; ‘slightly disagree’=2; etc.) taken by items belonging to the same underlying construct and divided by the number of items[9]. To test the reliability of the scores (i.e. whether the summary scores comprise items capturing the same underlying construct), I fitted confirmatory factor analysis models using the pooled 3-waves balanced data. Results summarised in Appendix B indicate that the selected items of Table 3.8 appropriately capture dimensions of proximity, traffic safety, street connectivity, aesthetics and crime-related safety. Some items of the original questionnaire (not presented in Table 3.8) had to be excluded because they captured different latent dimensions (i.e. the items on ‘hilly roads’ and ‘badly maintained buildings’ captured aspects of perceptions not related to the above dimensions). Results from the confirmatory factor analysis also indicate that the crime-related safety items of the MESA and ALPHA questionnaires capture different dimensions, which justifies the choice to use one of the instruments (MESA items) and not to combine them.

[9] From a statistical perspective, a more appropriate approach would have been to formulate measurement models assuming that observed items are the combination of underlying latent constructs and some measurement error (Bollen 1989). This approach was not deemed possible given the restriction on the number of variables imposed by the approach used to handle missing data (cf. section 4.3.3.2 of chapter 4). The use of summary scores has the disadvantage of ignoring measurement error, and therefore it underestimates the strength of associations.

Table 3.8 Selected perceptions of the neighbourhood environment from the ORiEL study

Attribute	Survey item	Response scale
Proximity to destinations (perceived access to nearest)	Local shop	5-point scale (1-5 / 6-10 / 11-20 / 21-30/ 30+ mins)
	Supermarket	same as above
	Local services such as bank, post office or library	same as above
	Fast food restaurant or takeaway	same as above
	Bus stop	same as above
	Tram, tube or train station	same as above
	Sport and leisure facility. e.g. swimming pool, fitness centre, gym	same as above
	Open recreation area. e.g. park, sports field or other open space	same as above
Perceived traffic safety	There are not enough safe places to cross busy streets in my neighbourhood	4-point Likert scale (strongly disagree/ slightly disagree/ slightly agree/ strongly agree)
	Walking is unsafe because of the traffic in my neighbourhood	same as above
	Cycling is unsafe because of the traffic in my neighbourhood	same as above
Perceived street connectivity	There are many shortcuts for walking in my neighbourhood	same as above
	Cycling is quicker than driving in my neighbourhood during the day	same as above
	There are many road junctions in my neighbourhood	same as above
	There are so many different routes that I don’t have to go the same way every time	same as above
Perceived aesthetics	My local neighbourhood is a nice environment for walking or cycling	same as above
	My neighbourhood is generally free from litter or graffiti	same as above
	There are trees along streets in my neighbourhood	same as above
Perceived crime-related safety (MESA)	I feel safe walking in my neighbourhood, day or night	5-point Likert scale (strongly disagree/ slightly disagree/ neither agree nor disagree/ slightly agree/ strongly agree)
	My neighbourhood is safe from crime	same as above
	Violence is not a problem in my neighbourhood	same as above

Table 3.9 Baseline distribution of selected measures of neighbourhood perceptions from the ORiEL questionnaire

Perceived proximity to	*1-5min*	*6-10 min*	*11-20 min*	*21-30 min*	*>30 min*	n
local shop	78.2	15.9	4.0	0.8	1.2	2,517
supermarket	23.8	37.4	24.6	8.7	5.5	2,466
local services	24.6	36.9	25.6	9.1	3.8	2,442
restaurant	36.5	29.4	19.6	8.8	5.7	2,461
bus stop	75.4	17.8	4.6	1.4	0.8	2,450
other public transport	22.9	31.9	26.7	11.1	7.4	2,395
sport and leisure facility	12.1	22.4	30.9	19.8	14.7	2,404
open recreation area	51.9	26.7	13.0	4.2	4.2	2,431
Perceived traffic safety	*strongly disagree*	*slightly disagree*	*slightly agree*	*strongly agree*		
not enough safe places to cross busy streets	42.7	29.0	18.5	9.7		2,364
walking is unsafe because of traffic	56.2	24.5	12.7	6.5		2,360
cycling is unsafe because of traffic	51.5	27.3	14.2	7.1		2,351
Perceived street connectivity	*strongly disagree*	*slightly disagree*	*slightly agree*	*strongly agree*		
many shortcuts for walking	10.1	13.9	37.7	38.2		2,259
cycling is quicker than driving during the day	26.3	30.5	24.9	18.2		2,204
many road junctions	24.7	31.6	30.1	13.6		2,146
Perceived aesthetics	*strongly disagree*	*slightly disagree*	*slightly agree*	*strongly agree*		
enjoyment of the neighbourhood for walking and cycling	9.4	15.6	33.9	41.2		2,330
generally free from litter or graffiti	20.1	29.2	29.3	21.4		2,308
trees along the streets	12.9	11.4	26.67	49.1		2,300
many different routes	16.2	22.7	34.6	26.4		2,178
Perceived crime-related safety (MESA)	*strongly disagree*	*slightly disagree*	*neither agree nor disagree*	*slightly agree*	*strongly agree*	
feel safe walking	11.3	16.8	22.9	23.6	25.4	2,189
violence is not a problem	18.1	22.4	19.9	18.4	21.2	2,169
safe from crime	16.0	24.8	19.2	18.3	21.6	2,171

Following Adams et al (2013), I used the summary scores as ordinal variables differentiating three types of perceptions: low support, medium support and high support of the environment. Apart from 'proximity', the same cut-off values are used across the summary scores and roughly correspond to the baseline tertiles (see Table 3.10 for cut-off definitions).

Complete case analysis of the 3-wave balanced panel indicates little cross-sectional change in perceptions of the neighbourhood over time. Perceived proximity was the only variable to display clear signs of change over time: high perception of proximity of destinations gradually increased over time (the prevalence of high proximity was 45.9%, 54.0% and 58.9% at waves 1, 2 and 3 respectively), whereas low perceived proximity gradually decreased. Conversely, there was a slight decrease in the perception of high aesthetics (wave 1=41.0%; wave 2=36.0%; wave 3=35.6%).

Table 3.10 Cut-off values for neighbourhood perceptions scores

Dimension	**Range of mean score**	**Low support**	**Medium support**	**High support**
Proximity	1-5	[3;5] (i.e. mean score ≥ 11-20 mins)	[2;3[(i.e. 11-20 mins > mean score ≥ 6-10 mins)	[1;2[(i.e. mean score< 6-10 mins)
Traffic safety	1-4	[1;2]	]2;3]	]3;4]
Street connectivity	1-4	[1;2]	]2;3]	]3;4]
Aesthetics	1-4	[1;2]	]2;3]	]3;4]
Crime-related safety (MESA)	1-5	[1;2.33]	[2.34;3.66]	[3.67;5]

The distributions of traffic-related safety, street connectivity, and crime-related safety were virtually constant over time. Despite the stability in the overall distributions, important within individual changes were observed. Longitudinal descriptive statistics for traffic-related safety (Table 3.11) and street connectivity (Table 3.12) are described to illustrate the extent of within individual changes. Longitudinal descriptive statistics of proximity, aesthetics and crime-related safety are similar and therefore only presented in Appendix B (Table B.2, Table B.3 and Table B.4).

Table 3.11 Longitudinal descriptive analysis of perceived traffic-related safety (n=2,244)

Perceived traffic-related safety	Overall		Between		Within
	Freq.	**Percent**	**Freq.**	**Percent**	**Percent**
Low	599	10.2	493	22.0	46.4
Medium	1970	33.6	1358	60.5	56.2
High	3300	56.2	1772	79.0	70.6
Total	5869	100.0	3623	161.5	61.9

Table 3.11 describes the distribution of perceived traffic-related safety across the sample. 10.2% of the total 5,869 responses over the three waves had low perception of traffic-related safety, and 56.2% had high perception. 22.0% of the respondents in the study reported low perception of traffic-related safety in at least one wave. Low perception of traffic-related safety was the least stable category: for those who reported low perception at least once, only 46.4% of their other responses were also low perception. Conversely, high perception of traffic-related safety was reported by 79.0% of the participants in at least one wave. High perception of traffic-related safety was the most stable category: 70.6% of those who reported high perception at least once, also reported so in other waves. Medium perception of traffic-related safety had intermediate values of both frequency of reporting and stability (60.5% and 56.2% respectively).

As shown in Table 3.12, 20.4% of participants reported low perceived street connectivity, over the three waves. Low perceived street connectivity was reported by 37.5% of the respondents in at least one wave of the survey. For this group, 54.2% of responses were also classified in the same low perception category. Patterns for the high perception category of street connectivity were almost identical (overall, between, and within values are respectively 21.8%, 38.8% and 55.7%). Medium perceived street connectivity was reported 57.9% of the time and reported at least once by 82.6% of participants. It was also the most stable category: for those who reported medium perceived street connectivity at least once, 70.3% of their other responses were also medium.

Table 3.12 Longitudinal descriptive analysis of perceived street connectivity (n=2,224)

Perceived street connectivity	Overall		Between		Within
	Freq.	**Percent**	**Freq.**	**Percent**	**Percent**
Low	1121	20.4	835	37.5	54.2
Medium	3186	57.9	1836	82.6	70.3
High	1198	21.8	863	38.8	55.7
Total	5505	100.0	3534	158.9	62.9

At baseline, few gender differences were observed across neighbourhood perceptions variables. Girls had a slightly lower chance of reporting low aesthetics and street connectivity than boys (respectively 13.6% vs. 16.7% and 19.0% vs. 24.3%) and a slightly higher chance of reporting low perception of traffic-related and crime-related safety (respectively 11.5% vs. 9.7% and 31.4% vs. 29.2%). There were also few ethnic differences. The most noticeable difference was that the Black African and Pakistani groups reported worse perceptions of proximity to destinations than other groups.

Most of the analyses of chapters 5 and 6 use the ordinal scores to capture perceptions of the neighbourhood. Some of the individual items, in particular bus stop proximity, enjoyment of the neighbourhood for walking/cycling and personal safety ('I feel safe') are also used because they are expected to better capture the associations with some of the physical activity outcomes.

In addition, longitudinal-specific exposure variables were created to answer questions about the nature of the relationships between perceptions of the environment and physical activity. Exposure variables were derived to capture cumulative perceptions of the neighbourhood and trajectory of perceptions of the neighbourhood.

Cumulative perception of the neighbourhood

Cumulative exposure scores are created using the numeric values to which each response category is coded in the ordinal scores (e.g. 'strongly disagree'=1, 'slightly disagree'=2 , …, 'strongly agree'=5). For each adolescent a total score is calculated as the sum of the values across the three waves. Given that the ordinal scores are coded as numeric, the derived cumulative scores assume equivalent qualitative differences between any two successive categories (e.g. a difference between strongly disagree and disagree receives equal weight as a difference between agree and strongly agree). The cumulative scores also assume that the weight of exposure is equivalent at each wave. Variables were all initially recoded so that high scores reflect an overall good perception of the neighbourhood environment during the study period.

Trajectory of perceptions of the neighbourhood

The same numeric values of the ordinal scores are used to compute the difference between wave 3 values and baseline. The trajectory scores measure changes since baseline on a continuous scale so that a value of 1 (or 2, 3, etc.) represents improvement of perception by 1 category (or 2, 3 etc. categories) between the baseline and wave 3. Negative values represent decreases in perceptions. Trajectory scores also assume equivalence of change between response categories.

3.5.2.2. Own-group ethnic density

Own-group ethnic density measures were used as the key exposure variables of interest in the analyses presented in chapter 6. Own-group ethnic density (referred to as ethnic density in what follows) is defined as the percentage of individuals in a certain geographical or social context who are of the same ethnic group as the participant. Two distinct measures were computed: ethnic density at school and ethnic density in the neighbourhood.

School-level own-group ethnic density

To compute ethnic density at school-level, I combined ORiEL self-reported ethnicity information (see section 3.5.3.2.) with ethnicity statistics from the Department for Education. School-level data on the number of pupils by ethnic group are publicly available and annually published online. Data were downloaded for the 3 years during which the survey took place (Department for Education 2012, 2013, 2014) and recoded to match the 8-category ethnicity variable of the ORiEL study, i.e. White UK, White Mixed, Indian, Pakistani, Bangladeshi, Black African, Black Caribbean and Other. For each of the participating schools, I calculated the prevalence of each ethnic group in 2012, 2013 and 2014.

The school-level distribution of ethnicity only marginally changed over the 3-year period. Mean changes were below 1 percent (with SD below 2.5 points) for all ethnic group except the White UK and White Mixed groups, for which average changes of 2.9 points and -1.4 points were observed between 2012 and 2014, respectively (SD were 3.7 and 1.7 and highest absolute changes were 12.6 and 3.7, respectively). Given the few changes observed in the distributions over time, I averaged the ethnicity prevalence values over the three years of measurements in each school. I then created the measure of school-level ethnic density by assigning to each participant the mean prevalence of his/her own ethnic group in his/her school. As a sensitivity analysis, I also calculated ethnic density in 2012 and 2014. The variables were highly correlated (Pearson r=0.981), the mean change over time was -0.3 and few adolescents had changes in ethnic density values greater than 5 percent (5th percentile=7.90; 95th percentile=6.40). I therefore restricted the analysis to the average ethnic density during 2012-2014. Five adolescents for the study sample changed school to another school of the study during the study period. These were assigned their baseline school ethnic density value, so that the school-level ethnic density variable would remain time-invariant[10]. The variable was treated as a continuous variable in the analyses, in the absence of established cut-off values in the literature (Shaw et al. 2012)[11].

Due to sample size limitations, the study of ethnic density was restricted to the White UK, White Mixed, Bangladeshi, and Black African groups (cf. section 3.3. on analytical samples). Figure 3.6 shows the distribution of ethnic density in each of the four ethnic groups.

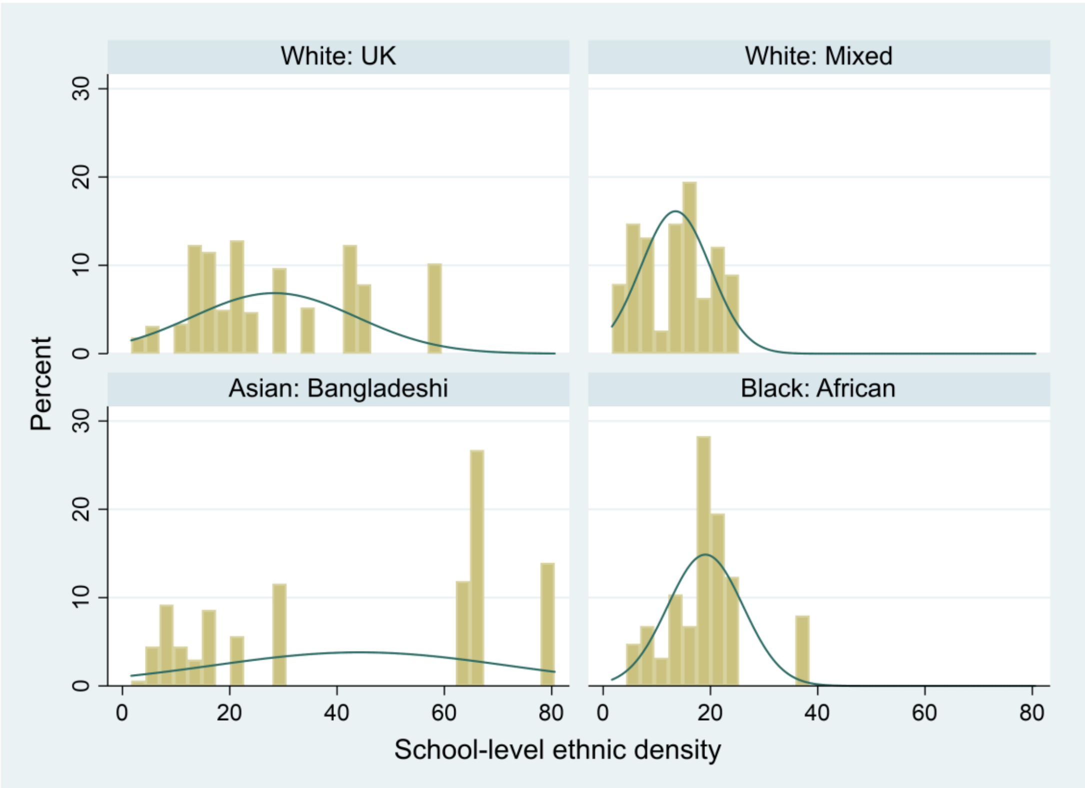

Figure 3.6 Distribution of school-level ethnic density for the four main ethnic groups (n=1,160)

[10] This approximation proved useful when dealing with missing data by means of reduction of the number of variables in the multiple imputation model of chapter 6 (section 6.4.1.2).

[11] Treating the variable as continuous further eased the modelling by reducing the number of parameters involved.

On average, ethnic density is higher for the Bangladeshi adolescents (median=63.3%), intermediate for the White UK and Black African adolescents (22.7% and 19.3% respectively), and lower for the White Mixed adolescents (14.2%). Large variations within the Bangladeshi group are observed (with values ranging from 2.8% to 80.6%), and to a lesser extent within the White UK group (ranging from 1.8% to 57.6%). Variations are smallest for the White Mixed and Black African groups (ranging from 1.6% to 24.0% and 6.1% to 36.6% respectively) and these distributions have a slightly more Gaussian appearance.

Neighbourhood-level own-group ethnic density

To compute neighbourhood-level ethnic density, I combined ORiEL ethnicity data with neighbourhood data on ethnic composition from the 2011 UK Census of Population. Census data on number of residents by ethnic groups at the lower layer super output area (LSOA) were downloaded from the Infuse website (Office for National Statistics 2011). The LSOA was previously suggested to be the best administrative area with available data to characterise ethnic density effects (Stafford et al. 2009). LSOA data were merged with the home-address of the ORiEL participants for each of the wave, recoded to match the ethnicity variable of the ORiEL study and the prevalence of each ethnic group was calculated in each LSOA. I then created a measure of neighbourhood-level ethnic density by assigning to each participant the prevalence of his/her own ethnic group in his/her LSOA.

Although the ethnicity information at LSOA was obtained in 2011 (and is therefore cross-sectional), the ethnic density variable was allowed to change over time to reflect residential changes of the ORiEL participants. Amongst adolescents belonging to one of the four main ethnic groups who reported a home address, 5.2% change LSOA at wave 2, and another 5.9% changed LSOA wave 3. The neighbourhood-level ethnic density variable is therefore time-varying. Changes only reflect residential mobility; change in neighbourhood ethnic composition is not captured. In the analyses, the variable was used on its continuous scale. Home-addresses, and therefore LSOA and derived ethnic density, were missing for 279 measurement points amongst the four main ethnic groups of interest.

The baseline distribution of ethnic densities at neighbourhood-level (Figure 3.7) reflects, for the most part, what is described at school-level. However, the two variables do not capture the exact same dimension (Pearson r = 0.54). The White Mixed and Black African groups display low average neighbourhood-level ethnic densities (median=12.7% and 13.6% respectively) and limited variability (ethnic densities ranging from 3.6% to 31.4%, and 1.5% to 35.1% respectively). Median neighbourhood-level ethnic densities are 40.5% for the White UK group and 22.3% for the Bangladeshi group. At neighbourhood-level, ethnic density of the

White UK adolescents is much higher than at school-level, while it is lower for the Bangladeshi adolescents. These two groups still display notable within group variability in neighbourhood-level ethnic density (values ranging from 5.0% to 90.8%, and 0.2% to 65.2% respectively). All distributions have a more Gaussian appearance than at the school-level. Amongst those who changed LSOA, change in ethnic density before and after the move was 10.2% on average (median 7.2%).

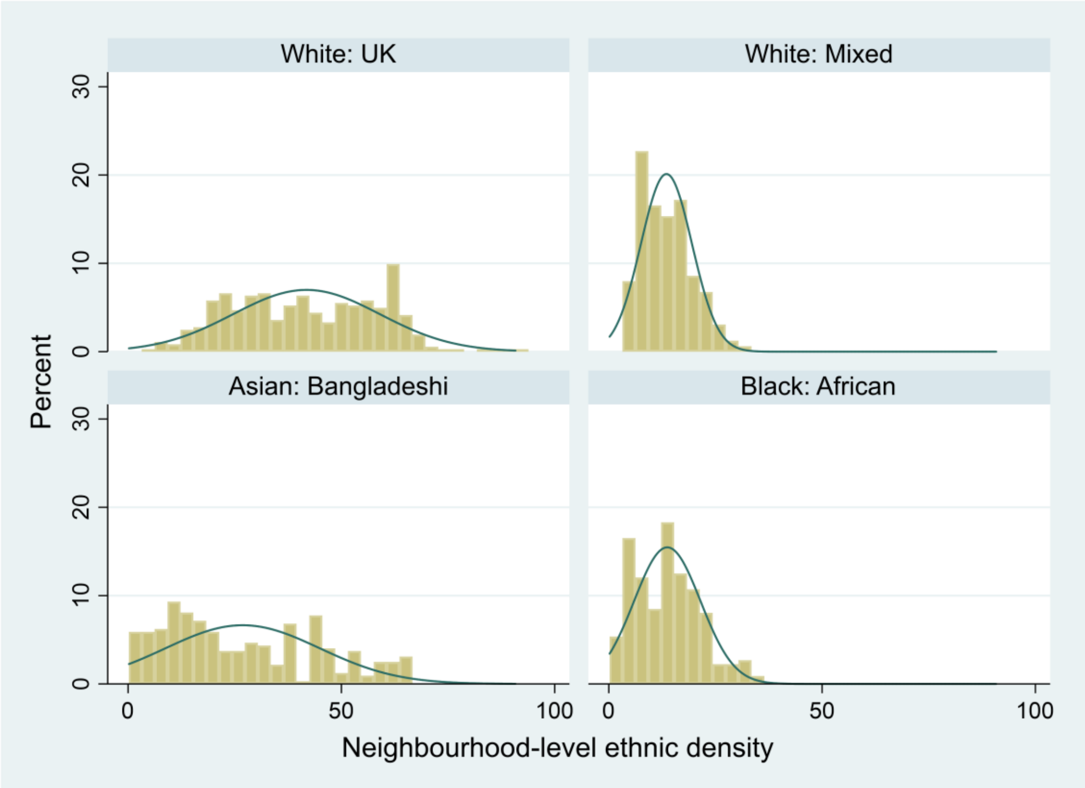

Figure 3.7 Distribution of neighbourhood-level ethnic density for the four main ethnic groups at baseline (n=1,160)

3.5.2.3. Neighbourhood trust

Neighbourhood trust is one of the key exposure variables of interest in the analyses presented in chapter 8. The neighbourhood trust variable is part of a broader set of questions on trust in different groups of people, which were asked at waves 2 and 3. The specific item captures to what extent the participants ‘trust people in your neighbourhood’ and uses a four-level Likert scale (i.e. 1=’not at all’, 2=’a little’, 3=’some’, 4=’a lot’). Analyses use the variable on its original scale in addition to a score measuring individual change in the variable over time. That variable was computed as the difference between wave 3 and wave 2 numeric values to which each response category is coded. Positive scores indicate improvement in the exposure variables over time. Such a variable assumes equivalence in the meaning of change between any two adjacent response categories (e.g. change from ’some’ to ‘a lot’ and from ‘a little’ to ‘some’ are both coded as 1). At wave 2, 21.9% reported a lot of trust, 42.1% some trust, 27.3% a little of trust, and 8.7% reported no trust at all. A slight decrease in trust is observed over time, with more adolescents reporting no trust at all at wave 3 (12.2%) and fewer reporting a lot of trust (17.3%).

Table 3.13 describes the longitudinal changes in the neighbourhood trust variable across waves 2 and 3. The four response categories of the variable appear to have similar stability levels, despite their different prevalence: for each response category, between 67% (not at all) and 72.3% (some) of the participant responses did not change across the two waves.

Table 3.13 Longitudinal descriptive analysis of neighbourhood trust (n=2,197)

Neighbourhood trust	Overall		Between		Within
	Freq.	**Percent**	**Freq.**	**Percent**	**Percent**
Not at all	411	10.5	350	15.9	67.0
A little	1068	27.2	893	40.7	67.7
Some	1677	42.8	1282	58.3	72.3
A lot	766	19.5	611	27.8	70.5
Total	3922	100.0	3136	142.7	70.1

Overall, boys tend to have much higher neighbourhood trust than girls. They are about twice as likely to report a lot of trust (24.5% vs. 13.4%), and less likely to report a little trust (23.9% vs. 31.4%) and no trust at all (9.1% vs. 12.2%). Neighbourhood trust appears to be highest in the Bangladeshi adolescents and lowest in the Black Caribbean adolescents (respectively, 24.6% and 14.0% reported a lot of trust).

3.5.2.4. Social support

In addition to neighbourhood trust, chapter 8 uses perceptions of social support, which are also measured at waves 2 and 3. The social support measures are derived from the Multidimensional Scale of Perceived Social Support (Zimet et al. 1990). The scale was designed to measure general social support and does not capture specific aspects of social support relevant to physical activity (e.g. encouragement, co-participation, transportation). The 12-item instrument assesses perceptions about support from family, friends and significant others. Each item contains a single statement (e.g. ‘my family is willing to help me make decisions’, ‘I can talk about my problems with my friends’, and ‘there is a special person in my life who cares about my feelings’) and is rated on a seven point Likert scale ranging from ‘agree very strongly' to 'disagree very strongly'. The scale was shown to have a high construct and discriminant validity and high test-retest reliability (Zimet et al. 1990). Summed scores for each source of social support have good internal consistency in the ORiEL sample used (Cronbach α>0.9 for each source of support). Owing to positively skewed distributions, scores were split into tertiles (1='low', 2='medium', 3='high'). As with neighbourhood trust, a score measuring individual change in the three tertile scores was computed as the difference between wave 3 and wave 2 numeric values to which each response category is coded.

At wave 2, 36.7% reported low social support from friends, 28.9% medium social support, and the remaining 34.4% reported high perceived social support. A slight decrease is observed at wave 3, with more adolescents reporting low and medium social support (39.9% and 31.5% respectively) and less reporting high social support from friends (29.2%). At wave 2, 28.1% reported low social support from family, 26.7% reported medium social support, and 45.1% reported high social support. A more marked decline is observed for the family source: more adolescents reported low and medium social support from family (32.7% and 29.9% respectively) and less reported high social support (37.4%). Social support from significant others has a very similar distribution to that of family social support at wave 2 (38.4%, 26.6% and 35.0% for low, medium and high social support respectively). The distribution appeared to be more stable over time, with only a small increase in low social support (40.9%) and a small decrease in high social support (32.2%).

Social support from family was similar in boys and girls across the two waves of data, while high social support from friends and significant others was more frequently reported by girls than boys (respectively 40.7% and 41.2% for girls and 27.0% and 29.5% for boys). Ethnic differences are also observed: social support was generally highest in the White UK and Indian groups, and lowest in the Pakistani adolescents.

As shown in Table 3.14, 50.2% of the adolescents reported low social support from friends at least once. 77.0% of those responses were also classified in the same low perception category at the other wave. Medium and high perception categories were used by slightly less respondents (43.6% and 41.8% respectively), and were also slightly less stable over time (70.0% and 73.7% respectively).

Longitudinal descriptive statistics for family social support give a slightly different picture. Table 3.15 indicates that high social support was used at least once by most participants (51.1%), followed by medium (40.2%) and low categories (39.8%). However, the low and high categories were equally stable: 78.5% and 78.3% of those who reported any of those values, reported the same value in other waves. Stability was slightly lower for the medium response category (71.6%).

Longitudinal descriptive statistics for the significant others sources are very similar to social support from friends, and therefore presented in Appendix B (Table B.5).

Table 3.14 Longitudinal descriptive analysis of social support from friends (n=2,123)

Social support: friends	Overall		Between		Within
	Freq.	Percent	Freq.	Percent	Percent
Low	1381	38.1	1066	50.2	77.0
Medium	1097	30.3	926	43.6	70.0
High	1144	31.6	887	41.8	73.7
Total	3622	100.0	2879	135.6	73.7

Table 3.15 Longitudinal descriptive analysis of social support from family (n=2,123)

Social support: family	Overall		Between		Within
	Freq.	Percent	Freq.	Percent	Percent
Low	1112	30.6	844	39.8	78.5
Medium	1033	28.4	853	40.2	71.6
High	1488	41.0	1085	51.1	78.3
Total	3633	100.0	2782	131.0	76.3

3.5.3. Confounders

The following variables were conceptualised as factors that may confound the associations between the neighbourhood and home environments and physical activity. A confounding factor is associated with both exposure and outcome and yet is not on the hypothesised causal pathway (Kirkwood & Sterne 2003). Failure to adequately control for the effects of such variables can result in bias. A core set of potential confounders were defined and used throughout the thesis. In addition to these core confounders, further confounders were identified for use in specific sets of analyses (see Table 3.16). In this section, I describe the main confounding factors and their (repeated) cross-sectional distribution.

Table 3.16 Use of potential confounders across the different chapters of the thesis

Potential confounder	Chapter 5 Baseline neighbourhood perceptions	Chapter 6 Neighbourhood perceptions	Chapter 7 Ethnic density	Chapter 8 Trust + Social support
Gender	✓	✓	✓	✓
Ethnicity	✓	✓		✓
Family affluence	✓	✓	✓	✓
Free school meals	✓	✓	✓	✓*
Health condition	✓	✓	✓	✓
Household composition			✓	✓
Time lived in the neighbourhood			✓	✓
Parental employment	✓			
Country of birth	✓			
Season of interview	✓			
Borough	✓			
Distance to school			(✓)	

*time-varying indicator used as opposed to baseline indicator because the analysis does not include the baseline data.

3.5.3.1. Gender

Previous research has identified associations between gender and physical activity (Health and Social Care Information Centre 2017) and also between gender and i) perceptions of the neighbourhood environment (Foster & Giles-Corti 2008), and ii) social support (Zimet et al. 1990). Gender differences in ethnic density were also observed in the sample. Thus, gender is a likely potential confounder. Gender is time-invariant during the study period, and the sample includes 56.4% of boys and 43.6% of girls.

3.5.3.2. Ethnicity

Ethnicity is an important potential confounder. Ethnic differences in physical activity are well documented in the UK (Fischbacher et al. 2004, Griffiths et al. 2013, Owen et al. 2009). In addition, ethnic differences in perceptions of the neighbourhood (Koshoedo et al. 2015, Lovasi et al. 2009, Rawlins et al. 2013), ethnic density (Pickett & Wilkinson 2008) and social support (Klineberg et al. 2006) are documented in the literature. ORiEL participants were asked to report their race or ethnic background using a question based on the 2011 Census (Office for National Statistics 2013b). Twenty-four ethnicity options were provided in the questionnaire as well as an opportunity to self-define one's ethnicity. These were collapsed down to the eight largest group in the study, namely: White UK, White Mixed ('White UK and any other background'), Indian, Pakistani, Bangladeshi, Black Caribbean, and Black African. All other ethnic minority groups were collapsed to the Other category. A time-invariant variable was constructed based on the answer at wave 3, which was assessed to be more reliable by the ORiEL research team. If missing, information from previous waves was used to impute the data. 16.9% reported being White UK, 14.9% being Bangladeshi, 11.1% being Black African, and 8.4% having a White Mixed background. Remaining ethnic groups (Indian, Pakistani, and Black Caribbean) have a prevalence lower than 5% (3.8%, 3.8% and 4.9% respectively) and the Other category accounts for 36.2% of the sample.

3.5.3.3. Family affluence

Socioeconomic circumstances are also expected to confound the associations between physical activity and aspects of the neighbourhood and home environments studied in this thesis (Bécares et al. 2012b, Giles-Corti & Donovan 2002, Laird et al. 2016). I used the revised Family Affluence Scale II (FAS) and the receipt of free school meal as my main measures of socio-economic circumstances. The revised FAS is a four-item instrument which has been validated in studies of adolescents cross-nationally (Boyce et al. 2006) and is predictive of physical activity (Currie et al. 2008). The FAS is a material deprivation index of socioeconomic status and includes items asking how often the family has taken a holiday in the past year, if the family has access to a car/van/truck, if the adolescent shares his/her bedroom and the number of computers in the household. Total scores on the FAS range from 0 to 9 and cut-off values were defined to result in a 3-category ordinal scale (Boyce et al. 2006): low family affluence (score=0,1,2), medium family affluence (scores=3,4,5) or high family affluence (scores= 6,7,8,9). At baseline, 53.4% were classified with moderate affluence, 36.1% with high affluence, and 10.6% with low affluence. The proportion with low affluence dropped to 5.0% and the proportion with high influence increased to 43.9% at wave 3.

Despite evidence that FAS has good external validity (Boudreau & Poulin 2009), the scale has a poor reliability in the ORiEL study (Cronbach's alpha ≤0.4 at each wave) and in other settings (Boudreau & Poulin 2009, Molcho et al. 2007). In addition, the item on car-ownership appears to be over-reported compared to official figures available in London (Roads Task Force 2013). Nonetheless, given the difficulty of capturing socioeconomic circumstances in adolescents, FAS was used in the main analyses, as it appears to be associated with physical activity in the expected direction. FAS was however always used in combination with another measure of socio-economic circumstances, as recommended in the literature (Molcho et al. 2007).

3.5.3.4. Free school meal status

Adolescents were asked whether they receive of free school meal (FSM). At baseline, 37.7% of adolescents reported receiving FSM, a figure that decreased to 36.6% at wave 2 and 32.2% at wave 3. Investigation of official statistics on FSM in the ORiEL schools revealed that the sharp decrease in self-reported receipt of FSM observed between wave 3 and wave 2 could not be fully explained by changes in either eligibility or in the actual receipt of FSM (Hatton 2014, Iniesta-Martinez & Evans 2012). Previous work on FSM reporting (Hobbs & Vignoles 2007) also revealed a tendency among adolescents to not claim free school meal at older ages even if they are entitled to them. This suggests that, at age 12, compared to age 13 or 14, self-reported receipt of FSM is likely to be a better predictor of FSM eligibility and therefore a better proxy for socio-economic status. I therefore treated the variable as time invariant, using the baseline values. This use of the baseline variable assumes no change in the affluence level over the 3 years of the study.

3.5.3.5. Health condition

The health status of participants was captured with a series of question on health problems that have troubled the participant over a period of time or are likely to affect the participant over a period of time (The Health Survey for England 2011). Possible conditions relevant to physical activity include mobility problems, longstanding illness, anaemia, asthma, diabetes, Chronic Fatigue Syndrome, hay fever, hearing and eyesight problems. A summary variable was created and categorised into those reporting no condition; one condition; and, two or more conditions. At baseline, 57.5% reported no health condition, 27.7% reported one condition, and 14.8% reported two or more conditions. The proportion of those reporting two conditions or more slightly decreased at wave 2 (9.6%) and the proportion reporting one condition increased (31.3%), probably due to a modification of the response scale between the two waves.

3.5.3.6. Household composition

Household composition was expected to be a potential confounding factor for associations between ethnic density, social support and physical activity. Family composition is known to be associated with poverty (McLanahan & Percheski 2008). I therefore hypothesised that single families are more likely to live in poorer neighbourhoods, which are themselves more likely to have greater ethnic densities (Karlsen et al. 2002). Social support was also expected to be higher amongst adolescents living with both parents, which is another indicator of socio-economic circumstances (Laird et al. 2016). The questionnaire asked adolescents whom they lived with most of the time. The variable was recoded into those living with both parents and those with other living circumstances, due to small prevalence of other forms of household composition. The proportion living with both parents was constant over time and was estimated to be 67.7% at wave 1, 69% at wave 2, and 67.5% at wave 3.

3.5.3.7. Time lived in the neighbourhood

The time lived in the neighbourhood was expected to be a potential confounder, in particular for the associations with ethnic density and neighbourhood trust. Time lived in the neighbourhood is a measure of social circumstances which is expected to be related to the overall residential mobility process which results in some ethnic minorities living in more or less segregated areas. It is also expected to be related to neighbourhood trust in such a way that the longer the time spent in the neighbourhood, the higher the level of trust. The ORiEL questionnaire included a question asking how long adolescents have lived in their current neighbourhood. The question was recoded into 5 years or less vs. 6 years or more. 38.9% reported having lived 5 years or less in their current neighbourhood at baseline. That figure slightly decreased over time to reach 34.4% at wave 3.

3.5.3.8. Parental employment

The baseline analysis presented in chapter 5 explores the possibility of including parental employment as a measure of socio-economic circumstances. The variable has six response categories: both parents unemployed (9.4% at baseline); one parent employed (34.7%); both parents employed (40.8%); lone parent employed (7.9%); lone parent unemployed (6.3%); don't live with parents (1%).

3.5.3.9. Country of birth

The analysis of the baseline data (chapter 5) hypothesises that country of birth might moderate the association between perceptions of the neighbourhood environment and physical activity. In the baseline questionnaire, adolescents were asked to report their country of birth. The variable was recoded as UK vs not UK. 79.8% reported being born in the UK. The variable was however not associated with any of the outcome variables, and was therefore not considered for subsequent analyses.

3.5.3.10. Season of interview

The season of interview was expected to be related to perceptions of the neighbourhood environment and physical activity, and therefore to be a potential confounder. Using the interview date, I create a binary variable that differentiates between interviews taking place in winter (57.4% of the interviews) and those taking place in spring (42.6%).

3.5.3.11. Borough

It was hypothesised that the borough in which adolescents go to school might be a potential confounder for the association between perceptions of the neighbourhood environment and physical activity. However, no association was found between the physical activity outcomes and borough. The variable was therefore not considered beyond the baseline analysis.

3.5.3.12. Distance to school

Finally, distance between the home address and school, was expected to confound the association between ethnic density and walking to school (chapter 7). Such a variable was made available by the ORiEL research team who calculated a road network distance between participant residential address and school address (Cummins et al. 2017).

3.5.4. Moderators

Gender and ethnicity are the two moderators used in this thesis. Due to sample size limitations and restrictions imposed by the strategy used to handle missing data (section 4.3.), only one moderator could be used for each analysis. Gender was used as a moderator for the analysis of perceptions of the neighbourhood (chapter 6), social support and neighbourhood trust (chapter 8), as the literature has suggested that it would be an important moderator to investigate (Laird et al. 2016, Owen et al. 2004, Stafford et al. 2007). With respect to the analysis of ethnic density (chapter 7), the main expectation is that the ethnic density effect differs by ethnic group (Das-Munshi et al. 2010). Ethnicity is therefore the moderator used in chapter 7. Due to sample size limitations, those analyses are limited to the four main ethnic groups, i.e. White UK, White Mixed, Bangladeshi and Black African.

3.6. Summary

This chapter has set out the key physical activity outcomes and exposures used in the thesis. As different types of physical activity are expected to have different determinants, I created variables measuring four forms of physical activity[12]: walking to school, walking for leisure, outdoor physical activity, and pay and play physical activity. To explain differences in physical activity in adolescents, I operationalised variables of four aspects of the neighbourhood and home environments: perceptions of the neighbourhood environment, own-group ethnic densities, neighbourhood trust, and social support.

The descriptive analysis presented in this chapter confirms that many adolescents do not meet minimum recommendations for physical activity. At baseline, 20.1% reported not meeting physical activity recommendations, a figure that increased to 31.0% two years later. Although physical activity appears to be largely over-reported in the ORiEL study, in light of available evidence (Scholes 2016), it nevertheless confirms that reported level of physical activity decreases as adolescents age. A decrease in all forms of physical activity, except walking to school, is observed during the study period. Each of the exposure variables displayed sufficient cross-sectional and/or longitudinal variability to justify further investigation of their association with the forms of physical activity.

The next chapter describes the general analytical approach used throughout the thesis in order to explore these associations, and outlines a framework for handling missing data using multiple imputation.

[12] In addition, two general measures of physical activity were defined: (log of) total physical activity and daily recommended physical activity.

Chapter 4: Methods

4.1. Introduction

This chapter sets out a general approach to the methods and analyses employed in the thesis. In the data chapter (chapter 3), I presented the ORiEL study and the variables as operationalised in this thesis. In this methods chapter, I describe how missing data are handled in the thesis, strategies for imputing missing data where relevant, and the statistical methods used to analyse the data including both cross-sectional and longitudinal models. Whereas this chapter justifies the broader analytical choices and provides a non-technical introduction to the statistical methods employed, the subsequent results chapters will lay out the specific models employed for each analysis.

Three important aspects of the ORiEL data guide the overall analytical strategy of this thesis: i) the presence of missing data, ii) the complex structure of the data, and iii) the types of outcome variable. First, missing values are observed on many variables in the ORiEL study (section 3.4). These are a likely source of bias and can decrease precision of the estimates if they are not properly handled. Second, the ORiEL study has a complex data structure (section 3.2.): participating adolescents were surveyed on three occasions (repeated measurements) based on their belonging to a school that had been randomly drawn at baseline from eligible schools in the ORiEL study context (Smith et al. 2012). Repeated measurements on individuals are likely to be more alike than between individuals, likewise adolescents belonging to the same school are also likely to be more similar than adolescents in different schools (Rabe-Hesketh & Skrondal 2012). The two sources of correlation that arise due to the ORiEL study design (clustering within individuals, and within schools) must be accounted for because they violate the crucial assumption of independence, the foundation of many standard statistical techniques (Fitzmaurice et al. 2011). Third, I am interested in a set of physical activity outcomes that are predominantly operationalised as binary variables (cf. section 3.5.1.), and therefore models for hierarchical discrete data have to be used.

The analytical strategy of this thesis comprises to main components: missing data handling and the selection of a general approach for the main analysis models (also known as the models of interest in the missing data literature). With respect to missing data handling, a major methodological aspect of this thesis is to provide suitable solution for dealing with missing values given: i) the complex data structure of ORiEL; ii) the types of variables (discrete and continuous); and, iii) the interest in interaction terms (e.g. between gender and exposure variables). While, this setting might seem quite typical in quantitative epidemiology, only recently have software tools been developed that allow for all three circumstances, and some gaps remain. Part of this chapter therefore describes how missing data are handled using multilevel multiple imputation, and provides sufficient elaboration of the methods used as to allow the reader to grasp the statistical complexity of the solution.

The second component is the choice of a general approach for the main analyses. This decision is driven by: i) the types of outcome variables; ii) the complex data structure of ORiEL; iii) the interpretability of the parameters; iv) the compatibility with multiple imputation. Models for discrete data will be used to handle binary and ordinal outcomes. When clustering is fully taken into account, generalised linear models cannot be used however. Alternative models for hierarchical discrete data are more complicated and substantially differ from those used for Gaussian data. When selecting an approach amongst those available, an important consideration is the interpretability of the parameters. In this thesis, the main objective of the research questions is to draw inferences about the population-average, as opposed to subject-specific inference, so that marginal models are preferred. Finally, only models that are compatible with multiple imputation are considered, which restricts the choice of the models for ordinal outcomes, as indicated in this chapter.

This chapter presents the two main analytical approaches used in this thesis. It starts with a description of the problem of missing data. It then describes how I propose to handle item-missingness using multilevel multiple imputation. The section includes a general introduction to multiple imputation and to the specific approach to imputation used in this thesis. Finally, the chapter presents and justifies the analytical approach employed in order to answer the epidemiological research questions of this thesis, using generalised estimating equations.

4.2. Missing data: definitions and implications

This section provides an overview of the consequences that missing data might have on the validity of the analyses conducted in this thesis. I first introduce the different types of missing data mechanism, then present the potential implications of missing data for this thesis, and finally, outline how the two types of missingness (item non-response and unit non-response) will be handled in the proposed analyses.

Missing data are a common problem in investigations involving human participants. Missing data are observations we intended to make but did not. Participants may refuse to take part to a study or may choose not to answer survey questions. In longitudinal studies, participants may drop out over time or be unable to take part to all waves of data collection.

Depending on the process by which missing data are generated, known as 'missing data mechanisms', a standard analysis of the complete cases – participants with no missing data in any of the variables required for that analysis – might not lead to valid statistical inference about the population targeted. In particular, estimators might be inconsistent (leading to biased estimates), confidence intervals might be incorrect, and p-values might be erroneous under the null hypothesis (Carpenter & Kenward 2012, Enders 2010). Missing data also decrease the statistical power of the analysis by decreasing the effective sample size, and may further complicate comparisons across models that differ in the strategy of analysis and in the number of observations included. For all these reasons, it is important to explore, interpret and reduce the influence of missing data in analyses.

4.2.1. Missing data mechanisms

In a seminal paper, Rubin (1976) proposed a general framework for the analysis of data with missing information and defined three types of missing data mechanism: missing completely at random (MCAR), missing at random (MAR), and missing not at random (MNAR). The process generating the data is crucial as the validity of the analyses conducted depends on it. A formal definition of the three missing data mechanisms is provided in Appendix C (section C.1).

Broadly speaking, a mechanism is *missing completely at random* – MCAR – when missingness is independent of both observed and unobserved data. This means that missing values are not systematically different from the observed values. For example, a respondent might have missing values in some questions because a page was missing in his/her questionnaire.

Missing at random – MAR – means that missingness depends on the observed data, but not on the unobserved data. In other words, differences between the observed values and the missing values can be explained by differences in the observed data. For example, males might be more likely to answer sensitive questions about depression than females, such that once gender is taken into account, there are no more differences in the probability in answering the questions.

Missing not at random – MNAR – means that missingness depends on unobserved data, so that after the observed data were taken into account, systematic differences remain between the missing values and the observed values. For example, adults with very low or very high BMI may be more likely to have missing values in a study because they refuse to be weighed.

4.2.2. Implication of missing data

The missing data mechanism might have serious implications for the validity of the analyses conducted. In particular, an analysis of complete cases is only valid, in general, if the data are MCAR. In practice, however, the missingness mechanism is usually unknown and the MCAR conditions are very rarely satisfied. More generally, the statistical literature indicates that the bias caused by missing data depends on various factors, which include: the missing data mechanism; the role of variable with missing values in the analysis model (i.e. outcome or covariate); the estimation method used (e.g. likelihood-based method, moment-based method); the statistical method used (e.g. logistic regression); and the role of the variable in the analysis model (i.e. outcome or covariate) on which missingness in another variable depends (Bartlett et al. 2015a, Carpenter & Kenward 2012, Fitzmaurice et al. 2011, Molenberghs & Verbeke 2005). For example, a well-documented scenario in which missingness does not generate bias (even if the data are MAR or MNAR) occurs when missingness in the covariates does not depend on the outcome (Carpenter & Kenward 2012).

A detailed investigation of missing data is therefore very important to establishing the mechanism at play and the consequent risk of bias. In this thesis, analyses of missing data are presented in the appendix of each longitudinal results chapter (Appendix E, Appendix F and Appendix G). Although it is not possible to distinguish between MAR and MNAR using observed data only, it is possible to rule out the MCAR assumption. In practice, and when the hypothesis is coherent with the data, researchers will often assume the data to be MAR, an assumption also made in this thesis. The statistical literature also strongly advises that sensitivity analyses are conducted, and that different assumptions are made about the missing data mechanism (in particular MNAR) to investigate if these affect the conclusions (Carpenter & Kenward 2012). This proves difficult however in complex settings and is therefore beyond the scope of this thesis. Therefore, a generally accepted practice is to conduct analyses under MAR, if shown to be plausible, while bearing in mind that the gold standard would be to perform additional sensitivity analyses.

4.2.3. Dealing with unit non-response and item non-response in this thesis

In longitudinal studies, researchers are faced with two types of missing data: unit non-response and item non-response (Fitzmaurice et al. 2011). Unit non-response, or 'attrition', indicates the loss of participant over time and includes situations where participants return to the study after missing measurement occasions (Goldstein 2009). Patterns of participation in a study are described either as 'monotone' if a participant drops out, or 'non-monotone' when participation is intermittent. In addition to the risk of attrition, missingness can also occur if an individual participates in a data collection occasion but then fails to provide information on one or more variables. This is called item non-response or item missingness. Both sources of missingness, unit non-response and item non-response, are likely to lead to bias in the analyses if the process is not MCAR.

In the presence of item-missingness on many variables, multiple imputation is the most popular approach to handling missing data when the missing data mechanism is hypothesised to be MAR (Carpenter & Kenward 2012, Enders 2010). In particular, multiple imputation allows the use of additional variables – known as auxiliary variables – to strengthen the likelihood of meeting the MAR assumption (Fitzmaurice et al. 2011). In this thesis, I apply multiple imputation to handle item missingness, the general strategy that I employ for multiple imputation is discussed in the next section. Prior to the implementation of multiple imputation, I establish, for each results chapter, that the complete case analysis is likely to lead to invalid inference, and that the MAR mechanism is plausible. The validity of the complete case analysis is assessed by analysing whether the probability of being a complete case is independent of the outcome, conditional on the covariates in the analysis models (Carpenter & Kenward 2012); and the plausibility of the MAR assumption is explored for the variables with the highest proportions of missing values, using logistic regression models to identify variables predicting missingness (cf. Appendix E section E.1, Appendix F section F.1 and Appendix G section G.1).

Accounting for unit non-response is a more difficult task in the context of this thesis. In the statistical literature on missing data in longitudinal analysis, unit non-response, and dropouts in particular, have often been discussed as a separate topic from item non-response. The use of inverse probability weighting, is for example presented as a valid way of accounting for dropouts (Fitzmaurice et al. 2011). When unit non-response is not monotone, however, and/or when item-missingness is also present, propensity weighting can become very cumbersome in practice (Molenberghs & Verbeke 2005). As an alternative, Goldstein (2009) proposed a framework for dealing with attrition and item missingness simultaneously, using multiple imputation. This approach treats unit non-response as a special case of item non-response, such that the variables that are missing at a given missing measurement point are imputed, even if no observation was made on any of the variables at that time.

Implementing this approach within ORiEL is problematic. In fact, the ORiEL study is an area-based cohort study, which targets adolescents living in East London between 2012 and 2014. Attrition is frequent in ORiEL, and there are various reasons for which adolescents may have been missed at follow-up. Adolescents may have been absent on the survey day (e.g. due to sickness); they may have changed class within their school; they may have transferred to a different school within the study area that did not participate in the study; or they may have moved out of East London altogether. The later possibility is particularly problematic, as inference from the ORiEL study should not include participants who are no longer part of the study area. This is the case because of the so-called 'selection mechanism' in neighbourhood effects research (Oakes 2004). The socio-economic processes that sort individuals into or out of particular places suggests that it is very likely that adolescents who have moved, are dissimilar to those who have remained (Sampson 2012). In this sense, adolescents who move out of the study areas may not be representative of the targeted study population, and imputing attrition for those adolescents might generate bias with respect to the inference on residents living in the area over the study period. Whereas imputation would be recommended for attrition of adolescents who have stayed in East London, it was not deemed possible to distinguish reasons for unit non-response. As a result, any difference in the observed survey responses between individuals with or without attrition would not provide meaningful information about bias. I therefore decided not to impute unit non-response in this thesis and to restrict the analysis to the balanced panels as described in section 3.3. As a result, inference is restricted to adolescents who attended schools in the ORiEL study area over the study period. It is noteworthy that even if I had wished to impute unit non-responses, this would have proved computationally challenging and very time consuming due to the much increased frequency of missing data and the sophisticated imputation strategy implemented in the thesis. The next section presents the approach used to handle item non-response with multiple imputation.

4.3. Handling missing data with multiple imputation

Making an informed decision on how to best approach multiple imputation, given the specificity of the ORiEL data, has been an important undertaking of this thesis. Advanced multiple imputation methods are implemented to account for the 3-level hierarchical structure of the data (repeated measurements, individuals, schools), to allow for mixed response types (continuous and discrete) and to allow for interaction terms between exposure variables and hypothesised moderators (gender and ethnicity). Given the relative novelty of the approach and the level of computational and statistical sophistication of the methods used, the following section provides an extensive description of the imputation approach used in this thesis. I first introduce the general principles of multiple imputation. Then I present how the imputation model was chosen in light of three important considerations: the multilevel structure of the data, the presence of mixed response types; and, the inclusion of interaction terms. On this basis, I present the general multiple imputation framework used: multilevel joint models with underlying latent normal distributions for discrete variables. I conclude this section with a description of variable selection, diagnostics, and a brief presentation of the statistical package used to impute the data ('jomo' package in R).

4.3.1. Multiple imputation: an overview

Multiple imputation (MI) is a general approach used to handle missing data, which is particularly suitable when missingness is present on multiple variables. MI works by replacing each missing value not with a single missing value estimate, but with a set of plausible values (creating *M* plausible sets). These *imputed* values are sampled from their predictive distribution based on observed data, which incorporates uncertainty about the *true* value of the missing data into the imputation model. Each *M* imputed data set is then analysed in turn, using standard statistical methods. Individual estimates for each of the imputed datasets will differ because of the uncertainty introduced around the imputed values. Combined estimates for all *M* datasets are made by taking the average of the *M* results, standard errors are calculated using Rubin's rules (1987) which combine the *M* standard errors and account for the variability in the results between the imputed datasets (Figure 4.1). Throughout this thesis, the MI analyses will be assumed data to be MAR; the plausibility of the assumption is explored in each separate results chapter (cf. Appendix E section E.1, Appendix F section F.1 and Appendix G section G.1).

Under the MAR assumption, the MI procedure models the distribution of each variable with missing values, based on the observed data. An advantage of MI is that there is no need for the analysis model to exactly match the imputation model. The main requirement is that the imputation model should be at least as complex as the model used to analyse the data. Having a richer imputation model can be an advantage by allowing the inclusion of some variables that might provide further information about the missing data mechanism. In practice, under the MAR assumption, such auxiliary variables should be included in the imputation model if they are either predictive of missing values; or predictive of missing values and predictive of the chance of the data being missing. In the first scenario, efficiency will be improved (i.e.

standard errors will be smaller), whereas in the second scenario both an improvement of efficiency and a reduction in bias will result (Carpenter & Kenward 2012, Fitzmaurice et al. 2011). In this thesis, such auxiliary variables are identified for each results chapter separately, using generalised linear models (cf. Appendix E section E.1, Appendix F section F.1 and Appendix G section G.1). Finally, it should be stressed that all variables included in the analysis model have to be included in the imputation model. To not include all variables might cause bias and does not guarantee that Rubin's rules hold (Carpenter & Kenward 2012). More details on the imputation procedure are presented in Appendix C (section C.2).

If θ is a parameter of interest, let the multiple imputation estimate of θ be $\hat{\theta}_{MI}$. Then,

$$\hat{\theta}_{MI} = \frac{1}{M}\sum_{m=1}^{M}\hat{\theta}_m$$

Where m is an imputed dataset in the set of M imputed datasets.

Further define the within imputation ($\hat{\sigma}_w^2$) and between imputation ($\hat{\sigma}_b^2$) components of variance by

$$\hat{\sigma}_w^2 = \frac{1}{M}\sum_{m=1}^{M}\hat{\sigma}_m^2, \quad \text{and} \quad \hat{\sigma}_b^2 = \frac{1}{M-1}\sum_{m=1}^{M}(\hat{\theta}_m - \hat{\theta}_{MI})^2,$$

$$\text{then} \qquad \hat{\sigma}_{MI}^2 = \left(1+\frac{1}{M}\right)\hat{\sigma}_b^2 + \hat{\sigma}_w^2,$$

Where $\hat{\sigma}_{MI}^2$ is the multiple imputation estimate of the variance of θ.

Figure 4.1 Rubin's rules to combine multiple imputation estimates

4.3.2. Selection of the imputation approach in this thesis

Beyond the general MI procedure, there are two main approaches to conducting multiple imputation: joint modelling and full conditional specification[13]. Joint modelling imposes a multivariate normal distribution of continuous variables with missing values, while discrete variables are treated using a latent normal distribution approach (Goldstein et al. 2009). Full conditional specification allows the specification of different imputation models for different variables with missing values, and better handles a mixture of continuous and discrete

[13] Note that MI models are also implemented within a fully Bayesian approach to inference (and not just at the imputation stage). Those models are beyond the scope of this thesis, which takes a frequentist approach to inference.

variables. Joint modelling is more well-grounded theoretically than full conditional specification (also known as imputation by chained equations), but results are comparable in simple multivariate normal settings (Goldstein et al. 2009). Whereas full conditional specification is appealing in simple settings with mixed variable types, the choice of the imputation framework requires further consideration in more complicated situations, such as the one tackled in this thesis.

In this thesis, the choice of imputation framework was guided by the nature of the data. Key elements considered are the data structure (3-level structure: repeated measurements, individuals, schools), the variable types (continuous and discrete variables), and the presence of interaction terms (gender*exposure interactions and ethnicity*exposure interactions). Following an examination of the literature, I decided to impute the data using a multilevel approach within the joint modelling framework. The justification for this approach is described in the following three sections.

4.3.2.1. Handling the hierarchical structure

The ORiEL data have a three-level hierarchical structure: adolescents are nested within schools and repeated measurements are made on the adolescents. In these contexts, observations cannot be assumed to be independent, they are nested within a group or cluster and therefore correlated (Fitzmaurice et al. 2011). The imputation method used needs to account for such correlations, otherwise bias in both point estimates and standard errors are likely to occur (Carpenter et al. 2011). Multilevel models offer the most flexible approach to handling missing data with a complex structure.

Despite widespread use of multilevel models in general, multilevel solutions for MI that allow for a mixture of variable types have only been recently proposed in the literature, and they are still not widely implemented in statistical packages (Bartlett 2011, Carpenter et al. 2011, Enders et al. 2016, Goldstein et al. 2009, Grund et al. 2016, Kalaycioglu et al. 2016, Lüdtke et al. 2017, Quartagno et al. 2018).

Whereas full condition specification and joint modelling are often equivalent with single-level data, the methods tend to be quite different in a multilevel context, even if the data are normally distributed (Enders et al. 2016). Joint modelling has the advantage of more naturally extending from a single level structure to a multilevel one, using the multivariate normal distribution (Goldstein et al. 2009). Conversely, random effects implementations of the full conditional specification do not allow for the specification of a separate model for each type of variable, which is the most appealing feature of the fully conditional specification approach.

Attempts to combine generalised linear mixed models with chained equation imputation have been unsuccessful and cast doubt on the viability of the overall strategy (Enders et al. 2016). As a result, current multilevel full conditional specification approaches are only well suited for normally distributed variables, which makes the approach unusable in the context of this thesis. Joint modelling, on the other hand, can handle discrete data in its multilevel extension by relying on the latent normal distribution. This is the approach followed in this thesis. However, the current implementation of joint modelling is restricted to 2-level models in the presence of discrete variables (Goldstein & Carpenter 2015).

It should be noted that alternatives to multilevel multiple imputation exist. 'Fixed effects' models have been suggested as an alternative analytical strategy which is able to benefit from the flexibility of the full conditional specification while accounting for the hierarchical structure of the data (Enders et al. 2016). Fixed effects models are particularly relevant for repeated measurements. Such models incorporate values of the measures at previous and subsequent time points as fixed effects in the imputation model (Kalaycioglu et al. 2016) and correlation between repeated measurements is accounted for by using an auto-regressive correlation structure. Fixed effects estimations have several drawbacks, however: they are computationally demanding, they often require many parameters in the imputation model, and they are subject to model convergence problems (Enders et al. 2016, Kalaycioglu et al. 2016). An alternative solution that accounts for the correlation across repeated measurements is to structure the data in the wide format (so that each measurement occasion is treated as a separate variable, and each row is a single participant) in combination with a single-level joint modelling or full conditional specification. This approach is also known as the multivariable approach (Verbeke & Molenberghs 2009). It proves to be viable when the number of repeated measurements is limited and observations are made at fixed time points. This approach is also explored in this thesis, in combination with a multilevel joint model in order to be able to fully account for the 3-level structure of the data.

4.3.2.2. Handling non-Gaussian variables

The joint modelling framework is particularly suitable for handling Gaussian variables. However, as shown in the data chapter (section 3.5.), the variables used in this thesis include a mixture of continuous Gaussian, continuous non-Gaussian, ordinal, nominal, and binary variables. To handle these, I am following the recommendations from Goldstein et al. (2009) within the joint modelling framework.

Goldstein et al. (2009) advise that continuous non-Gaussian variables are transformed to make them look approximately normally distributed. If no suitable transformation is available, they suggest categorising the distribution and treating it as an ordinal variable. Transforming key variables, that are included in the analysis models, might have serious consequences however. For example, a recent simulation study (von Hippel 2013) indicates that transforming skewed variables to make them look Gaussian might distort the relationship between the variables on their original scales and therefore might introduce more bias than the bias caused by the violation of the normality assumption. In this thesis, the continuous, approximately Gaussian variables (e.g. ethnic density variables) are used as such. Skewed variables (e.g. social support variables) are categorised in the imputation model and in the analysis models. Some auxiliary variables, not used in the analysis models, are transformed to the Gaussian distribution (e.g. log of total physical activity and squared WEMWBS mental health score).

For discrete imputation, Goldstein et al. (2009) propose making the assumption that a normal distribution underlies each discrete variable. This 'latent variable' formulation is very convenient because it does not entail any substantial modification of the imputation strategy used for Gaussian variables. The fitted multivariate normal response model simply allows for the generation of numerically continuous imputed values for the latent normal variables, as with the continuous Gaussian variables. The imputed values on the latent normal variable then need to be converted into the appropriate observable discrete scores.

Binary variables are handled using a probit link function. For ordinal variables, a probit analogue of the proportional odds model for ordinal data is used. The joint model predicts mean value of the latent variable distribution, while the variance of the latent variable is set to one to ensure identification. The latent variable distribution is divided into segments, using threshold cut-offs (one fewer than the number of modalities). These allow for the attribution of a discrete score corresponding to each value of the latent distribution.

Finally, unordered discrete variables are handled using the maximum indicant model (Carpenter & Kenward 2012). The model specifies a latent Gaussian variable for all but one category of the variable, which forms a multivariate Gaussian distribution. Restrictions are included on the covariance of the latent variables.

The latent normal distribution approach requires a slight modification of the Markov Chain Monte Carlo (MCMC) estimate used to estimate the imputation model (cf. Appendix C section C.2). Given that latent scores are never observed, the procedure for sampling plausible latent variable scores and imputing missing values are the same. There is a slight difference in the procedure however: if a value was observed, the sampling procedure restricts latent variable scores to the range of latent values corresponding to the observed value (this is known as the rejection sampling procedure). If a value was missing, the sampling of values does not make such a restriction, allowing imputed values to be obtained. Note also that the Metropolis-Hastings algorithm (Gelman et al. 2003) is needed to update the covariance matrix (due to a constraint set on the variance of the latent variables), as opposed to the Gibbs sampler used in the multivariate normal case. For ordinal variables, the Gibbs sampler also necessitates an additional step to generate the thresholds parameters (Carpenter & Kenward 2012).

Most of the variables used in this thesis are discrete, meaning that the imputation approach relies heavily on the latent normal distribution. Using separate models as in single-level full conditional specification would have been the preferred approach, but I have explained (section 4.3.2.1) that this was not possible in the multilevel context. It should also be noted that the recommended approach to dealing with ordinal variables is not implemented in the software package used for imputation, so the approach for unordered variables is used instead.

4.3.2.3. Handling interactions

So far, I have discussed how I account for the multilevel structure of the data using multilevel joint modelling and how I handle a mixture of variable types with the underlying latent normal variable approach. A third important characteristic to take into account when specifying an approach to multiple imputation is the presence of interactions or linearities. The inclusion of interaction terms or non-linear relationships in the analysis model (i.e. model of interest) has non-trivial implications for the specification of the imputation model. In this thesis, I am interested in the interactions between a number of exposure variables (with missing values) and gender (fully observed), and between exposure variables (with missing values) and ethnicity (fully observed). This sections presents an overview of the issue and specifies the solution used in this thesis.

When MI is used, it is important to ensure that all the parameters of the analysis model are included in the imputation model. In other words, the analysis model should be at least as rich as the imputation model (Bartlett et al. 2015b). An important practical consequence is that interaction terms and non-linear effects in the analysis model should be included in the imputation model. Ignoring them would most likely attenuate estimates of the corresponding parameters (Carpenter & Kenward 2012)[14].

Unfortunately, handling interactions/non-linearities is not straightforward. Methods used to properly handle interaction/non-linearities go beyond simply adding an interaction/quadratic variable into the imputation model. This approach known as 'just another variable' has been shown to perform poorly under MAR (Carpenter & Kenward 2012). Overall, the ability and ease of handling interactions/non-linearities depends on the type of variable, whether missing values are involved, and the imputation framework used. Additional complications might also arise when the hierarchical structure of the data needs to be accounted for in the imputation model. Fitting appropriate imputation models with interactions within the joint modelling framework or within the fully conditional specification can then become very complicated (Bartlett et al. 2015b).

However, if the interaction involves a discrete variable that is fully observed, it is possible to impute the data separately for each stratum of the variable and then to combine the imputed datasets at the end of the imputation phase (Carpenter & Kenward 2012). Doing so allows for the preservation of interaction terms between the stratification variable and other variables included in the imputation model. This simple solution is used in this thesis, meaning that imputations will be stratified and imputed either by gender, or by ethnic group, depending on the research question.

4.3.3. Joint modelling framework

In the preceding section, I have provided a general justification as to why I am using a joint modelling framework to impute the data. In this section I provide a more detailed presentation of the framework. I first present joint modelling in a single-level setting, and then specify how the approach can be extended to a multilevel setting.

4.3.3.1. Schafer's joint model

Joint modelling became a very popular and pragmatic solution to missing data problems in the 2000s, particularly following Schafer's work (1997). The joint modelling approach is

[14] Note that even if interaction and non-linear effects are not of direct interest, it has been suggested that they be included if they improve the model fit of the imputation model and therefore increase the likelihood that the MAR assumption is satisfied (Carpenter & Kenward 2012).

theoretically well justified and computationally efficient, at least when the data follow a multivariate normal distribution (Goldstein & Carpenter 2015). Essentially, variables with missing data (represented by the vector **Y**) are assumed to form a joint model that follows a multivariate normal distribution:

$$\boldsymbol{Y} \sim \boldsymbol{N}(\boldsymbol{\beta}, \boldsymbol{\Omega}) \tag{1}$$

where $\boldsymbol{\Omega}$ is the unstructured covariance matrix, and $\boldsymbol{\beta}$ a vector representing the mean value of each variable.

Using joint models as an imputation framework is appealing because these models preserve important features of the joint distributions of the data in the imputed data sets (such as means, variances and correlations). They also preserve the joint distribution of the variables in **Y** and, therefore, automatically preserve linear relationships between any of these variables.

The Gibbs sampler is the MCMC algorithm commonly used both to estimate the parameters of the multivariate normal joint model of equation (1) and to impute the missing data (Carpenter & Kenward 2012) (cf. Appendix C section C.2 for more detail on the imputation procedure). The Gibbs sampler is first initialised by choosing starting values for the parameters of the model, including the missing values, which are treated as parameters in the Bayesian sense (i.e. distributions, cf. Appendix C section C.2). In practice, the expectation-maximisation (EM) algorithm (Molenberghs & Verbeke 2005) is often used to obtain initial values, which is convenient because convergence is usually quicker, and the non-convergence of the EM algorithm can indicate data problems early on (Carpenter & Kenward 2012). The Gibbs sampler then draws new values for each parameter in turn, including the missing data. Given that each observation might have a different missingness pattern, the draw of missing values is done for each observation in turn. The sampler runs a number of times which results in different draws every time, as the distribution of the parameters is updated at each cycle. Once the Gibbs sampler has converged to its distribution, the current draws of missing values together with observed values, are used to form the first imputed dataset. The sampler is then updated another *n* times until an approximately independent draw is obtained. A second imputed dataset can then be retained. This is repeated until the desired number (*M*) of imputed datasets is reached. *M* is set to 20 in this thesis.

4.3.3.2. Multilevel joint modelling

Goldstein et al. (2009) generalised Schafer's joint model (1997) to account for a multilevel structure. In addition, Goldstein et al.'s approach is able to handle non-Gaussian variables that might be partially missing at different hierarchical levels (section 4.3.2.2.). Multilevel models with multivariate mixed response types are the types of models used to impute the data in this thesis. This section describes these models in more detail, using Goldstein and Carpenter's terminology (2015).

Consider a two-level analysis model:

$$\begin{gathered} Y_{ij} = X_{ij}^{(1)}\alpha_1 + X_j^{(2)}\alpha_2 + Z_{ij}u_j + \epsilon_{ij} \\ u_j \sim N(0, \Omega_u^2), \\ \epsilon_{ij} \sim N(0, \sigma_\epsilon^2). \end{gathered} \tag{2}$$

Where j=1,…,J indexes level 2 units and i=1,…,n indexes level 1 units, as conventionally done in the multilevel literature. Y_{ij} refers to the outcome measured at level 1, X_{ij} to level 1 covariates, X_j to level 2 covariates, Z_{ij} to covariates with random coefficients u_j at level 2. The random coefficients u_j are assumed to follow a multivariate normal distribution, independent of the level 1 residuals ϵ_{ij}.

Any of the variables of the multilevel analysis model of equation (2) might have missing observations. For now, I assume that these variables are jointly multivariate normal, but this can be extended using the latent multivariate normal approach (section 4.3.2.2.). A multilevel imputation model can be formed using the response and the covariates and treating them as joint outcome variables of a so-called joint multilevel multivariate normal model. The model can be written as:

$$\begin{gathered} Y_{ij}^{(1)} = \beta^{(1)} + u_j^{(1)} + \epsilon_{1ij} \\ Y_j^{(2)} = \beta^{(2)} + u_j^{(2)} \\ \epsilon_{1ij} \sim MVN(0, \Omega_1), \\ u_j = \left(u_j^{(1)^T}, u_j^{(2)^T}\right)^T, \\ u_j \sim MVN(0, \Omega_2). \end{gathered} \tag{3}$$

There are as many level 1 outcomes as there are level 1 variables in the analysis model (outcome and covariates) and there are as many level 2 outcomes as there are level 2 covariates. Note that the superscripts $^{(1)}$ and $^{(2)}$ in the analysis model presented in equation (2) indicate the equation which the covariates end up in the imputation model of equation (3). Each outcome is represented by a β parameter, which corresponds to the mean value of the variable, and some variation (residuals ϵ_{1ij} and random effect $u_j^{(1)}$for level 1 variables $Y_{ij}^{(1)}$

and random effect $u_j^{(2)}$for level 2 variables $Y_j^{(2)}$). Both ϵ_{1ij} and u_j are assumed to follow a multivariate normal distribution. The individual and cluster level residuals are treated as independent and unstructured covariance matrices are assumed.

The attractiveness of such a model (3) is that it can be used to impute missing values in both level 1 and level 2 variables. The model is (at least) as complex as the analysis model, as required to ensure the validity of Rubin's rules and consistency of parameter estimates (Carpenter & Kenward 2012). Auxiliary variables can be included in the imputation model if they provide information about the missingness mechanism. These should be included as outcomes if they include missing data. If fully observed, they could be included as covariates, although including them as outcomes might have advantages, such as allowing easily to verify if the imputation model is compatible with the analysis model (Quartagno & Carpenter 2016).

Details on how the imputation model is fitted are given in Carpenter and Kenward (2012) and in Goldstein et al. (2009). The overall MCMC algorithm described in section 4.3.3.1. is also used (see also Appendix C section C.2 for an overview of the imputation procedure). In practice, the Gibbs MCMC sampler is updated a number of times (typically at least 1,000) so that the model converges to the posterior distribution (known as the 'burn-in' period). Datasets can then be drawn from the posterior distribution (including both imputed and observed data). The sampler then needs to be updated a number of times (typically at least 100 times) between two retained imputed datasets in order to ensure that datasets are stochastically independent given the observed data (known as the 'n-between'). The analysis model can then be applied to each imputed dataset and the results combined for inference using Rubin's rules.

4.3.4. Variables selection and convergence

Having chosen and detailed the general approach used to impute the data in this thesis, this section specifies two more practical aspects of multiple imputation. I briefly describe the variable selection process in an imputation model and specify how convergence of the model should be assessed before using a model to impute the data.

4.3.4.1. Variables selection

To ensure the validity of the inference made, the imputation model should be at least as rich as the analysis model that uses the imputed data. This means that the imputation model should include all the variables included in the analysis model, it should account for the hierarchical structure of the data (at least to the same extent as in the model if interest), and it should handle non-linearities and interactions. In addition, auxiliary variables could be included in the imputation model if they are expected to provide additional information about the missingness mechanism. Under the MAR assumption, auxiliary variables can potentially reduce bias compared to an analysis conducted as a complete case analysis and can increase efficiency, i.e. lead to more precise estimations (Carpenter & Kenward 2012).

To identify auxiliary variables, preliminary analyses are conducted using the complete cases (restricted to almost fully observed variables), in order to identify which variables are predictive of the chance of missing values, and which variables are predictive of the variables with missing values. Such analyses are presented in appendix of each longitudinal results chapter (Appendix E section E.1, Appendix F section F.1 and Appendix G section G.1). It was shown (Carpenter & Kenward 2012) that an auxiliary variable should be included in the imputation model in two different scenarios under MAR. If the auxiliary variable predicts the variable with missing values, then including it can improve efficiency of the inference made (i.e. reduce the standard errors). In addition, if the auxiliary variable predicts both the variable with missing values and the probability of being missing, it should also be included because it is likely to reduce bias and improve efficiency. An auxiliary variable should however be excluded if it only predicts the probability of being missing. Including it would not add anything, and would most likely slow the imputation process down. It is also important to bear in mind that, in the joint modelling framework, the same imputation model is used for all variables, so that any auxiliary variable is going to be used to predict the missing values of all variables with missingness.

Once a set of auxiliary variables has been selected and an imputation model specified, the next step is to ensure that the model parameters converge to a posterior distribution. Once convergence has been confirmed, the model can be used to impute the data.

4.3.4.2. Diagnostic analysis: ensuring convergence

The purpose of diagnostic analysis is to ensure that the results of the MCMC procedure can be used to impute missing data. One needs to decide on two parameters before registering imputations: the number of burn-in iterations and the between-imputation iterations (n-between). A burn-in period is used in order to allow the MCMC sampler to reach convergence, implying that the distribution is stationary. The burn-in period should be sufficiently long so that, after a series of iterations, the distribution of data points does not change as the chain progresses (relatively constant mean and variance). Convergence should be checked for all parameters using time-series plots (or trace plots) of the MCMC chains of the parameters. The same time-series plots, together with autocorrelation plots are also useful to determine the between-iteration length. Ideally, the number of iterations between imputation registrations should be longer than the systematic cycles observed in the time-series plots. A general rule of thumb is that the n-between should be selected so that the autocorrelation function (ACF) lies between -0.05 and 0.05 from the corresponding lag value.

Because of the constraint of the latent variable model, the covariance matrices are not estimated with the Gibbs sampler but with a Metropolis-Hastings step (Carpenter & Kenward 2012). Consequently, time-series plots of elements of covariance matrices related to discrete variables look quite different because the parameters are not updated at each iteration. It is generally considered that a sampler is satisfactory when it is updated for at least 10 percent of the iterations and possibly 25 percent (Roberts et al. 1997). A good mixing of the MCMC chain is still expected in the long run. Note that with the Metropolis-Hastings step, the autocorrelation plots become very difficult to interpret and are therefore not presented.

Given the complexity of the multilevel imputation models used, it is not possible to analyse the convergence of all the parameters in the models. Focus therefore fell on the analysis on the β parameters (including level 2 β's), the level 1 and level 2 variances, and the level 1 and level 2 covariances involving the outcomes of the analysis models (e.g. walking to school, walking for leisure and outdoor physical activity). In this thesis, level 1 and level 2 β coefficient matrices are referred to as 'Beta' and 'Beta2' respectively and level 1 and level 2 covariance matrices are referred to as 'Omega' and 'Cov u' (or 'Covariance u') respectively. Relevant diagnostic graphs are presented in the longitudinal results chapters (chapters 6-8).

4.3.4.3. Re-specification of the model

If the diagnostic analysis indicates poor evidence of convergence, the imputation model can be re-specified such that convergence is achieved. This process may involve a reduction in the number of categories of some of the non-continuous variables or the exclusion of problematic auxiliary variables. The overall structure of the imputation model could also be changed. In particular, the ORiEL data has a 3-level structure and available packages only allow for multi-level models with a 2-level structure (with discrete variables). There are therefore different ways of specifying the imputation model (cf. section 6.4.1.2. for an illustration). Including fully observed variables as outcomes instead of covariates is also another modification that might solve convergence issues (Quartagno & Carpenter 2016).

4.3.5. Statistical package used in this thesis

This final section on multiple imputation describes the statistical package used to implement the analytical approach proposed. Considerable detail is provided in this section given the relative novelty of the package and the imputation approach used.

Multilevel joint models are available in a number of major statistical packages such as SAS, Stata, Mplus, MLwiN and R ('pan' and 'jomo' packages). However, few packages allow for the use of non-Gaussian variables. Mplus implements an algorithm that deals with ordinal and binary variables, but offers no solution for un-ordered discrete variables, which is a major drawback given that such variable types are very frequent (see Enders (2016) for an overview). The multilevel imputation model proposed by Goldstein et al. (2009) was implemented in REALCOM-IMPUTE (Bartlett 2011, Carpenter et al. 2011) and more recently in the 'jomo' R package (Quartagno et al. 2018). These two implementations use the latent normal distribution approach described in section 4.3.2.2. Current implementations only allow for 2-level models in the presence of discrete variables (Goldstein & Carpenter 2015).

For this thesis, the 'jomo' package used only implements the solutions for unordered and binary variables, whereas REALCOM-IMPUTE also accommodates the proportional probit model for ordinal variables. Despite this limitation, Quartagno (2016) showed in a simulation study that the algorithm for unordered discrete variables works relatively well with ordinal data. More generally, the 'jomo' package is preferred over REALCOM-IMPUTE because it is more computationally efficient, which means that requires much less time to run the imputation models (Quartagno 2016). In fact, it was designed to overcome the computational inefficiency of REALCOM-IMPUTE, which was perceived as a major drawback. Consequently, the 'jomo' package allows for the implementation of much more comprehensive imputation models than REALCOM-IMPUTE. Previous work using the ORiEL data in REALCOM-IMPUTE required restrictions on the number of discrete variables used and the re-categorisation of many of the included variables (Fahy et al. 2016). Given that I wanted to avoid such a limitation in my thesis, and to explore whether it was possible to handle missing data without having to restrain the main analyses, I opted for the 'jomo' R package.

4.3.5.1. The 'jomo' R package

To run imputation models with 'jomo', one first needs to load and 'attach' the data in R (R Foundation for Statistical Computing 2017) and to define 'data.frames' for each type of variables: level 1 outcomes Y, level 2 outcomes Y2, level 1 fully observed covariates X1, and level 2 fully observed covariates X2. At least a Y data.frame should be specified. The following example uses the dataset 'mypanel' to define 4 data.frames:

```
data("mypanel") # load the dataset
attach(mypanel) # attach it

# define the data.frame with the level 1 outcomes
Y <- data.frame(lntotpa, walk, health)

# define the data.frame with the level 2 outcomes
Y2 <- data.frame(fsm)

# define the data.frame with the level 1 covariates
X <- data.frame(rep(1,nrow(Y)),gender)

# define the data.frame with the level 2 covariates
X2 <- data.frame(rep(1,nrow(Y)),gender)
```

R automatically distinguishes continuous from discrete variables. Discrete covariates in the imputation model with more than two categories should be manually included using n-1 dummy variables. In order to add an intercept to the imputation model, a column of ones must be included in the X and X2 data.frames. If the data have a hierarchical structure that needs to be accounted for, a data.frame should also specify a cluster identifier. In this example, with repeated measurements on the same units, the respondent 'id' is specified as the cluster data.frame:

```
clus <- data.frame(id)
```

The jomo package contains two core functions: the imputation function and an MCMC diagnostic function.

jomo: is the primary function of the package. It is used to define and run the imputation model. One simply has to specify the role of the data.frames in the imputation model. The following command runs the multilevel model with level 1 and level 2 outcomes and covariates above defined:

```
imp <- jomo(Y=Y, Y2=Y2, X=X, X2=X2, clus=clus)
```

The desired numbers of burn-in (nburn), n-between (nbetween) and imputed datasets (nimp) can be specified, as well as the values of the parameters of the model at which the sampler starts. The latter option is useful if a series of burn-in iterations was previously run and the last values of the parameters was saved at the end of the process. The output of the *jomo* function is a data.frame which includes the original and the imputed datasets.

jomo.MCMCchain: this function is used to check whether the sampler has reached a stationary distribution by running a certain number of iterations, nburn. To assess whether the model in this example has converged after 5,000 iterations, the following function is used:

```
imp <- jomo.MCMCchain (Y=Y, Y2=Y2, X=X, X2=X2, clus=clus,
nburn=5000)
```

The function collects the value of all parameters of the imputation model at each of the 5,000 iterations. Values can be used to draw a trace plot (i.e. time-series plot) and autocorrelation plots for convergence assessment of parameters from the four matrices of the model: Beta (level 1 β coefficients), Beta2 (level 2 β coefficients), Omega (level 1 covariances of residuals) and Cov u (level 2 covariances of random effects). *Jomo.MCMCchain* is also used for each imputation model with a burn-in n_{burn}=2 to make sure that the intended model was correctly specified. This is equivalent to the 'dryrun' command in Stata.

Because of the complexity of some of the imputation models tested, R faced memory issues when trying to store parameters values over many iterations. Running long MCMC chains and saving the results is possible by breaking the long chain into smaller chains. This is possible using *jomo.MCMCchain* and saving the final values of the parameters at the end of a block of iterations and subsequently using those values as starting values of the next block. This strategy allows the user to run as many burn-in iterations as necessary for convergence assessment.

A real-life example is provided in Appendix C (section C.3). The example corresponds to the final imputation model of chapter 6 (section 6.4.1.2.). The model equation is provided, followed by the R codes used to fit the model. As the appendix shows, using 'jomo' allowed me to fit a very comprehensive model that includes all the variables I wanted to include in my analysis model, it accounts for the hierarchical structure of the data and it further includes a series of auxiliary variables which are used to improve efficiency and reduce potential bias. To my knowledge, no such comprehensive multilevel imputation models that includes so many discrete variables has been fitted to date.

In the next section, I describe the analytical approach used to answer the epidemiological research question of this thesis. The analytical approach will have to be able to handle the imputed datasets produced in a first instance.

4.4. Analysis models: general analytical approach

This section sets out the general analytical approach used to answer the research questions posed in this thesis (section 2.5.). The focus here is on the analytical strategy for the main results chapters (chapters 6-8) in which I use the longitudinal data and handle missing data as detailed in section 4.3. The research questions of those chapters (sections 6.2., 7.2., and 8.2.) involve the use of the longitudinal data, for which a 3-level structure is observed (repeated measurements, individual, school). Secondary research questions in chapters 5 and 7 do not require longitudinal modelling (e.g. after the creation of cumulative exposure variables over time, or the calculation of change scores between two waves) but still involve a 2-level structure (adolescents clustered in schools) that needs to be accounted for. These models are referred to as cross-sectional models in this thesis[15].

As described in section 4.1., the choice of the analytical approach in this thesis is driven by: i) the use of binary and ordinal outcomes; ii) the hierarchical structure of ORiEL data; iii) the interpretability of the parameters in terms of population average; iv) the compatibility with multiple imputation.

In this section I briefly explain why marginal models estimated with the generalised estimating equations (GEE) method are the preferred approach and then further present the GEE method, and its application for logistic and proportional odds models in combination with multiple imputation described above. Detail on the choice of GEE as opposed to alternative modelling approaches (including generalised linear models with cluster-robust standard errors, fixed effects models and random effects models) is provided in Appendix C (section C.4).

4.4.1. Estimating marginal models with generalised estimating equations (GEE)

Marginal models for hierarchical discrete data are used throughout this thesis. This analytical approach is convenient because it can be used to answer research questions involving repeated measurements on the same adolescents and research questions involving cross-sectional data with clustering at school-level.

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[15] Note that the exploratory cross-sectional results from chapter 5 use the complete cases of the baseline data and do not use the GEE methodology.

Marginal models, and GEE in particular, are preferred over alternative approaches owning to the interpretation of their parameters. In the context of hierarchical discrete data, marginal models and conditional models (e.g. generalised linear mixed models) provide parameters with different interpretations (Molenberghs & Verbeke 2005). The choice between the two approaches has to be made in the context of the research questions asked. Marginal models describe population-average effects whereas conditional models describe conditional subject-specific effects. In public health and epidemiological research, the population-averaged effect of a treatment or an intervention is often of interest, as opposed to the specific effect observed on individuals (Agresti 2002, Fitzmaurice et al. 2011, Hubbard et al. 2010, Lovasi & Goldsmith 2014). In this thesis, the interest lies in how changes in neighbourhood and home environments affect, *on average*, physical activity in the ORiEL population. For this reason, marginal models are preferred over conditional models.

Marginal models are estimated with the GEE method in this thesis. This method provides a convenient and flexible alternative to likelihood methods, which can be cumbersome to specify and/or fit when the responses are discrete (Agresti 2002, Fitzmaurice et al. 2011, Molenberghs & Verbeke 2005). In this thesis, the GEE approach is used to fit logistic regression models (binary outcomes) and proportional odds models (ordinal outcomes). The GEE approach for binary responses is computationally straightforward and has been implemented in standard statistical software (such as Stata, R and SAS). The GEE approach used for proportional odds models is only available in the SAS software (SAS Institute 2013). Current software implementations of GEE are also restricted to two-level structures in the data, which leads to the compromise that clustering at school-level is ignored in the longitudinal models.

Current software implementations for binary outcomes are compatible with multiple imputation, which is one of the criteria guiding the choice of my analytical approach. Standard statistical software provide a combined inference based on the results estimated with GEE in each imputed dataset. There are still some restrictions with the models for ordinal outcomes however, as the SAS software current does not currently provide a combined test for the proportional odds assumption (Donneau et al. 2015).

In the rest of this section, I describe the general principles of GEE. I then indicate how GEE is used in this thesis to estimate longitudinal and cross-sectional logistic and proportional odds models.

4.4.2. Basic principles of GEE

Given the difficulties of specifying a joint multivariate distribution for the outcome variable in marginal models when the responses are discrete (Molenberghs & Verbeke 2005), one requires an alternative to maximum likelihood estimation. Generalised estimation equations – or GEE – offers that alternative. Essentially, GEE makes use of the three-part specification of marginal models to obtain a valid estimation of the mean structure, which contains the population-average parameters of interest. The three components of marginal models are the following (Fitzmaurice et al. 2011):

1. the mean structure or marginal expectation of the response variable, as a function of the covariates (this is generally the component of interest);
2. the variance of each outcome variable (which depends on the mean), given the covariates;
3. the conditional within cluster association among the vector of clustered response, given the covariates.

GEE avoids the task of specifying a multivariate distribution for the marginal model. Instead, it uses an algorithm that obtains consistent[16] and asymptotically normal estimates of the mean structure. The focus of the estimation process is on the mean structure, and the associations between clustered observations are treated as a nuisance to be accounted for. An appealing property of GEE is that the consistency of the estimator of the mean structure only depends on the mean response to be correctly specified, even if the within cluster associations among the clustered measures are incorrect (Molenberghs & Verbeke 2005). Technical details on the GEE methodology are presented in Molenberghs and Verbeke (2005), Agresti (2002) and Fitzmaurice et al. (2011).

To initiate the GEE algorithm, one needs to specify the form of the correlation structure among the observed responses, known as the working correlation structure. Common working correlation structures are:

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[16] An estimator is consistent if it converges in probability to the true value of the parameter as *n* tends to infinity.

- independence: absence of correlation
- exchangeable or compound symmetry: same correlation for all within cluster pairs of observations
- autoregressive lag-1 or AR(1): correlation declines exponentially with the time-lag (for longitudinal data only)
- unstructured: a different correlation for each within cluster pair of observations

The choice of a working correlation structure has a direct impact on the efficiency of the estimators. More efficient estimates (i.e. with smaller standard errors) are obtained if the specified correlation structure resembles the true dependence structure (Fitzmaurice et al. 2011). It is generally recommended that you check the sensitivity to the selection of the working correlation by comparing results from different specifications (Agresti 2002).

However, the standard errors (called 'naïve' or 'model-based' standard errors) obtained under the misspecified model for the within cluster association are usually not valid. Valid standard errors can be obtained using the 'sandwich' estimator of the standard errors, also known as cluster-robust standard errors (see Appendix C section C.4)[17]. In general the 'sandwich' estimator of the standard errors is best suited to balanced designs where the number of clusters is relatively large and the number of observations per cluster is relatively small (Fitzmaurice et al. 2011). When the number of clusters is small, variances tend to be underestimated. In this thesis, the longitudinal analyses respect these conditions (many observations and few waves). There are however fewer schools (n=25) in the models accounting for clustering at school-level, which could lead to underestimation of standard errors. However, this bias is likely to be inconsequential given the limited clustering expected at school-level (Smith et al. 2015a)[18].

Overall, the GEE approach is appealing for discrete data because of its computational simplicity compared to maximum likelihood (Fitzmaurice et al. 2011). However, it has

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[17] Note that using GEE with an independent working correlation and robust standard error gives similar results as using cluster-robust standard error combined with a generalised linear model (GLM). However, specifying a working correlation that allows for correlations between units would generally improve the efficiency of the estimator. In general, GEE is preferred over cluster-robust standard error because it properly accounts for clustering in the estimation process, as opposed to simply correcting the standard errors (cf. Appendix C section C.4).

[18] Using GEE for cross-sectional analyses is still preferred over the alternative methods because i) GLM combined with cluster-robust standard errors suffers from the same drawbacks without having the advantages of GEE; ii) fixed effects are not desirable for school-level clustering as indicated in Appendix C section C.4; iii) random effects models would impose an undesirable school-specific interpretation.

limitations. Because it does not completely specify the joint distribution, it does not have a likelihood function. As a result, likelihood-based methods are not available for testing fit, comparing models, and conducting inference about parameters. Inference is based on Wald statistics instead (Agresti 2002). Another drawback of the GEE approach is that it does not explicitly model random effects and therefore does not allow these effects to be estimated (Fitzmaurice et al. 2011). Another disadvantage is the difficulty of estimating marginal models with a three-level structure, and the absence of statistical software that implements existing solutions. As a result, the longitudinal analyses of this thesis do not implement clustering at school-level. Including school as a fixed effects was not considered as an option given that it would restrict inference to a specific set of school sampled (Rabe-Hesketh & Skrondal 2012) (cf. Appendix C section C.4). A final limitation of GEE, is that the method is only valid when missing data follow MCAR mechanisms. When missing data are observed on many variables, it is therefore recommended that GEE be combined with multiple imputation, as implemented in this thesis.

4.4.3. Use of GEE in this thesis

Having provided a general introduction to the GEE methodology, I now turn to how GEE is used in this thesis. GEE is used to capture four types of longitudinal associations between the time-varying exposure and outcome variables. These are: i) pooled longitudinal association across all measurements; ii) association between accumulation of exposure and later stage outcome; iii) association between trajectory of exposure and changes in outcome; iv) association between change in exposure and change in outcome. These four types of associations are modelled using logistic regression models for i), ii) and iii), and proportional odds models for iv), and estimated with the GEE method. For each type of longitudinal association of interest, I describe the type of model fitted and present the software used.

4.4.3.1. Pooled longitudinal models for binary outcomes

In chapters 6 to 8, I assess the presence of pooled longitudinal association between the exposure variables and the binary physical activity outcomes. This way of exploring the associations is common in longitudinal studies of neighbourhood effects and informs on whether differences in exposure, coming either from two different individuals or the same individual at different measurement points, lead to differences in physical activity. In pooled longitudinal models, variables are all measured at the individual level i, and most variables vary across repeated measurements j[19]. The outcomes are all binary so that general form of the model for the mean response is a logistic regression model, expressed as follows:

$$logit\{\Pr(Y_{ij} = 1|\boldsymbol{x_{ij}})\} = \boldsymbol{x'_{ij}\beta} \tag{4}$$

Where:

i = individual

j = repeated measurements

Y_{ij} = physical activity outcome for individual *i* at occasion *j*

$\boldsymbol{x_{ij}}$ = a matrix representing the variables included in the model for all individuals i's at each occasion *j*

$\boldsymbol{\beta}$ = a vector representing the coefficients of the model, including a constant.

The logistic regression models of equation (4) are estimated with GEE using the unstructured working correlation structure to account for the association between repeated measurements[20]. Such a working correlation structure allows for greater flexibility in the correlation structure and is expected to better reflect the true underlying correlation. The 'sandwich' estimator is used to calculate standard errors. Sensitivity analyses are conducted using the exchangeable working correlation structure, which is usually preferred when they are many repeated measurements (Agresti 2002). Clustering at school-level could not be accounted for in these models, but it is generally expected to be small in the ORiEL study as shown for total physical activity (section 3.5.1.1.) and for mental health outcomes (Smith et al. 2015a).

Models are estimated in Stata versions 14 and 15 (StataCorp 2015, 2017) using the 'xtgee' command. The 'xtgee' command is compatible with the 'mi estimate' command which allows to estimate logistic regression models with GEE for each imputed dataset and to combine results into a final inference.

---

[19] Note that I used the standard subscript convention for longitudinal analyses where *i* indexes individuals (level 2) and *j* indexes repeated measurements (level 1). In the multilevel imputation models however, I used the convention for multilevel models where *i* indexes individuals (level 1) and *j* indexes schools (level 2).

[20] The third component of the marginal model, namely the variance function (i.e. the scaling parameter), is simply defined as a function of the mean response (Fitzmaurice et al. 2011).

Given that exposure variables are time-varying, the association between exposures and outcomes is either interpreted as cross-sectional (i.e. a change from one person to another person with a different level of exposure is related to difference in the outcome at a given time) or longitudinal with an immediate effect of the exposure on the outcome (i.e. within person change in the exposure is associated with within person change in the outcome). For example, an OR of 1.5 for an exposure variable is interpreted as: '*on average, the odds of the outcome are 1.5 times higher among those who are exposed compared to those who are not exposed (the difference in exposure might correspond to within individual change between two repeated measurements or differences between two persons with different levels of exposure)*'.

4.4.3.2. Cross-sectional models for cumulative exposure and binary outcome

In chapter 6, I test different types of associations between the time-varying exposures and the outcomes. One hypothesised form of association is that the accumulation of positive or negative exposure over time can lead to differences in physical activity at a later stage. I expect that the longer the exposure, the greater the effect on physical activity. This hypothesis assumes that the effect of an exposure is cumulative and long-lasting. For example, those who have maintained a positive view of the supportiveness of their neighbourhood are expected to do more physical activity compared to those who have recently improved their perception. Conversely, those with long-lasting negative perceptions will be the least likely to be physically active in the neighbourhood.

This type of longitudinal association is estimated using cross-sectional models, where the physical activity outcome is binary and measured at the end of the study period, and the exposure is a cumulative score of exposure across all measurement points (cf. section 3.5.). These cross-sectional models do no need to account for clustering at individual-level given that all variables are considered to be time invariant. School-level clustering can then be accounted for.

The general form of the model for the mean response is a logistic regression model, expressed as follows[21]:

$$logit\{\Pr(Y_{ij} = 1|\boldsymbol{x_{ij}})\} = \boldsymbol{x'_{ij}\beta} \qquad (5)$$

[21] Given that this model is multilevel, I used the subscript convention used in the literature on multilevel models.

Where:

i = individual

j = school

Y_{ij} = physical activity outcome for individual *i* in school *j*

$\boldsymbol{x_{ij}}$ = a matrix representing the variables included in the model for all individuals i's in each school *j*

$\boldsymbol{\beta}$ = a vector representing the coefficients of the model, including a constant.

The cross-sectional logistic regression models of equation (5) are estimated in Stata ('xtgee' combined with 'mi estimate') using exchangeable working correlation structures to account for the correlations between individuals within schools. The 'sandwich' estimator is used to calculate standard errors. Sensitivity analyses are conducted using the independence working correlation structure, assuming no correlation between individuals in the same cluster.

These models are technically cross-sectional and therefore their parameters have a standard interpretation.

4.4.3.3. Models for trajectories of exposure and binary outcome

In chapter 6, I also test whether the overall trajectory of exposure might be associated with the trajectory of change in the physical activity outcome for a given person. Unlike the pooled longitudinal model, this type of model does not conceptualise the effect of changes as immediate, but attempts to capture how the trends in exposures and outcomes covary.

Trajectories of exposure are modelled using longitudinal models where the physical activity outcome is time-varying and binary, and the exposure is a trajectory score of exposure considered to be time-invariant (cf. section 3.5.). Variables are all measured at the individual level i, and most variables, unlike the exposures, vary across repeated measurements j. The general form of the model for the mean response is a logistic regression model, expressed as in equation (4). The difference is that the exposures do not vary across measurements and that the main parameter of interest is an interaction term between time and each trajectory score. The resulting coefficient is an odds ratio indicating the extent to which individual trajectories of exposure and outcome covary. These models are also estimated in Stata using 'xtgee' combined with 'mi estimate' commands.

4.4.3.4. Models for change scores in exposures and outcome

A fourth approach to modelling longitudinal associations is used in chapter 8, where exposure variables are available for only two waves of data. Models are specified to capture the associations between the change between wave 2 and wave 3 in the exposures and changes in the outcomes (cf. section 3.5.). I estimate these associations using cross-sectional proportional odds models using the GEE method to account for clustering at school level (Agresti 2002). Variables are measured on individuals $i's$ and all considered as time-invariant, because they are either baseline confounders or measures of change between wave 2 and wave 3. The general form of the model for the mean response is a proportional odds model, expressed as follows[22]:

$$logit\{\Pr(Y_{ij}^{*} \leq k|\boldsymbol{x_{ij}})\} = \alpha_k + \boldsymbol{x'_{ij}\beta}, \qquad k = 1,2. \qquad (6)$$

Where:

i = individual

j = school

Y_{ij}^{*} = ordinal variable with three categories, indicating whether the physical activity outcome decreased, remained constant or increased for individual i in school *j.*

k = values taken by the ordinal outcome variables. In this analysis, the model is fully described using k = 1 and 2 because the outcome can take three distinct values.

$\boldsymbol{x_{ij}}$ = a matrix representing the variables included in the model for all individuals $i's$ in each school *j*

$\boldsymbol{\beta}$ = a vector representing the coefficients of the model associated with the covariates. The model has the same effects $\boldsymbol{\beta}$ for all cumulative logits.

α_k= a separate constant defined for each cumulative logit.

Models of equation (6) are estimated in SAS software version 9.4 (SAS Institute 2013) using the 'PROC GENMOD' procedure with a 'REPEATED' statement to account for clustering at school level (Fitzmaurice et al. 2011, Molenberghs & Verbeke 2005). SAS is the principal general statistical package in which the proportional odds model can be estimated with GEE and combined with multiple imputation using the 'PROC MIANALYZE' procedure. A limitation of the SAS implementation of the GEE method for the cumulative multinomial distribution

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[22] Given that this model is multilevel, I used the subscript convention used in the literature on multilevel models.

used is that only the independence working correlation structure can be specified. This means that sensitivity to the working correlation structure cannot be assessed for these models. As indicated in section 4.4.2., choosing a 'wrong' working correlation structure only affects the efficiency of the estimator, and not their consistency (Molenberghs & Verbeke 2005). The 'sandwich' estimator is used to calculate standard errors. As a sensitivity analysis, I also report results from proportional odds models, ignoring clustering at school-level.

The proportional odds assumption could not be formally tested in models estimated with GEE and/or in combination with multiple imputation as, to my knowledge, the test is not currently available in any general statistical software (Donneau et al. 2015). I achieved an informal evaluation of the assumption by fitting proportional odds models without accounting for clustering,[23] separately for each imputed dataset. Using the procedure 'PROC LOGISTIC' in SAS 9.4, I tested the proportional odds assumption for each imputed dataset. I ensured that the assumption was satisfied for the exposure variables. I then used partial proportional odds models (Agresti 2002) to allow for non-proportionality for some of the confounding factors, while maintaining the proportional odds assumptions for covariates which did not indicate a violation of the hypothesis in any of the imputed datasets ($p>0.05$).

Parameters of the models are interpreted as associations between within individual changes in exposure and outcomes.

4.5. Summary

In this chapter, I have presented the two-fold analytical approach for the analysis of the ORiEL data. First I offered a solution to handle item non-response. Finding such a solution has been a major methodological aspect of this chapter. The approach proposed uses multilevel multiple imputation and allows to deal with the 3-level structure of the ORiEL data (repeated measurements on adolescents, themselves clustered in schools), a mixture of discrete and continuous variables and some interaction terms in the analysis models (between gender/ethnicity and exposure variables). While the setting of this thesis might seem quite typical in epidemiology, only the recent R package 'jomo' allows for all three circumstances without severely constraining the number of variables included in the imputation model (and therefore in the analysis models).

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[23] Although it should be noted that accounting for clustering might reduce the risk of violating the proportional odds assumption (Agresti 2002).

Having specified an approach for missing data handling in ORiEL, I then selected the analytical approach for the main analyses. I estimate logistic regression models and proportional odds models using generalised estimating equations or GEE. GEE allows the estimation of marginal models, which have a desirable interpretation of the parameters in terms of population-average. Parameters of the estimated models therefore indicate how (changes in) neighbourhood and home environments affect, *on average*, physical activity in the ORiEL population. Estimating proportional odds models with GEE in combination with multiple imputation is another uniqueness of this thesis. Such an approach can only be implemented in SAS and is still experimental to some extent, given that no test for the proportional odds assumption is available yet.

The analytical approaches presented in this chapter are employed in the following chapters. A notable exception is the exploratory baseline chapter (chapter 5) which is based on a complete case analysis and uses GLM with cluster-robust estimators of the standard errors. Chapter 5 is indeed conceived as a guide to the variable selection for the subsequent longitudinal analyses and the building of the imputation models (especially chapter 6). Results using cluster-robust standard errors are expected to be very similar to those that would have been obtained with GEE. Chapters 6 and 7 use separate imputed datasets (to allow interaction terms with gender and ethnicity, respectively) and estimate longitudinal logistic regression models with GEE. Chapter 6 also estimates cross-sectional logistic regression models with GEE. Chapter 8 uses imputed datasets based on waves 2 and 3, and estimates longitudinal logistic regression models and cross-sectional proportional odds models with GEE. For all models estimated with GEE, longitudinal models account for clustering at individual level, whereas cross-sectional models account for clustering at school-level.

Chapter 5: Baseline associations between physical activity and perceptions of the neighbourhood environment

5.1. Introduction

In this chapter, I present an analysis of the baseline associations between six outcomes of physical activity and a range of perceptions of the neighbourhood environment. This chapter serves as a guide and preliminary analysis for the longitudinal analysis of the associations between perceptions of the neighbourhood and physical activity presented in chapter 6.

The evidence base on the relationship between the neighbourhood environment and physical activity has grown over the last decades (De Vet et al. 2011, Ding & Gebel 2012, Gebel et al. 2007). It has been acknowledged that measures of neighbourhood perceptions – for example safety, aesthetic quality, disorder – should be conceptually distinguished from objective measures, as each are hypothesised to independently influence health behaviours (Lakerveld et al. 2012). There is also a growing recognition that neighbourhood attributes should be understood beyond their associations with total physical activity because different attributes have been shown (and are expected) to be associated with different domains of physical activity (Owen et al. 2004).

Previous results on the relationships between perceptions of the neighbourhood and domains of physical activity have been mixed and there are still many research gaps (Van Holle et al. 2012). Most research has been conducted in the US and Australia and has received little attention elsewhere. This is a problem because North American and Australian cities may sometimes differ structurally from most European cities. Furthermore, few studies have investigated deprived populations, which are expected to be more affected by some features of their neighbourhood built and social environments, such as crime and disorder (Bauman & Bull 2007, Lovasi et al. 2009). The evidence on the extent to which adolescents' own perceptions of their neighbourhood features are associated with physical activity is still limited (Davison & Lawson 2006, Ding et al. 2011). Indeed, the gradual grain in independence mobility during adolescence (Mackett et al. 2007) might suggest that adolescents' own perceptions, as opposed to their parents', might become more prominent predictors of physicals activity behaviours during adolescence.

In this chapter, I use baseline data from the 3-wave balanced panel of the ORiEL study to test how adolescents' perceptions of the neighbourhood environment are associated with six forms of physical activity: total physical activity, daily recommended physical activity, walking to school, walking for leisure, outdoor physical activity and pay and play physical activity. Analyses are used to develop a preliminary indication of which variables of perceptions of the neighbourhood environment might be associated with physical activity outcomes, and results will be used to help select the variables used in the longitudinal analysis presented in chapter 6. I explore a broad range of physical activity outcomes expected to be associated with the neighbourhood perceptions data captured by the ORiEL questionnaire. Total physical activity and daily recommended physical activity were included to explore the presence or absence of overall associations with perceptions, although I anticipate some of those might be difficult to interpret if opposite associations are observed with more detailed forms of activity. Ten different measures of neighbourhood perceptions are investigated, with the objective of guiding the selection of exposure variables for longitudinal analyses.

5.2. Research questions

The following research questions are explored in this chapter.

Question 1: Are perceptions of the neighbourhood associated with physical activity in adolescents at baseline of the ORiEL study?

Specifically:

1.1. Are perceived proximity to destinations, traffic safety, street connectivity, aesthetics and crime-related safety associated with total physical activity?

1.2. Are perceived proximity to destinations, traffic safety, street connectivity, aesthetics and crime-related safety associated with meeting daily recommended physical activity?

1.3. Are perceived proximity to destinations, proximity to nearest bus stop, traffic safety, street connectivity, aesthetics, enjoyment of the neighbourhood for walking/cycling, crime-related safety and personal safety associated with walking to school?

1.4. Are perceived proximity to destinations, proximity to nearest recreation area, traffic safety, street connectivity, aesthetics, enjoyment of the neighbourhood for walking/cycling, crime-related safety and personal safety associated with walking for leisure?

1.5. Are perceived proximity to destinations, proximity to nearest bus stop, proximity to nearest recreation area, traffic safety, street connectivity, aesthetics, enjoyment of the neighbourhood for walking/cycling, crime-related safety and personal safety associated with outdoor physical activity?

1.6. Is perceived proximity to nearest sport and leisure centre associated with pay and play physical activity?

5.3. Methods

5.3.1. Analytical sample

To be consistent with the longitudinal analyses of chapter 6, the sample used for the baseline analysis was constructed by excluding ORiEL respondents that did not participate in all three waves and keeping wave 1 data from those participants (cf. section 3.3.). The final sample size includes 2,260 participants, each with various degrees of item response. The analyses conducted are on complete cases for specified outcomes, exposures and confounders. The analytical samples therefore differ for each analysis, depending on the extent of missingness on the outcome, exposure variables and potential confounders.

5.3.2. Variables

The variables used in this chapter were outlined in chapter 3 (section 3.5). These include six physical activity outcome variables, ten measures of neighbourhood perceptions and a set of potential confounders (Table 5.1). These are described below.

5.3.2.1. Outcomes

In this chapter, I explore a range of routine physical activities that could be associated with measures of neighbourhood perceptions in the ORiEL: total physical activity (in hours/week), daily recommended physical activity (i.e. $\geq$ 7hours of physical activity/week), walking to school, walking for leisure (dog/exercise), outdoor physical activity and pay and play physical activity. The walking to school and walking for leisure outcomes capture whether adolescents reported having participated in the activity at least once over the past week. The outdoor physical activity outcome combines participation at least once in any of the following activities: combines basketball/volleyball, blading, cricket, football, rounders, rugby and roller skating. The pay and play physical activity outcome combines aerobics, climbing, swimming, gymnastics, hockey, martial arts, netball, and tennis. Note that cycling participation could not be examined with the ORiEL data: cycling for leisure was not included in the questionnaire, and the prevalence of cycling to school was very low, especially at follow-up.

5.3.2.2. Exposures

Ten measures of neighbourhood perceptions hypothesised to be related to the outcomes were selected (Table 5.1). The measures are derived from the ALPHA questionnaire, which focuses primarily on walking and cycling (Spittaels et al. 2010), and from the MESA study for the crime-related safety (Mujahid et al. 2007) as described in section 3.5.2.1. Following results from a confirmatory factor analysis (Appendix B) five summary measures were used as 3-level ordinal scores (low/medium/high) to capture separate dimensions of neighbourhood perceptions: proximity to destinations, traffic safety, street connectivity, aesthetics, and crime-related safety. In addition, five separate items were used on their own because they capture exposure to aspects of perceptions in more detail, and therefore can better inform how specific perceptions relate to each form of physical activity. These were: proximity to bus stop, proximity to recreation area, proximity to sport and leisure centre, enjoyment of the neighbourhood for walking/cycling, and personal safety (i.e. feeling safe). Perceived proximity to a bus stop was recoded into a binary variable (1-5 minutes vs. further away) due to low reporting of more than 1-5 minutes. The other items were used on their original scale.

5.3.2.3. Potential confounders

The following variables were considered as potential confounders: gender, ethnicity (8 categories), family affluence (3 categories), health condition (3 categories), free school meal status, parental employment (6 categories), country of birth (UK vs. not), borough, and season of questionnaire completion.

Table 5.1 Variable definitions and item missingness at baseline of the 3-wave balanced panel (n = 2,260)

Variable	**Variable type and use in the analysis**	**% missing**
Outcomes		
Total physical activity	Continuous, approximately log Normal	2.8
Daily recommended physical activity	Binary (≥7 hours vs. less)	2.8
Walking to school	Ordinal (almost count), 4 categories, non-Normal; binary version used	8.4
Walking for leisure	Ordinal (almost count), 4 categories, non-Normal; binary version used	18.0
Outdoor physical activity	Count (0-7), non-Normal; binary version used	23.1
Pay and play physical activity	Count (0-8), non- Normal; binary version used	19.3
Exposures		
Perceived proximity to destinations	Continuous score based on 8 items ; categorised in 3 groups	28.7
Perceived traffic safety	Continuous score based on 3 items ; categorised in 3 groups	25.5
Perceived street connectivity	Continuous score based on 4 items ; categorised in 3 groups	32.3
Perceived aesthetics	Continuous score based on 4 items ; categorised in 3 groups	26.1
Crime-related safety	Continuous score based on 3 items ; categorised in 3 groups	30.3
Perceived bus stop proximity	Ordinal, 5 categories, skewed; binary version used	19.8
Perceived proximity to recreation area	Ordinal, 5 categories	20.4
Perceived proximity to sport and leisure centre	Ordinal, 5 categories	21.2
Enjoyment of the neighbourhood for walking/cycling	Ordinal, 4 categories	24.3
Feeling safe (personal safety)	Ordinal, 5 categories	29.0
Potential confounders		
Gender	Binary	Fully observed
Ethnicity	Nominal variable with 8 categories	Fully observed
Health condition	Count score of 9 binary items* (0-9), skewed; categorised in 3 groups (0/1/2+)	3.4
Family Affluence	Count score of 3 items (0-9), approximately Normal; categorised in 3 groups	4.6
Free school meal	Binary: Yes/No	2.0
Parental employment	Nominal variable with 6 categories	12.1
Country of birth	Binary (UK/non-UK)	2.0
Borough	Nominal variable with 4 categories	Fully observed
Season of interview	Binary variable (winter vs. spring)	Fully observed
Cluster variable		
School	Nominal variable with 25 categories	Fully observed

*requirement that at least five items should be completed to get a score because the interest is in whether any condition is reported.

5.3.3. Analytical strategy used in this chapter

Given the exploratory nature of this chapter, I did not handle missing data and 'missing completely at random' or MCAR is assumed. Missing data on the variables retained for the longitudinal analyses is examined in chapter 6 (Appendix E section E.1). Results indicate the MCAR assumption is likely not to hold and that the results are likely to be biased. Analyses are nonetheless used to develop a preliminary indication of which variables of perceptions of the neighbourhood environment might be associated with physical activity outcomes, in order to inform the selection of variables in the longitudinal analyses of chapter 6.

I used generalised linear models (GLM) to investigate the associations between exposure and outcome variables. For each outcome, separate GLM models were fitted to test which aspects of neighbourhood perceptions are associated with physical activity outcomes (model equations are presented in Appendix D section D.1). I used linear models for the log-transformed total physical activity outcome and logistic regression models for all other outcomes. I used cluster-robust standard errors to account for clustering at school-level, although the school-level correlation is expected to be small (cf. section 3.5.1.1.). Unadjusted and adjusted associations were calculated using analytical samples specific to each combination of exposure, confounders and outcome of interest. Separate unadjusted models included in turn an exposure variable and a physical activity outcome. For the linear model using the log-transformed total physical activity, the adjusted model included all five exposure variables and all potential confounders. In the multivariate logistic regression models, I adopted a more selective approach to the inclusion of covariates in the models because I explored associations with a broader range of exposure variables. Given the conceptual overlap and collinearity between some of the exposure variables (e.g. crime-related safety and personal safety), I fitted adjusted models for each exposure variable separately. In addition, I included fewer potential confounders in the adjusted models to avoid non-collapsibility of the odds ratios (Greenland et al. 1999). For each binary outcome and each exposure variable, I investigated associations with potential confounders. I then included in turn potential confounders in the models and investigated their impact on the change to the odds ratios. For convenience, however, and given that none of the covariates were strong confounders, I simplified the procedure in the final models presented here and adjusted for all potential confounders that were associated with at least one outcome. Unadjusted and adjusted association did not differ substantially, which gives an indication that the results presented are not affected by the non-collapsibility issue.

5.4. Results

In this section, I present the associations between perceptions of the neighbourhood and each physical activity outcome in turn.

5.4.1. Total physical activity

The baseline associations between the five summary measures of neighbourhood perceptions and physical activity are presented Table 5.2. Results are presented in the form of predicted geometric mean of hours of physical activity for each category of exposure, which is equivalent to the median given that the variable is approximately log-normal (cf. section 3.5.1.1.). Unadjusted and adjusted results provide no indication that total physical activity is associated with proximity of destinations, including grocery stores, local services, public transport, and leisure facilities (p-values=0.770 and 0.712 respectively). Estimated adjusted geometric mean of total physical activity is highest for those with low proximity (16.42; 95% CI: 13.48-20.02) and lowest for those with high proximity (15.02; 95% CI: 13.66-16.52), yet confidence intervals are wide and overlap considerably. Results are very similar for perceived traffic safety: neither the unadjusted nor the adjusted models indicate any evidence of differences in physical activity (p-values=0.394 and 0.618 respectively) and the estimated geometric means are slightly higher in the lowest perception group (16.10; 95% CI: 12.71-20.40), compared to the highest group (14.87; 95% CI: 13.69-16.15). Perceived street connectivity, however, indicates a significant positive association with total physical activity (unadjusted p-value=0.006; adjusted p-value=0.003): the adjusted geometric mean is lowest in the low perception group (13.21; 95% CI: 11.58-15.08), intermediate in the medium group (14.83; 95% CI: 13.37-16.45) and highest in the high perception group (18.53; 95% CI: 16.54-20.76). A significant association is also observed in unadjusted and adjusted models for aesthetics (p-values=0.002 and 0.007 respectively). The association here is U-shaped, the geometric mean of total physical activity is lowest in those who perceive aesthetics as medium (13.53; 95% CI: 12.18-15.02) and higher in those with high and low perceptions (respectively 16.52; 95% CI: 15.08-18.11 and 17.10; 95% CI: 14.63-19.97). Finally, no evidence of an association is observed between total physical activity and crime-related safety (unadjusted p-value=0.333; adjusted p-value=0.663). The estimated geometric means are around 15 hours in each of the three categories of perceptions (adjusted values are 15.77 (95% CI: 14.28-17.41), 14.80 (95% CI: 13.33-16.43) and 15.18 (95% CI: 13.27-17.37) for the low, medium and high groups respectively).

Table 5.2 Geometric mean of hours of physical activity by perception of the neighbourhood environment , adjusting for potential confounders (wave 1 of the ORiEL study, n= 1,054)

Exposure		**Unadjusted geometric mean**	**Adjusted geometric mean** [1]	**95%CI**	**P-value parameter**	**P-value unadjusted**	**P-value adjusted**[1]
Perceived proximity to destinations	Low	16.35	16.42	[13.48,20.02]		0.770	0.712
	Medium	14.92	15.21	[13.85,16.70]	0.480		
	High	15.29	15.02	[13.66,16.52]	0.415		
Perceived traffic safety	Low	17.20	16.10	[12.71,20.40]		0.394	0.618
	Medium	15.13	15.62	[14.09,17.32]	0.812		
	High	14.95	14.87	[13.69,16.15]	0.506		
Perceived street connectivity	Low	13.63	13.21	[11.58,15.08]		0.006	0.003
	Medium	14.60	14.83	[13.37,16.45]	0.173		
	High	18.76	18.53	[16.54,20.76]	0.001		
Perceived aesthetics	Low	17.38	17.10	[14.63,19.97]		0.002	0.007
	Medium	13.47	13.53	[12.18,15.02]	0.006		
	High	16.51	16.52	[15.08,18.11]	0.681		
Perceived crime-related safety	Low	15.93	15.77	[14.28,17.41]		0.333	0.663
	Medium	14.32	14.80	[13.33,16.43]	0.370		
	High	15.62	15.18	[13.27,17.37]	0.667		

Results are from linear regression using log of total physical activity as dependent variable and with cluster-robust standard errors.[1] Adjusted for gender, ethnicity, health condition, family affluence, free school meal status, parental employment, country of birth, borough, season and the other perception variables of the table.

5.4.2. Daily recommended physical activity

Table 5.3 presents the associations between the same five neighbourhood perception indicators and daily recommended physical activity, which is defined as reporting 7 hours of more of physical activity over the past week. For these analyses, adjusted models control for the four variables associated with daily recommended physical activity (gender, ethnicity family affluence and seasonality). As expected, results are similar to those observed for total physical activity (Table 5.2). There is no evidence of any association with proximity to destinations or perceived traffic safety (adjusted p-values=0.760 and 0.608 respectively): compared to the reference group (low category of perceptions), adjusted ORs are close to 1.00 and confidence intervals are wide. For proximity to destinations, unadjusted ORs were slightly higher (1.07 and 1.20 for medium and high categories of perceptions respectively), but there was no evidence of a significant difference (p-value=0.562). Similar to total physical activity, there is strong evidence of a positive association with perceived street connectivity (unadjusted p-value=0.031; adjusted p-value=0.010): compared to the low perception groups, the adjusted odds of daily recommended physical activity are 1.37 (95% CI: 0.99-1.90) times higher in the medium group and 1.76 (95% CI: 1.22-2.55) times higher in the high perception group. There is also similar evidence for a U-shaped association with aesthetics (unadjusted p-value=0.001; adjusted p-value=0.003): the adjusted odds of daily recommended physical activity are lowest in the medium perception category (0.79; 95% CI: 0.25-1.18) and highest in the high perception category (1.30; 95% CI: 0.85-1.98). Finally, there is very limited evidence that the odds of daily recommended physical activity depends on perception of crime-related safety (unadjusted and adjusted p-values=0.187 and 0.181 respectively). The adjusted odds of daily recommended physical activity are nevertheless estimated to be slightly lower in the medium perception group compared to the low perception group (0.75; 95% CI: 0.54-1.04; p-value=0.086).

Table 5.3 Odds ratios (OR) of daily recommended physical activity vs. not by perception of the neighbourhood environment , adjusting for potential confounders (wave 1 of the ORiEL study)*

Exposure		**Analytical sample (n)**	**Unadjusted OR**	**Adjusted OR[1]**	**95%CI**	**P-value parameter**	**P-value unadjusted**	**P-value adjusted[1]**
Perceived proximity to destinations	Low	1545	1.00	1.00			0.562	0.760
	Medium		1.07	1.01	[0.65,1.58]	0.966		
	High		1.20	1.11	[0.71,1.72]	0.656		
Perceived traffic safety	Low	1614	1.00	1.00			0.724	0.608
	Medium		1.12	1.12	[0.78,1.60]	0.542		
	High		1.05	1.01	[0.67,1.50]	0.980		
Perceived street connectivity	Low	1476	1.00	1.00			0.031	0.010
	Medium		1.27	1.37	[0.99,1.90]	0.060		
	High		1.62	1.76	[1.22,2.55]	0.002		
Perceived aesthetics	Low	1605	1.00	1.00			0.001	0.003
	Medium		0.75	0.79	[0.52,1.18]	0.246		
	High		1.25	1.30	[0.85,1.98]	0.228		
Perceived crime-related safety	Low	1514	1.00	1.00			0.187	0.181
	Medium		0.77	0.75	[0.54,1.04]	0.086		
	High		0.97	0.91	[0.59,1.42]	0.690		

Results are from logistic regression with cluster-robust standard errors.[1] Adjusted for gender, ethnicity, family affluence and season.*Defined as reporting 7 hours or more of physical activity over the past week.

5.4.3. Walking to school

Results from the associations between perceptions of the neighbourhood environment and walking to school are presented in Table 5.4 and Table 5.5. Table 5.4 includes the five neighbourhood perception indicators already studied in the previous sections, and Table 5.5 investigates separate survey items that were expected to be more consistently related to walking to school, i.e. proximity to bus stop, enjoyment of the neighbourhood for walking/cycling, and personal safety. Adjusted models control for the three potential confounders that are associated with walking to school: ethnicity, family affluence and seasonality.

Table 5.4 indicates no evidence that perceived proximity to destinations, traffic safety, street connectivity and aesthetics are associated with walking to school (all unadjusted and adjusted p-values>0.35). Unadjusted and adjusted coefficients are of similar magnitude, close to 1.00 (between 0.84 and 1.33) and have wide confidence intervals. The direction of the associations is negative for perceived proximity to destinations, bell-shaped for traffic safety (i.e. higher estimation in the medium group), positive for connectivity, and almost null for aesthetics. None of these associations are significant. Conversely, parameters associated with perceived crime-related safety provide evidence of an association with walking to school (unadjusted p-value=0.018, adjusted p-value=0.022). In particular, those reporting a medium perception of safety have 1.32 (95% CI: 1.03-1.68) times higher adjusted odds of walking to school compared to the other two groups (bell-shaped relationship).

Table 5.5 provides some weak evidence that a greater distance to a bus stop increases the odds of walking to school by a factor of 1.22 (adjusted 95% CI: 0.98-1.52; p-value=0.069). Perceiving the neighbourhood as pleasant for walking or cycling is not related to the outcome (unadjusted p-value=0.492, adjusted p-value=0.521). Finally, there is some weak evidence that personal safety (i.e. feeling safe) is associated with walking to school (unadjusted p-value=0.089, adjusted p-value=0.068). The odds of walking to school appear to be lower in general for those who feel very unsafe in the neighbourhood (all estimated ORs>1.00). The higher estimated probability of walking to school was observed for adolescents with no firm opinion about safety ('neither agree nor disagree'). For those adolescents, compared to those feeling very unsafe, the odds of walking to school were 2.05 times higher (95% CI: 1.25-3.36). This result is consistent with what I observed for crime-related safety.

Table 5.4 Odds ratios (OR) of walking to school vs. not by perception of the neighbourhood environment , adjusting for potential confounders (wave 1 of the ORiEL study)

Exposure		Analytical sample (n)	Unadjusted OR	Adjusted OR [1]	95%CI	P-value parameter	P-value unadjusted	P-value adjusted[1]
Perceived proximity to destinations	Low	1392	1.00	1.00			0.816	0.812
	Medium		0.85	0.84	[0.50,1.42]	0.525		
	High		0.88	0.88	[0.55,1.42]	0.607		
Perceived traffic safety	Low	1440	1.00	1.00			0.384	0.367
	Medium		1.33	1.31	[0.69,2.49]	0.402		
	High		1.06	1.05	[0.63,1.75]	0.864		
Perceived street connectivity	Low	1319	1.00	1.00			0.646	0.614
	Medium		1.13	1.15	[0.78,1.70]	0.472		
	High		1.23	1.25	[0.80,1.95]	0.332		
Perceived aesthetics	Low	1425	1.00	1.00			0.922	0.896
	Medium		1.06	1.01	[0.72,1.42]	0.934		
	High		1.10	1.08	[0.71,1.64]	0.714		
Perceived crime-related safety	Low	1354	1.00	1.00			0.018	0.022
	Medium		1.33	1.32	[1.03,1.68]	0.028		
	High		0.99	1.00	[0.68,1.45]	0.991		

Results are from logistic regression with cluster-robust standard errors[1] Adjusted for gender, ethnicity, family affluence and season

Table 5.5 Odds ratios (OR) of walking to school vs. not by perception of the neighbourhood environment using individual survey items , adjusting for potential confounders (wave 1 of the ORiEL study)

Exposure		**Analytical sample (n)**	**Unadjusted OR**	**Adjusted OR [1]**	**95%CI**	**P-value parameter**	**P-value unadjusted**	**P-value adjusted[1]**
Perceived bus stop proximity	1-5 minutes	1541	1.00	1.00			0.068	0.069
	Further away		1.24	1.22	[0.98,1.52]	0.069		
Enjoyment of neighbourhood for walking/cycling	Strongly disagree	1453	1.00	1.00			0.492	0.521
	Slightly disagree		1.05	1.08	[0.63,1.88]	0.771		
	Slightly agree		1.05	1.07	[0.64,1.77]	0.805		
	Strongly agree		0.86	0.87	[0.54,1.41]	0.580		
Feeling safe (personal safety)	Strongly disagree	1372	1.00	1.00			0.089	0.068
	Slightly disagree		1.35	1.38	[0.89,2.15]	0.148		
	Neither agree nor disagree		1.98	2.05	[1.25,3.36]	0.004		
	Slightly agree		1.44	1.48	[0.92,2.38]	0.110		
	Strongly agree		1.38	1.40	[0.89,2.21]	0.150		

Results are from logistic regression with cluster-robust standard errors.[1] Adjusted for ethnicity, family affluence and season.

5.4.4. Walking for leisure

Results for associations between perceptions of the neighbourhood and walking for leisure are presented in Table 5.6 and Table 5.7. Like walking to school, Table 5.6 includes the five neighbourhood perception indicators studied across all outcomes. Table 5.7 investigates separate survey items that are expected to be more consistently related to walking for leisure, i.e. proximity to recreational areas, enjoyment of the neighbourhood for walking/cycling, and personal safety. Adjusted models control for the three potential confounders that are associated with walking for leisure: gender, ethnicity and parental employment.

Table 5.6 gives no evidence that any of the five neighbourhood perception indicators are associated with walking for leisure (all unadjusted and adjusted p-values>0.27). Nonetheless, unadjusted and adjusted models for proximity to destinations, traffic safety, street connectivity and aesthetics all seem to indicate that the expected associations might be positive: the better the perception of the neighbourhood, the higher the estimated odds of walking for leisure. For example, compared to the low perception of aesthetics, the adjusted odds of walking for leisure are 1.08 (95% CI: 0.81-1.45) times higher for medium perception group and 1.29 times higher for high perception group (95% CI: 0.90-1.85). However, estimated ORs for all variables of Table 5.6 are between 1.02 and 1.30 and confidence intervals are wide, which means that there is no evidence of association. Parameters associated with crime-related safety are even closer to 1.00, and do not provide any indication of association.

Table 5.7 provides no evidence that proximity to a recreation area is related to walking for leisure (unadjusted p-value=0.793, adjusted p-value=0.870). There is some weak evidence that perceiving the neighbourhood as pleasant for walking or cycling increases the odds of walking for leisure (unadjusted p-value=0.064, adjusted p-value=0.097). Compared to those with a very low perception ('strongly disagree'), all other adolescents have higher odds of walking for leisure (adjusted ORs are 1.82 (95% CI: 1.09-3.04), 1.52 (95% CI: 1.05-2.21) and 1.70 (95% CI: 1.09-2.68) for the 'slightly disagree', slightly agree' and 'strongly agree' groups, respectively). There is finally some evidence that personal safety (i.e. feeling safe) is associated with walking for leisure (unadjusted p-value=0.103, adjusted p-value=0.020). The odds of walking for leisure appear to be lower for those who feel very unsafe in the neighbourhood (reference category) and for those who have no firm opinion about personal safety ('neither agree nor disagree') (adjusted OR=0.87; 95% CI: 0.54-1.41).

Table 5.6 Odds ratios (OR) of walking for leisure vs. not by perception of the neighbourhood environment , adjusting for potential confounders (wave 1 of the ORiEL study)

Exposure		**Analytical sample (n)**	**Unadjusted OR**	**Adjusted OR [1]**	**95%CI**	**P-value parameter**	**P-value unadjusted**	**P-value adjusted[1]**
Perceived proximity to destinations	Low	1303	1.00	1.00			0.702	0.473
	Medium		1.12	1.19	[0.88,1.61]	0.247		
	High		1.13	1.15	[0.86,1.52]	0.347		
Perceived traffic safety	Low	1356	1.00	1.00			0.831	0.734
	Medium		1.08	1.12	[0.75,1.68]	0.588		
	High		1.12	1.18	[0.77,1.81]	0.454		
Perceived street connectivity	Low	1227	1.00	1.00			0.790	0.525
	Medium		1.08	1.02	[0.70,1.49]	0.919		
	High		1.17	1.24	[0.77,1.99]	0.371		
Perceived aesthetics	Low	1340	1.00	1.00			0.575	0.277
	Medium		1.07	1.08	[0.81,1.45]	0.590		
	High		1.19	1.29	[0.90,1.85]	0.168		
Perceived crime-related safety	Low	1258	1.00	1.00			0.824	0.603
	Medium		0.94	1.00	[0.80,1.24]	0.990		
	High		1.01	1.13	[0.87,1.49]	0.356		

Results are from logistic regression with cluster-robust standard errors.[1] Adjusted for gender, ethnicity and parental employment.

Table 5.7 Odds ratios (OR) of walking for leisure vs. not by perception of the neighbourhood environment using individual survey items , adjusting for potential confounders (wave 1 of the ORiEL study)

Exposure		Analytical sample (n)	Unadjusted OR	Adjusted OR [1]	95%CI	P-value parameter	P-value unadjusted	P-value adjusted[1]
Perceived proximity to recreation area	1-5 minutes	1422	1.00	1.00			0.793	0.870
	6-10 minutes		1.00	1.00	[0.78,1.28]	0.987		
	11-20 minutes		0.99	1.02	[0.70,1.47]	0.932		
	21-30 minutes		1.22	1.25	[0.80,1.94]	0.326		
	More than 30 minutes		0.80	0.90	[0.54,1.51]	0.695		
Enjoyment of neighbourhood for walking/cycling	Strongly disagree	1364	1.00	1.00			0.064	0.097
	Slightly disagree		1.89	1.82	[1.09,3.04]	0.021		
	Slightly agree		1.53	1.52	[1.05,2.21]	0.027		
	Strongly agree		1.62	1.70	[1.09,2.68]	0.021		
Feeling safe (personal safety)	Strongly disagree	1272	1.00	1.00			0.103	0.020
	Slightly disagree		1.35	1.25	[0.75,2.07]	0.389		
	Neither agree nor disagree		0.92	0.87	[0.54,1.41]	0.580		
	Slightly agree		1.28	1.27	[0.82,1.97]	0.281		
	Strongly agree		1.16	1.20	[0.74,1.96]	0.452		

Results are from logistic regression with cluster-robust standard errors. [1] Adjusted for gender, ethnicity and parental employment.

5.4.5. Outdoor physical activity

Table 5.8 and Table 5.9 present the associations between perceptions of the neighbourhood environment and outdoor physical activity. The binary outdoor physical activity outcome captures the extent to which adolescents reported having participated at least once in the past week in an activity usually performed outdoors in the neighbourhood, including basketball (or volleyball), rollerblading, cricket, football, rounders, rugby and roller skating. Table 5.8 presents the results for the five neighbourhood perception indicators studied across all outcomes. Table 5.9 investigates separate survey items that are expected to be more consistently related to outdoor physical activity, i.e. proximity to bus stop, proximity to recreational areas, enjoyment of the neighbourhood for walking/cycling, and personal safety. Adjusted models control for gender, ethnicity, family affluence and free school meal status, which were all associated with the outcome.

As for the other outcomes, results set out in Table 5.8 indicate no evidence of association between outdoor physical activity and proximity to destinations (unadjusted p-value=0.475, adjusted p-value=0.704). Similarly, there is no evidence of an association with crime-related safety (unadjusted p-value=0.387, adjusted p-value=0.520). The other three indicators show moderate to strong evidence of an association with the outcome. There is moderate evidence that traffic safety is associated with outdoor physical activity (unadjusted p-value=0.053, adjusted p-value=0.048). Unadjusted and adjusted coefficients are similar and indicate that the odds of outdoor physical activity are highest in the group reporting moderate perception (compared to low perception: adjusted OR=1.60; 95% CI: 0.99-2.60), and intermediate in the high perception group (adjusted OR=1.19; 95%CI: 0.73-1.94). There is also strong evidence of a dose-response relationship with perceived street connectivity (unadjusted p-value=0.007, adjusted p-value=0.001): compared to the low perception category, the adjusted odds of outdoor physical activity are 1.48 (95% CI: 1.01-2.17) times higher in the medium category and 2.49 (95% CI: 1.52-4.07) times higher in the high perception category. Aesthetics are also positively associated with outdoor physical activity (p-value <0.001). In particular, the odds of outdoor physical activity are 1.63 (95% CI: 1.03-2.56) times higher for those with the best perception compared to those with the worse perception.

Table 5.9 confirms that none of the proximity variables are associated with outdoor physical activity (adjusted p-values are 0.691 and 0.901 for bus stop proximity and proximity to recreation area, respectively).

Table 5.8 Odds ratios (OR) of reporting at least one outdoor physical activity vs. not by perception of the neighbourhood environment , adjusting for potential confounders (wave 1 of the ORiEL Study)*

Exposure		Analytical sample (n)	Unadjusted OR	Adjusted OR [1]	95%CI	P-value parameter	P-value unadjusted	P-value adjusted[1]
Perceived proximity to destinations	Low	1296	1.00	1.00			0.475	0.704
	Medium		1.38	1.22	[0.64,2.36]	0.544		
	High		1.43	1.27	[0.69,2.35]	0.439		
Perceived traffic safety	Low	1346	1.00	1.00			0.053	0.048
	Medium		1.56	1.60	[0.99,2.60]	0.056		
	High		1.22	1.19	[0.73,1.94]	0.488		
Perceived street connectivity	Low	1229	1.00	1.00			0.007	0.001
	Medium		1.29	1.48	[1.01,2.17]	0.044		
	High		2.19	2.49	[1.52,4.07]	<0.001		
Perceived aesthetics	Low	1334	1.00	1.00			<0.001	<0.001
	Medium		0.91	0.95	[0.62,1.44]	0.792		
	High		1.50	1.63	[1.03,2.56]	0.036		
Perceived crime-related safety	Low	1253	1.00	1.00			0.387	0.520
	Medium		0.84	0.82	[0.57,1.19]	0.306		
	High		1.09	0.98	[0.67,1.42]	0.901		

Results are from logistic regression with cluster-robust standard errors.[1] Adjusted for gender, ethnicity, family affluence and free school meal status.* Outdoor physical activities include: basketball (or volleyball), blading, cricket, football, rounders, rugby and roller skating.

Table 5.9 Odds ratios (OR) of reporting at least one outdoor physical activity by perception of the neighbourhood environment using individual survey items , adjusting for potential confounders (wave 1 of the ORiEL Study)*

Exposure		**Analytical sample (n)**	**Unadjusted OR**	**Adjusted OR [1]**	**95%CI**	**P-value parameter**	**P-value unadjusted**	**P-value adjusted[1]**
Perceived bus stop proximity	1-5 minutes	1432	1.00	1.00			0.659	0.691
	Further away		0.93	0.94	[0.68,1.29]	0.691		
Perceived proximity to recreation area	1-5 minutes	1418	1.00	1.00			0.770	0.901
	6-10 minutes		0.98	1.06	[0.69,1.62]	0.796		
	11-20 minutes		0.78	0.85	[0.52,1.40]	0.526		
	21-30 minutes		0.96	1.08	[0.50,2.34]	0.841		
	More than 30 minutes		1.27	1.24	[0.47,3.31]	0.664		
Enjoyment of neighbourhood for walking/cycling	Strongly disagree	1360	1.00	1.00			0.272	0.230
	Slightly disagree		0.93	0.99	[0.51,1.93]	0.972		
	Slightly agree		0.92	1.01	[0.54,1.91]	0.971		
	Strongly agree		1.19	1.33	[0.73,2.42]	0.352		
Feeling safe (personal safety)	Strongly disagree	1267	1.00	1.00			0.076	0.253
	Slightly disagree		0.62	0.69	[0.35,1.39]	0.303		
	Neither agree nor disagree		0.54	0.58	[0.33,1.03]	0.063		
	Slightly agree		0.61	0.66	[0.36,1.21]	0.177		
	Strongly agree		0.87	0.81	[0.48,1.37]	0.429		

Results are from logistic regression with cluster-robust standard errors.[1] Adjusted for gender, ethnicity, family affluence and free school meal status.* Outdoor physical activities include: basketball (or volleyball), blading, cricket, football, rounders, rugby and roller skating.

Unlike for the overall aesthetics indicator, there is less evidence of an association for perceiving the neighbourhood as pleasant for walking or cycling (unadjusted p-value=0.272, adjusted p-value=0.230), although those who have a good perception again indicate higher estimated odds of outdoor physical activity (compared to 'strongly disagree': adjusted OR=1.33; 95%CI: 0.73-2.42; p-value=0.352). Finally, there is very little evidence of an association with personal safety in the adjusted model (p-value=0.253), despite some indication of a negative association in the unadjusted model (p-value=0.076). In unadjusted and adjusted models, the estimated odds of outdoor physical activity are lower in adolescents reporting better perception of safety, but confidence intervals are wide and include 1.00.

5.4.6. Pay and play physical activity

I finally tested whether pay and play physical activity was associated with the proximity to a sport and leisure centre. The binary pay and play physical activity outcome indicates the extent to which adolescents reported having participated at least once in the past week in more structured forms of activity for which one usually has to pay, including aerobics, climbing, swimming, gymnastics, hockey, martial arts, netball, and tennis. Although it was hypothesised that greater perceived proximity would mean higher odds of pay and play physical activity, I have found no evidence of an association between the two variables. Unadjusted p-value=0.829 and estimated ORs are all close to 1.00 and have wide confidence intervals (results not presented). Given this lack of association, I did not further investigate the association between the two variables in adjusted models.

5.5. Summary

In this chapter, I have explored the cross-sectional associations between various perceptions of the neighbourhood and six physical activity outcomes. To do so, I conducted a complete case analysis of the baseline ORiEL data. I performed unadjusted and adjusted analyses on the same analytical samples and accounted for clustering at school-level using cluster-robust standard errors. This section summarises the main results by dimension of neighbourhood perception and offers some lessons learned and their implications for further analyses.

Overall perceived proximity to destinations was not related to any of the physical activity outcomes. Similarly, I have found no association with perceived proximity to recreation area and proximity to sport and leisure centre.

The absence of association might partly be explained by the question wording which focused on proximity to the closest destination, without information on the quality or density of destinations. However, I have found some indication that proximity to bus stop might decrease the odds of walking to school.

Perceived traffic safety was not associated with total physical activity, daily recommended physical activity or walking to school and for leisure. It nevertheless displayed a bell-shaped association with outdoor physical activity, which is difficult to interpret.

Perceived street connectivity was positively associated with all five outcomes for which an association was investigated. The associations were only significant for total physical activity, daily recommended physical activity and outdoor physical activity. The associations were particularly strong for total physical activity and outdoor physical activity.

Aesthetics was not consistently associated with all outcomes. No associations were found for walking to school or for leisure. Aesthetics were significantly associated with total physical activity and daily recommended physical activity (U-shaped relationships). Significant associations were also observed for outdoor physical activity, such that those with best level of perception had higher odds of outdoor physical activity, but no differences were observed between the other categories. The shape of the observed associations is compatible with two competing explanations. On the one hand, better aesthetics could favour outdoor physical activity; while on the other hand, reporting more physical activity might imply a better awareness of the neighbourhood, which might lead to a more objective, and therefore less favourable perception of its aesthetics. In addition to the summary aesthetics score, I have also investigated the association between the enjoyment of the neighbourhood for walking/cycling and three forms of physical activity. Whereas no association was found with walking to school and with outdoor physical activity, walking for leisure appeared to be positively associated with that specific item. The association was such that those with very negative and those with no firm perception had lower odds of walking for leisure compared to others.

Finally, crime-related safety was not associated with most of the physical activity outcomes. The only significant association found was with walking to school, such that those with a medium level perception reported greater probability of walking. Using the more specific item capturing personal safety (i.e. ‘I feel safe’), I found some evidence that those reporting feeling very unsafe were less likely to report walking to school and walking for leisure. These results are more in line with the qualitative evidence on safety and physical activity (cf. section

2.4.1.4.). There is however some very small indication that the association might be in the opposite direction for outdoor physical activity, which was not anticipated.

This baseline analysis of the complete cases helped better understand the ORiEL data and serves as a guide to subsequent analyses. The first lesson learned is that the measures of proximity, except for proximity to bus stop, are not associated with any of the physical activity outcomes. Second, aesthetics and crime-related safety, which do not capture the relevant exposures as well as the two specific items used (enjoyment of the neighbourhood for walking/cycling and personal safety), have weaker associations with the physical activity outcomes, which are also more difficult to interpret. For these domains of perceptions, it therefore seems more relevant to keep the specific items as opposed to the overall scores in further analyses. Third, there seems to be no major difference in the results between total physical activity and daily recommended physical activity. This might suggest that results from the other binary outcomes (walking to school, walking for leisure, outdoor physical activity, pay and play physical activity) could also reflect what would have been observed using their original scales (which could not be used owing to their distributions as shown in section 3.5.1.). Fourth, adjusting for potential confounders only marginally altered the coefficients and not all expected confounding factors proved relevant. Borough and country of birth were not associated with any of the physical activity outcomes. Seasonality was associated with some of the outcomes, but in the opposite direction (such that more physical activity is reported in winter compared to spring). Including season in the model did not change the coefficient estimates. Parental employment has many response categories with small number of observations, which might cause estimation problems in more complex models. I would therefore recommend not using these variables as potential confounders in subsequent analyses.

Overall, these results suggest that some perceptions of the neighbourhood are associated with some forms of physical activity. Yet, these results are cross-sectional and are likely to be biased due to missing data. In the next chapter, I will use the three waves of the ORiEL data together with a method for handling missing data to further investigate the associations between perceptions of the neighbourhood and physical activity. Given that important changes have occurred in the neighbourhood environment during the study period, I expect to observe positive changes in perceptions which would allow testing as to whether these are accompanied by changes in physical activity. In the next chapters, I will move from a general examination of physical activity as a global measure to a set of disaggregated measures of physical activity. Therefore, the two global physical activity outcomes explored in the preliminary analyses presented in this chapter (total physical activity and meeting daily recommended physical activity) will not be investigated in subsequent chapters. In the next chapters, I will examine four forms of physical activity, namely walking to school, walking for leisure, outdoor physical activity, and pay and play physical activity.

Chapter 6: Longitudinal associations between perceptions of the neighbourhood environment and physical activity

6.1. Introduction

In this chapter, I present an analysis of the longitudinal associations between five measures of neighbourhood perceptions and three physical activity outcomes. In chapter 5, I presented an exploratory analysis of the associations between perceptions of the neighbourhood and physical activity, using baseline data from the ORiEL study. The results have allowed selecting relevant exposures (perceived bus stop proximity, traffic-related safety, street connectivity, enjoyment of the neighbourhood for walking/cycling and personal safety) and physical activity outcomes (walking to school, walking for leisure and outdoor physical activity) to be used in the longitudinal analyses and presented in this chapter.

To date, the vast majority of the literature on the associations between perceptions of the neighbourhood environment and physical activity comes from cross-sectional data (cf. section 2.4.1.). These cross-sectional analyses provide little insight into causality and do not allow assessing the temporality between change in exposure and change in outcome. Over the last years, some longitudinal studies have emerged in the field (An et al. 2017, Crawford et al. 2010, Knuiman et al. 2014, Remmers et al. 2014, Wong et al. 2014). Despite this progress, it appears that the current empirical literature still overlooks discussions on the temporal dimensions of neighbourhood effects (Boone-Heinonen & Gordon-Larsen 2012, Hedman et al. 2015, Sharkey & Faber 2014). Hypotheses regarding the accumulation of exposure, time-lags or the trajectories of changes in the exposure are usually absent from conceptual discussions and empirical applications in the field (Boone-Heinonen & Gordon-Larsen 2012, Galster 2012). As a result, there is currently little understanding on *how* physical activity evolves in response to changes in perceptions of the neighbourhood environment.

A longitudinal study design adds to the modelling challenge when data are missing. Multiple imputation (MI) is the favoured approach to handle missing data on many variables when the missing data mechanism is hypothesised to be missing at random or MAR (cf. section 4.3.). The recent consensus in the statistical literature is that it is important to use MI models that account for the hierarchical structure of the data (Carpenter & Kenward 2012, Enders et al. 2016, Grund et al. 2016). However, only very recently have software implementations of MI become general and flexible enough to allow for integration with typical epidemiological analysis problems that involve hierarchical data and a mix of continuous and discrete variables with many response categories (Quartagno 2016).

Gender is hypothesised to be the main moderator of the associations between measures of neighbourhood perceptions and physical activity, although it has received limited attention in the empirical literature (Papas et al. 2007). Patterns of physical activity and perceptions of the neighbourhood are known to differ by gender as the construction of gender identity at adolescence leads to different lifestyles for boys and girls (Allender et al. 2006). It is therefore expected that boys and girls might not be affected by environmental factors and their perceptions in the same way. In particular, more restricted independent mobility in girls (Carver et al. 2008) might condition how perceived safety could influence physical activity in the neighbourhood.

In this chapter, I use the 3-wave balanced panel of the ORiEL study (cf. section 3.3.) to test alternative hypotheses on how measures of neighbourhood perceptions might influence three common forms of physical activity: walking to school, walking for leisure, and a composite measure of outdoor physical activity. These three forms of physical activity were chosen because they are most likely to be influenced by measures of neighbourhood perceptions used in the ORiEL study (Esteban-Cornejo et al. 2016, Evenson et al. 2012, Foster et al. 2014a, Spittaels et al. 2010). I further investigate the moderating role of gender in the associations. From a methodological perspective, this chapter informs on the feasibility of multilevel MI in the case of a typical epidemiological analysis problem that involves the use of data with a 3-level hierarchical structure, mix of response types and interaction terms.

6.2. Research questions

The following research questions are explored in this chapter.

Question 1: Are perceptions of the neighbourhood environment longitudinally associated with physical activity in adolescents in the ORiEL study?

Specifically, I formulated three questions about the form of the longitudinal associations between the exposures and the outcomes, and one question on the role of gender as a moderator:

1.1. Are perceptions of the neighbourhood (perceived proximity to nearest bus stop, traffic safety, street connectivity, enjoyment of the neighbourhood for walking/cycling and personal safety) associated with physical activity (walking to school; walking for leisure; outdoor physical activity) across all measurements (i.e. general associations)?

1.2. Do these perceptions of the neighbourhood (perceived proximity to nearest bus stop, traffic safety, street connectivity, enjoyment of the neighbourhood for walking/cycling and personal safety) have a cumulative influence on walking to school, walking for leisure and outdoor physical activity?

1.3. Do trajectories of these perceptions of the neighbourhood (perceived proximity to nearest bus stop, traffic safety, street connectivity, enjoyment of the neighbourhood for walking/cycling and personal safety) relate to changes in walking to school, walking for leisure and outdoor physical activity?

1.4. Do the above associations between perceptions of the neighbourhood and physical activity differ for boys and girls?

6.3. Methods

To explore the longitudinal associations between perceptions of the neighbourhood environment and physical activity, I estimated longitudinal and cross-sectional models with generalised estimating equation (GEE) methods using imputed datasets. The data and methods used are outlined below.

6.3.1. Analytical sample

The final sample used for these longitudinal analyses was constructed by excluding ORiEL respondents that did not participate in all three waves. The final sample size includes 2,260 participants and 6,780 observations and is referred to as the 3-wave balanced panel (cf. section 3.3.).

6.3.2. Variables

The variables used are summarised in Table 6.1 and were outlined in section 3.5. These include three binary physical activity outcomes, five measures of neighbourhood perceptions, a set of potential confounders, and a cluster variable. These are described below.

Table 6.1 Variable definitions and item missingness at each wave for the 3-wave balanced panel (n = 2,260; 6,780 measurements)

Variable	Variable type and use in the analysis	% missing W1	W2	W3
Outcomes				
Walking to school	Ordinal (almost count), 4 categories, non-Normal; binary version used	8.4	3.3	3.0
Walking for leisure	Ordinal (almost count), 4 categories, non-Normal; binary version used	18.1	6.7	5.3
Outdoor physical activity	Count (0-7), non-Normal; binary version used	23.1	11.6	8.8
Exposures				
Perceived bus stop proximity	Ordinal, 5 categories, skewed; binary version used	19.8	6.7	4.6
Perceived traffic safety	Continuous score based on 3 items ; categorised in 3 groups	25.5	9.3	5.5
Perceived street connectivity	Continuous score based on 4 items, approximately Normal ; categorised in 3 groups	32.3	14.1	10.0
Enjoyment of the neighbourhood for walking/cycling	Ordinal 4 categories, skewed; categorised in 3 groups in the final model	24.3	8.4	5.2
Feeling safe (personal safety)	Ordinal 5 categories, non-Normal	29.3	10.1	6.1
Potential confounders				
Gender	Binary	Fully observed		
Ethnicity	Nominal variable with 8 categories	Fully observed		
Health condition	Count score of 9 binary items* (0-9), skewed; categorised in 3 groups (0/1/2+) and in 2 groups (0/1+) in the final model	3.4	14.7	14.6
Family affluence	Count score of 3 items (0-9), approximately N; categorised in 3 groups	4.6	3.7	3.4
Baseline free school meal status	Binary: Yes/No	2.0		
Cluster variable				
School	Assumed to be time invariant (W1 value used for those changing school)	Fully observed		
Missing values predictors				
Total physical activity	Continuous, approximately log Normal	2.8	0.7	0.5
Country of birth	Binary (UK/non-UK)	2.0		
Mental health (WEMWBS)	Continuous, approximately square Normal	2.9	2.1	2.0
BMI (BMI z score)	Continuous, Normal	8.5	8.2	6.9
Crime safety during day (ALPHA)	Ordinal variable with 4 categories; categorised in 3 groups in the final model	23.6	7.8	5.8
Self-rated health	Ordinal variable with 3 categories	1.6	0.9	1.0

*requirement that at least five items are completed to get a score because the interest is in whether any condition is reported.

6.3.2.1. Outcomes

Three measures of routine physical activity hypothesised to be associated with measures of neighbourhood perceptions in the ORiEL study are examined: walking to school, walking for leisure (dog/exercise) and outdoor physical activity. As detailed in the data chapter (section 3.5.1.), each binary physical activity outcome captures whether adolescents reported having participated in the activity over the past week. The outdoor physical activity outcome combines participation in any of the following activities: basketball/volleyball, blading, cricket, football, rounders, rugby and roller skating.

6.3.2.2. Exposures

Following exploratory analysis of the baseline data presented in chapter 5, I selected five measures of neighbourhood perceptions hypothesised to be related to the outcomes (Table 6.1). The measures are derived from the ALPHA questionnaire which specifically targets walking and cycling (Spittaels et al. 2010), and the personal safety item comes from the MESA study (Mujahid et al. 2007). Perceived proximity to a bus stop was recoded into a binary variable owing to sparseness (1-5 minutes vs. further away); the ALPHA traffic safety and street connectivity scores were used as 3-level ordinal scores (low/medium/high); enjoyment of the neighbourhood for walking/cycling was used as a 3-level ordinal score ((strongly)disagree/ agree/ strongly agree); and the MESA personal safety item was kept to its original five-level Likert scale (cf. section 3.5.2.1.).

These measures of neighbourhood perceptions were used to answer question 1.1. about the general associations between the exposure and outcome variables. In addition, longitudinal-specific exposure variables were created to answer questions 1.2. and 1.3. about the nature of the relationships between perceptions of the environment and physical activity. For each aspect of neighbourhood perception, exposure variables were derived to capture cumulative exposure (question 1.2.) and trajectory of exposure (question 1.3.), as detailed in the data chapter (section 3.5.2.1.). Briefly, the cumulative score summed the values of the above ordinal scores across all three waves; and the trajectory of exposure measured change in perceptions of the neighbourhood between the baseline and wave 3, so that a positive value represents an improvement of perception.

6.3.2.3. Potential confounder

The following potential confounders were included in all models: gender, ethnicity (8 categories), family affluence (3 categories derived from the family affluence scale), health condition (no condition vs. 1+ condition(s)), and free school meal status. Gender, ethnicity and free school meal status were considered as time-invariant. Baseline free school meal status was used following preliminary analysis of the reliability of the item (cf. section 3.5.3.4.). The other variables were treated as time-varying, except in the models testing the cumulative hypothesis, where only wave 3 values of the time-varying confounders were used. Note that distance to school was not included as a potential confounder because the variable was not available at the time of analysis. Including it retrospectively would have required re-imputation of the data. It was judged to be an unnecessary undertaking given that the results of this chapter indicate no evidence of associations between the exposures and walking to school.

6.3.2.4. School

School was considered as time-invariant for ease of modelling (see below). During the study period, n=6 adolescents moved within the surveyed school sample. In the models accounting for school-level clustering, baseline-school were used for these six adolescents. This simplification is highly unlikely to have any impact on the interpretation of the results.

6.3.3. Analytical strategy used in this chapter

As detailed in the methods chapter (chapter 4), the analytical strategy for the longitudinal analyses is twofold: it involves the handling of missing data with multilevel multiple imputation and the specification of models used to answer the research questions, known as analysis models (or models of interest). The specific models used in this chapter are presented in this section.

6.3.3.1. Handling missing data with multilevel multiple imputation

This first longitudinal results chapter explored the feasibility of multilevel MI to handle missing data for the typical epidemiological analysis problems tackled in this thesis, and which involves missing values in a dataset with a 3-level hierarchical structure (measurements, individuals and schools), mix of discrete and continuous variables, and interaction terms.

I first described the extent of missingness in each variable of interest and explored the plausibility of different missing data mechanisms.

I have shown in the data chapter that many variables have missing values in the ORiEL study (section 3.4.). I conducted preliminary analyses in order to explore the validity of a complete case analysis. Analyses reported in Appendix E (section E.1) indicate that such an analysis is likely to be invalid and to generate bias. Clark et al. (2017) have previously shown that the 'missing at random' (MAR) assumption was plausible for many variables of the ORiEL study, which I corroborated for the main variables used in this chapter (Appendix E section E.1). As explained in the methods chapter (section 4.2.3.), MI was used to handle item non-response on all the variables of interest concurrently. To increase the plausibility of the MAR assumption, reduce bias and improve efficiency (Carpenter & Kenward 2012), I included the following auxiliary variables in the imputation models: log total physical activity (centred), country of birth, squared WEMWBS score for positive mental wellbeing (centred), BMI z-score (centred), crime safety during the day (from the ALPHA questionnaire) and self-rated health. The selection process of these auxiliary variables is reported in Appendix E (section E.1).

Multilevel MI solutions were explored in order to account for the correlations implied by the 3-level hierarchical structure of the data (repeated measurements, individuals, schools). The models of analysis include continuous variables, discrete variables with many categories and interaction terms between the exposure variables and gender. Potential interactions were handled by imputing the data separately for boys and girls. As explained in the methods chapter (section 4.3.), I used a joint modelling approach (Goldstein et al. 2009) in order to handle both continuous and discrete variables, the latter with the latent normal distribution assumption. The imputation models were fitted using the R package 'jomo' (Quartagno et al. 2018), which is the best package available to run complex multilevel MI models with numerous continuous and unordered discrete variables. 'Jomo' currently allows for 2-level models with missing values at each level (Quartagno et al. 2018).

Given the exploratory nature of this undertaking, the imputation strategies investigated in this chapter are reported in greater detail compared to chapters 7 and 8, where I applied the general approach developed in the present chapter. Results of this chapter include the process of fitting and evaluating various imputation models. I first specified an imputation model comparable to the imputation models used in the ORiEL project (Clark et al. 2017, Cummins et al. 2017). The viability of the model was assessed in terms of convergence of the parameters of the coefficient matrices (Beta, Beta2, Omega and Cov u) and computational requirements, which are memory need and computational speed (cf. section 4.3.4.). Alternative models were then considered until I obtained an imputation model that was satisfactory in terms of conceptual comprehensiveness, computational time and convergence. An arbitrary limit of 20 days was set for the production of the imputed datasets with the final imputation model. A random seed was set to initiate the MCMC sampler for all analyses to allow reproducibility of the results[24].

6.3.3.2. Analysis models

To answer the research questions of this chapter, I estimated logistic regression models ('xtgee') using GEE in Stata 14 as detailed in the methods chapter (section 4.4.3.). Marginal models estimated with GEE have a desirable population-average interpretation of the parameters (Fitzmaurice et al. 2011), although current software implementations only allow for models with 2-level structures.

Three types of models were fitted to answer the research questions about the nature of the longitudinal associations. The general form of these models is detailed in the methods chapter (section 4.4.3.). Models for questions 1.1. (general association obtained with pooled longitudinal models) and 1.3. (longitudinal models for trajectory of exposure) accounted for clustering due to repeated measurements on the same individuals (using unstructured working correlation structures), whereas models for research question 1.2. (cross-sectional models for cumulative exposure) treated the data as cross-sectional and therefore could account for clustering at school-level (using exchangeable working correlation structures). I first fitted unadjusted models including each of the five exposure variables in turn and a physical activity outcome. Fully adjusted models were then specified, adjusting for all five exposure variables together and the potential confounders. Finally, I explored whether gender was moderator (question 1.4.) by running a series of fully adjusted models that further included an interaction term between each exposure of interest and gender, with one gender*exposure interaction at a time (i.e. one per model). Stratum-specific results are reported for p-values for the interactions <0.1. The general form of the model equations are given in Appendix E (section E.2). The choice of the working correlation structure for each model was guided by a preliminary comparison between model-based and robust standard errors under different specification of the working correlation structure, using the complete cases Appendix E (section E.3).

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[24] Models were run on a PC with an Intel i5 2.90 GHz CPU and 8GB of RAM in Windows 7, using R version 3.3.2 (64 bit).

Analyses were conducted on the imputed datasets and final inferences obtained using the 'mi estimate' command in Stata. For sensitivity purposes, analyses were replicated using different specifications of the working correlation structure in the GEE estimation process and standard errors compared (Appendix E section E.4). Finally, results from analyses of the complete cases are reported (Appendix E section E.5).

6.4. Results

This section presents the results of the analyses conducted to answer the research questions on the relationships between perceptions of the neighbourhood environment and physical activity. The first part presents how item non-response is handled using a multilevel multiple imputation model specific to the analyses presented in this chapter. Results on the selection of a final imputation model are extensively discussed in this first longitudinal results chapter, as one of the methodological aim is to assess the feasibility of the imputation approach, given the data and the research questions addressed in this thesis. The second part presents the results of the analysis models fitted to answer the research questions.

6.4.1. Missing data handling

6.4.1.1. Description of item missingness

All variables, except gender, ethnicity and school, have some non-response at each wave (Table 6.1). As described in the data chapter (section 3.4.) the closer the question was to the end of the questionnaire, the higher the chance of missingness. Item missingness is also more likely at baseline when participants are younger and less familiar with the interview process. Missingness is highest for the perceptions of the neighbourhood variables, in which the proportion of missing values roughly lies between 20% and 32% at wave 1, between 7% and 15% at wave 2 and between 5% and 10% at wave 3. Missingness is slightly lower for the physical activity variables: missingness is lowest for walking to school (8% at wave 1 and 3% subsequently), higher for walking for leisure (18% at wave 1, 7% at wave 2 and 5% at wave 3), and highest for outdoor physical activity (23% at wave 1, 12% at wave 2 and 9% at wave 3). Outdoor physical activity has more missing values because it combines multiple items with missing values each. Potential confounders were either fully observed (gender, ethnicity, and school) or had less than 5% of missing values. An exception is health condition, whose non-response was close to 3% at baseline and then increased to 15% at later waves, due to a small change in the response scale.

6.4.1.2. Imputation models

The ORiEL data has a 3-level structure. Adolescents were surveyed on 3 occasions with school-level sampling selection (cf. section 3.2.). As a result, the 1st level is the measurement, the 2nd level is adolescent, and the 3rd level is school. Given the inability to model 3-level structures in jomo, alternative operationalisations had to be found. The first option, which was followed by researchers of the ORiEL project using the software REALCOM-Impute (Clark et al. 2017, Cummins et al. 2017), was to account for the hierarchical structure between level 1 and level 2 variables and to include school as a fixed effect. Such a model was formulated (Model 1) and refined (Models 2 and 3) in order to improve convergence and computational time. However, even Models 2 and 3 had both theoretical and practical limitations, and therefore, a separate option was investigated: I transformed the dataset in the wide format (so that each participant is represented by a single row and repeated measurements as separate columns) and I formulated an imputation model in which each measurement point of each variable is an outcome of the joint model. This fixed effects or multivariable approach to within adolescent correlations allowed for the use of school as a level 2 variable (Model 4). The four models considered are summarised in Table 6.2 and discussed below with their advantages and disadvantages. Given the interest in gender*exposure interactions the imputation models are run separately for boys and girls and the suitability of the final model (Model 4) was assessed for the two groups.

Model 1: Ethnicity and school as covariates

Model 1 treated all variables with missing values as outcomes: baseline free school meal status and country of birth were treated as level 2 outcomes (`Y2 data.frame` in jomo) and the other variables as level 1, i.e. time-varying outcomes (`Y data.frame`). Fully observed variables - ethnicity and school - were treated as time-invariant covariates, with an influence on both level 1 and level 2 outcomes. They were represented by n-1 dummy variables in the `data.frames X` and `X2` (cf. section 4.3.5.1. for an introduction to the jomo syntax).

Initial analysis revealed that Model 1 is very demanding computationally (Table 6.2). I estimated that in the best-case scenario, assuming quick convergence of the parameters, Model 1 for boys would need about 20 days to run (=20,000x 86 sec). An additional week would be needed in the first place to be able to assess the convergence without any guarantee that evidence of convergence would be obtained. Instead of waiting a week to obtain a first assessment of the model, I immediately moved on to a simplified version. The poor performance of simplified specifications explored subsequently (Models 2-3) confirmed that Model 1 most likely has very poor convergence and mixing and it is not usable to impute missing data.

Model 2: Ethnicity and school as outcomes

To simplify the initial model (Model 1), I treated completely observed variables – ethnicity and school – as outcomes instead of as covariates (Model 2). Quartagno and Carpenter (2018) showed that this was a viable alternative specification that sometimes improved convergence. Consequently, completely observed variables are assumed to follow latent normal distributions, whereas no such assumption is made when treated as covariate. Model 2 was specified for each gender, adding ethnicity and schools to the list of level 2 outcomes.

This specification of the model dramatically improved the computational time (decreasing from 86 to 11 sec for the 1st iteration of the model in boys) which is attributed to the reduction in the number of level 1 and level 2 β coefficients estimated in Beta and Beta2 matrices, respectively. Model 2 still had a very complex level 1 residual Omega matrix (and many parameters in general) which means that a lot of memory space is required to store the parameters of successive iterations (about 530 MB for 1,000 iterations).

An initial run of 2,000 iterations indicated slow convergence and high autocorrelation, which prevented the identification of burn-in and n-between values for imputation purposes. Results were subsequently obtained for 20,000 iterations for girls and 16,000 for boys. Parameters in both gender indicated poor evidence of convergence with some important parameters producing high autocorrelation values. For example, the level 1 β parameter associated with walking to school (β_4) exhibited very high autocorrelation (Figure 6.1B) and indicated variation on the MCMC chain between 10,000th and 15,000th iterations (Figure 6.1A). This suggests that the distribution may not be stable until the 15,000th iteration, and worse, that a very large (unknown) n-between value is needed. Similarly high autocorrelation was observed for outdoor physical activity in boys (not presented).

In addition, level 2 covariances u associated with the WEMWBS score for positive mental wellbeing were very high and poorly estimated (not presented). The WEMWBS score in Model 2 had been squared (and centred) in order to approximate a normal distribution, however this was inadequate on its own, and these results indicate that the variable should be additionally rescaled to have a variance more similar to the other continuous variables.

Overall, Model 2 did not show sufficient evidence that it could be used with confidence to impute the missing data. Necessary improvements would include the recoding of some variables and a reduction in the number of parameters.

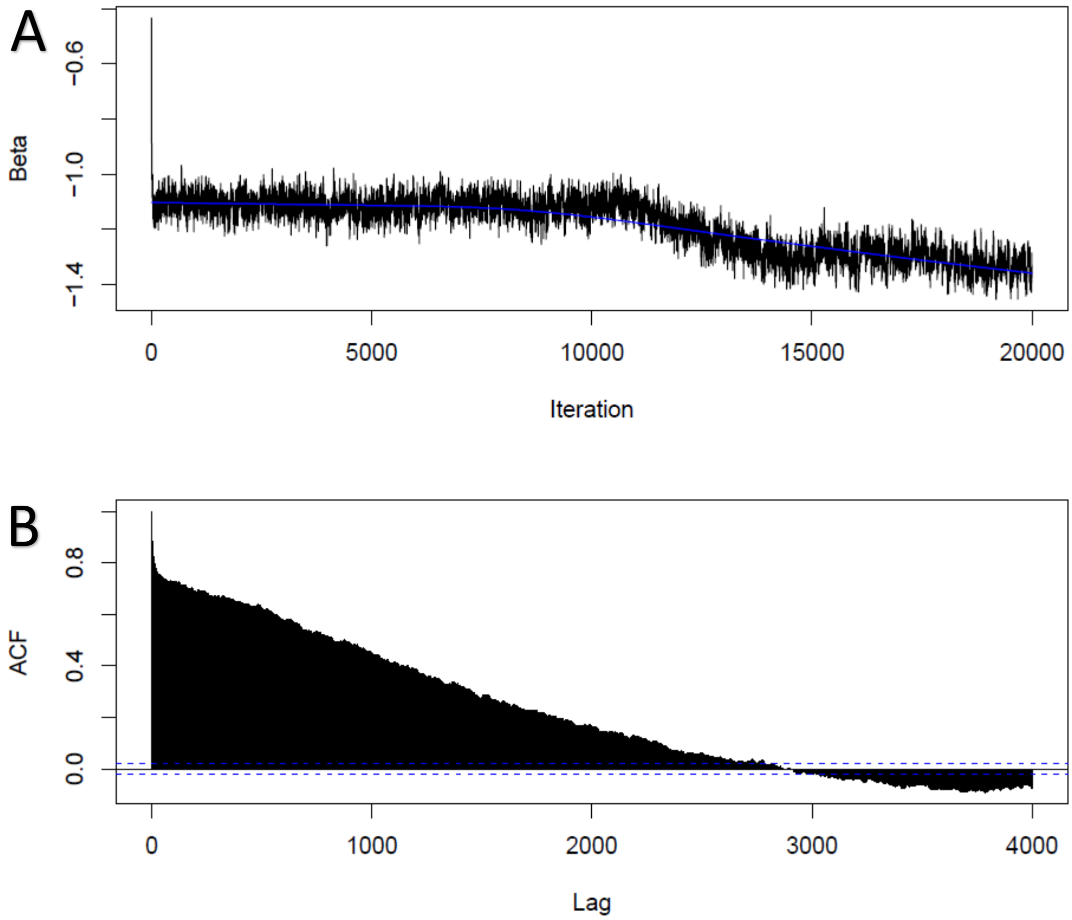


Figure 6.1 Example of time series plot (A) and autocorrelation plot (B) of a β parameter with poor convergence in Model 2. The β parameter of this example corresponds to walking to school (β_4) for girls. The autocorrelation plot (B) starts at iteration 10,000 ACF – Autocorrelation Function

Model 3: Ethnicity as outcome and school excluded

Model 3 is based on Model 2 and adopts a series of simplifications. Slow convergence of Model 2 is partly attributed to the estimation of many parameters. In particular, school – represented by 24 latent normal variables – requires estimating many parameters.

Removing school from the imputation model and rescaling the mental health score (by dividing the previously squared and centred WEMWBS score for positive mental wellbeing by 1,000) produced a simpler model.

Table 6.2 Summary of imputation models of chapter 6

Model	Data format	Cluster variable	Variables recoding	Coefficients matrices*	Computational time for 1 iteration*	Memory needed to store 1,000 iterations*	MCMC convergence
Model 1: Ethnicity and School as covariates	long	id	normal transformation and centring of continuous variables	Beta [33x 27] Beta2 [33x2] Cov u [29x29] Omega [27 x 27]	86 sec	NA	NA
Model 2: Ethnicity and school as outcomes	long	id	same as Model 1	Beta [1x 27] Beta2 [1 x 32] Cov u [59x59] Omega [27 x 27]	11 sec	530 MB	slow convergence, high auto-correlation; problematic parameters
Model 3: Ethnicity as outcome and school excluded	long	id	same as Model 1 + Mental-Health score rescaled; recoding of: crime safety during day (ALPHA), health and enjoyment of the neighbourhood for walking/cycling recoded	Beta [1x 24] Beta2 [1 x 9] Cov u [33x33] Omega [24 x 24]	3 sec	309 MB	slow convergence and some high auto-correlations; problematic parameters
Model 4: Fixed effects approach with school as a cluster	wide	school	same as Model 3	Beta [1x 81] Cov u [81x81] Omega [81 x 81]	42 sec	78 MB	quicker convergence, low auto-correlation; recommended burn-in of n_{burn} = 200 and n-between of n_{between} =500

* Results specific for boys. Note that there are 3 girls-only and 1 boys-only schools and therefore models are slightly different.

However, despite these changes, three variables still appeared to have slow converging parameters for both boys and girls. Analysis of convergence suggested that reducing the number of response categories for some variables might improve the model without restricting too drastically its complexity. Additional three variables were thus recoded in Model 3:

Enjoyment of the neighbourhood for walking/cycling: the original variable, which is an exposure in the analysis model, had four categories and few observations in the poor aesthetics category. The estimation of the β parameter for that category was poor in the improved Model 2. The diagnosis graphs for those parameters in the improved Model 2 are given as an illustration in Figure 6.2. To improve convergence, I regrouped the two negative perception categories into a single one.

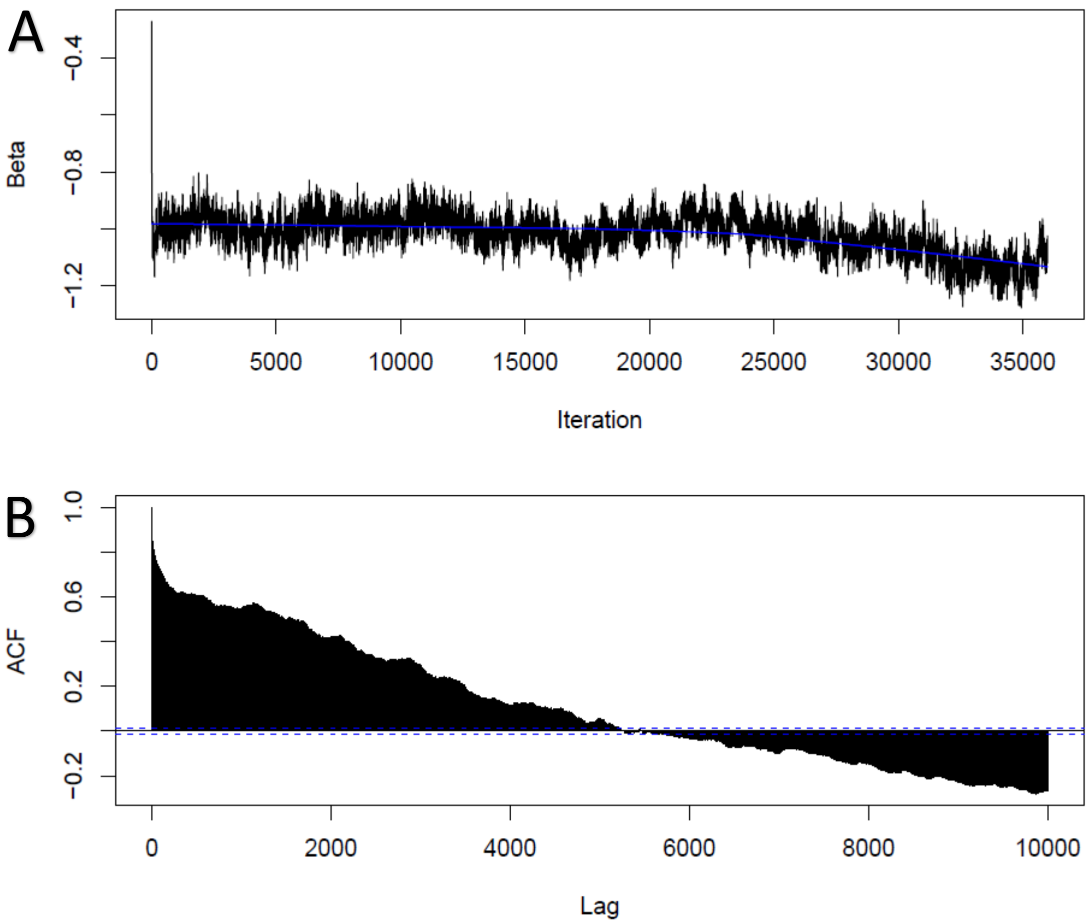


Figure 6.2 Example of time series plot (A) and autocorrelation plot (B) with high autocorrelation in a β parameter for a response category with few observations in an improved version of Model 2. The β parameter of this example corresponds to the low response category of enjoyment of the neighbourhood for walking/cycling in boys (β_{12}). Results are from the multilevel imputation Model 2 (without school, with ethnicity included as an outcome and a rescaled WEMWBS score for positive mental wellbeing). The autocorrelation plot starts at iteration 20,000. ACF – Autocorrelation Function

Health condition: the variable is a potential confounder with 3 response categories. Few reported two or more conditions (3rd category) and MCMC chains for associated β parameter had high autocorrelation. The variable was then dichotomised into none vs. 1+ health condition(s).

Crime safety during day (ALPHA): This auxiliary variable had 4 response categories. The 'strongly agree' and 'slightly agree' categories were grouped together because of the small number of observation in each of those and poor convergence of the associated β parameters. A new variable with 3 response categories was created.

Model 3 has improved computational efficiency (3 sec for 1 iterations in boys) and data storage needs (309 MB for 1,000 iterations) compared to Model 2 (Table 6.2). Large burn-in values were used in order to be able to fully examine the MCMC chain on which the imputation would be conducted, resulting in 54,000 iterations for boys and 66,000 for girls.

Overall, final results were not as good as expected. Convergence seemed to be achieved for most level 1 and level 2 β parameters after 15,000 iterations, although not always with a clear distribution. Yet, some β values did not fall within the 0.025 autocorrelation threshold even with a lag of 10,000 iterations (Figure 6.3). Without even having to mention issues related to the Omega and the Covariance u parameters (not presented), these results overall indicate that Model 3 is not a viable imputation model.

One solution to the challenges experienced would be to further compromise on the number of parameters in the imputation model, either by regrouping some of the response categories or by reducing the number of variables. However, given that the objective of this analysis was to explore the viability of multilevel multiple imputation within a realistically complex epidemiological setting, an alternative formulation of the model was prioritised over an additional restriction of the complexity of the imputation model. Excluding school in Model 3 already drastically simplifies the initial model, and challenges the veracity of any subsequent analytical models in light of a research sample design that employs schools as clusters.

Additionally, in spite of apparent computational efficiency, the failure of the model to converge might indicate problems with the specification of the model itself. In fact, Models 1-3 use many clusters of three observations to estimate parameters at each cluster-level. This is likely to cause estimation problems in the covariance matrices, and therefore it could explain why Model 3 did not converge well.

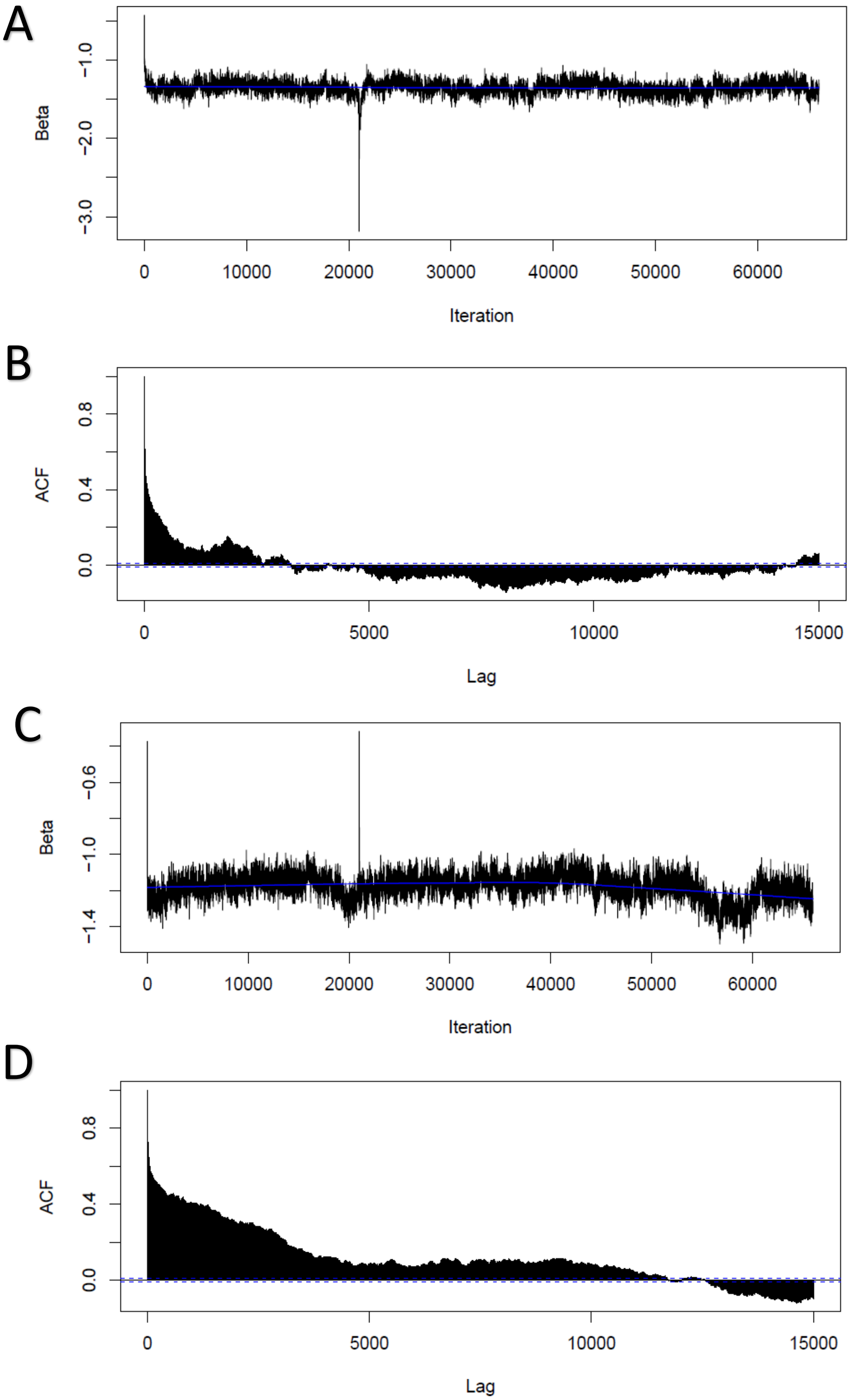


Figure 6.3 Examples of time series plots (A and C) and autocorrelation plots (B and D) with high autocorrelation in some of the β parameters of Model 3. A and B correspond to walking to school (β_4) and C and D correspond to traffic safety (β_8) in boys. The autocorrelation plots start at iteration 15,000. ACF – Autocorrelation Function

Model 4: Fixed effects approach with school as a cluster

To overcome difficulties of previous model specifications, Model 4 uses the longitudinal data in wide format (as opposed to long format). Each time-varying variable is represented by three variables, one variable for each measurement occasion. Time-invariant variables only need to be represented with one variable. The imputation model specifies all variables as level 1 outcomes. This is known as a fixed effects (Kalaycioglu et al. 2016) or multivariable (Verbeke & Molenberghs 2009) specification. The advantage of Model 4 is that information from other waves can be used to impute the data without the need of a multilevel structure, allowing for the use of school as the cluster variable and therefore accounting for both sources of correlation. By using school as the cluster instead of respondent, the model no longer has the drawback of having only 3 observations per cluster. Model 4 also uses the recoded variables as given in Model 3 (The model equation and the associated R codes to fit it in jomo are given in Appendix C section C.3).

Model 4 includes 81 outcomes and therefore 81 β parameters: 9 continuous variables, representing each continuous measure at each time point (log total physical activity (centred), squared Mental-Health score (rescaled and centred), and BMI (centred)), 15 latent variables representing the five binary measures at each time point (walking to school, walking for leisure, outdoor physical activity, bus stop proximity, and health condition), 48 latent variables for the time-varying ordinal measures at each time point (traffic safety (6), street connectivity (6), enjoyment of the neighbourhood for walking/cycling (6), personal safety (8+6), self-rated health (8), and family affluence (8)), and 9 latent variables for the time-invariant confounders (1 for free school meal status and country of birth each, and 7 for ethnicity).

Model 4 is conceptually simpler than Models 1-3 because it does not have a Beta2 matrix (Table 6.2). The advantage of not having level 2 β parameters associated with latent variable outcomes is that the level 2 covariance matrix is estimated with the Gibbs sampler and does not require a Metropolis-Hastings step. Experience with Models 1-3 indicated that the Metropolis-Hastings samplers had more difficulty converging, and generally lead to higher levels of auto-correlation between successive draws. The disadvantage of Model 4 lies in the large number of parameters to estimate the Beta (81) and covariance matrices (81x81 parameters each), which results in increased computational time (42 sec for 1 iteration for the boys model). The memory size required to store the parameters for the MCMC chains is lower than for the other models due to the smaller number of clusters. Under acceptable convergence, the estimated time required for the imputation using Model 4 is about 10 days (=20,000x 42 sec) for boys, which falls within my arbitrary limit of 20 days.

Convergence of model 4

The parameters of 4,000 iterations were saved for the models for girls and boys to assess convergence. Model 4 indicated quick convergence of the β parameters and lower autocorrelations between successive iterations than in the previous models. Figure 6.4 gives, for one of the outcome variables, an example of good parameter convergence for girls. A parameter associated with ethnicity (β_{79}) had the poorest convergence, although still acceptable (Figure 6.5 for girls). Note that for some parameters, like β_{79} , there was still evidence of autocorrelation after 500 iterations due to poor mixing. The use of the Metropolis-Hastings step to update the Omega parameters had some effect on the $\beta's$ Betas, since $\beta's$ are drawn from a distribution conditional on Omega.

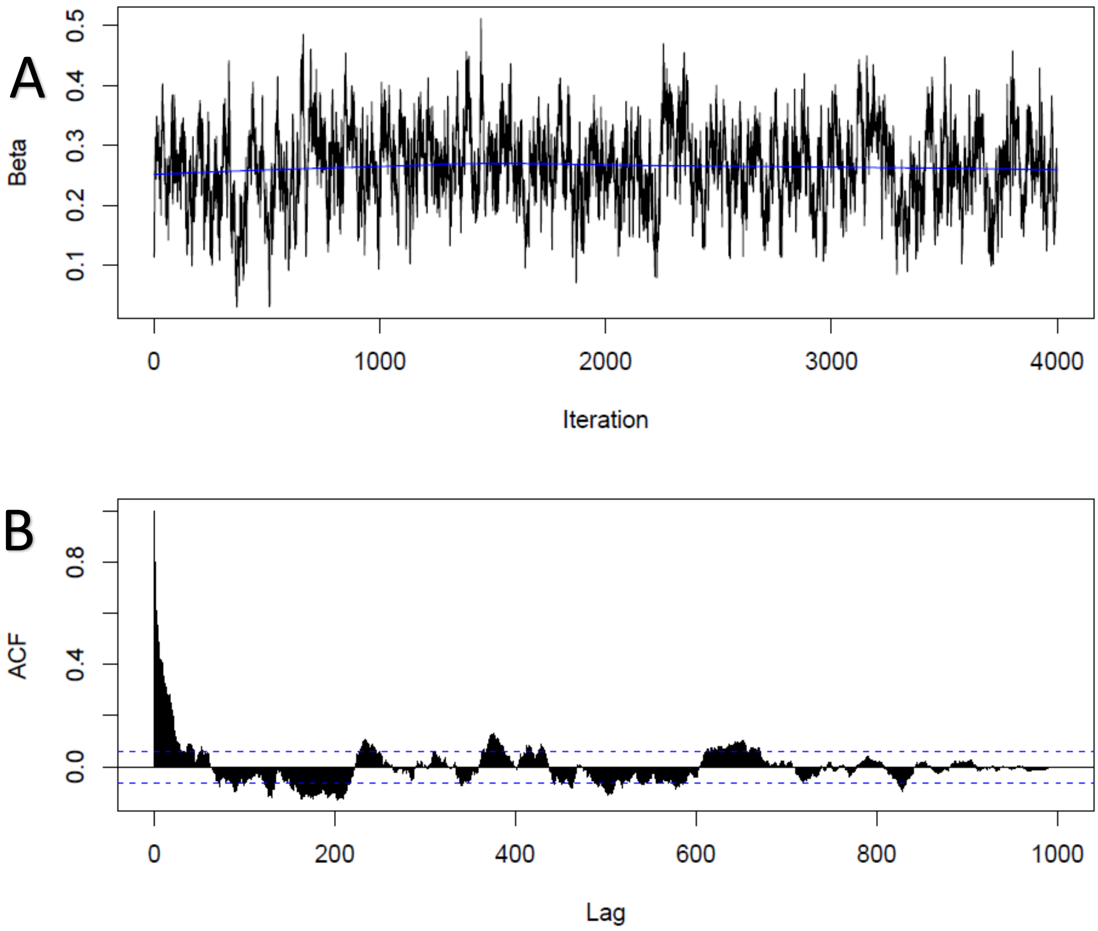


Figure 6.4 Example of time series plot (A) and autocorrelation plot (B) of a β parameter with good convergence in Model 4. The β parameter of this example corresponds to walking for leisure (β_{14}) at wave 2 in the model for girls. Results are from the multilevel imputation Model 4 (fixed effects approach with school as a cluster). The autocorrelation plot starts at iteration 3,000. ACF – Autocorrelation Function

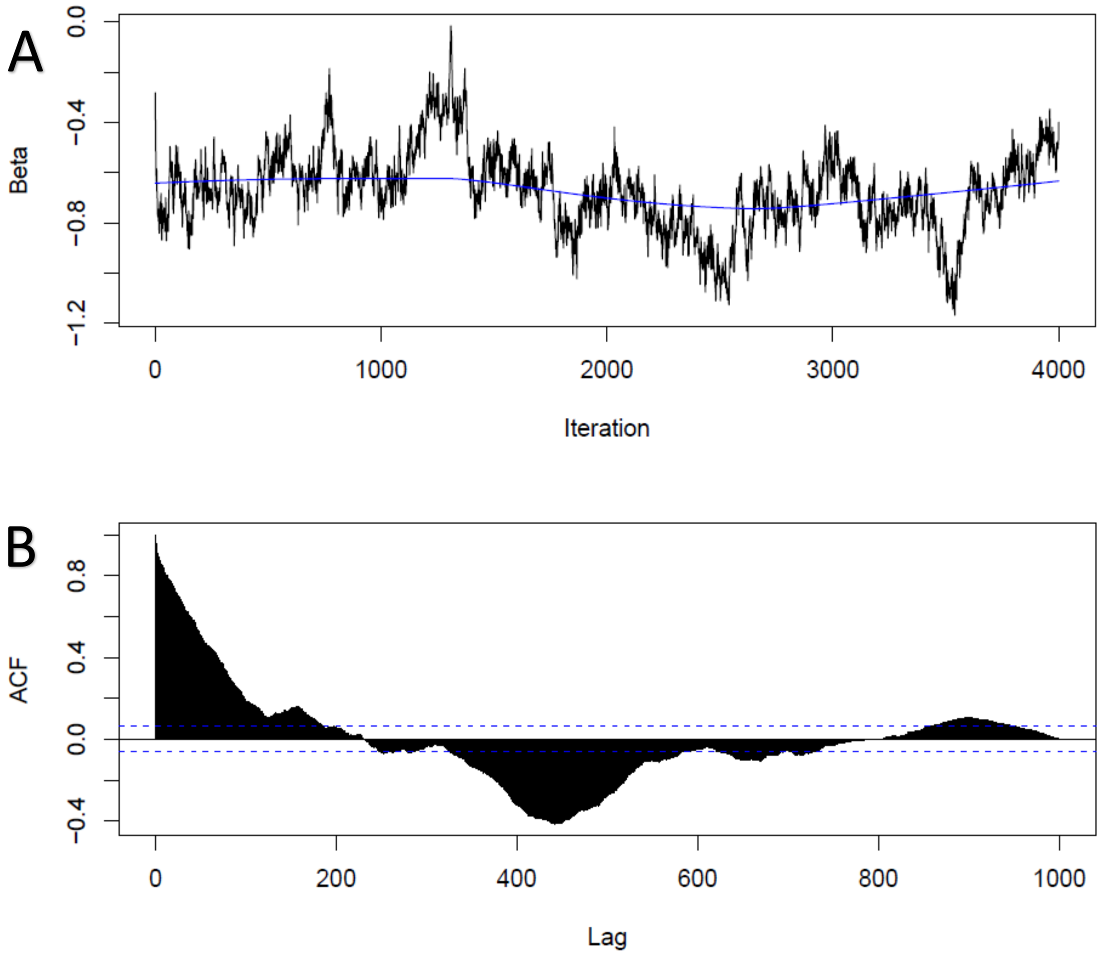


Figure 6.5 Example of time series plot (A) and autocorrelation plot (B) of a β parameter with non-optimal convergence in Model 4. The parameter of this example corresponds to the Black Caribbean ethnic group in the model for girls (β_{79}). Results are from the multilevel imputation Model 4 (fixed effects approach with school as a cluster). The autocorrelation plot starts at iteration 3,000. ACF – Autocorrelation Function

As a rule of thumb, the autocorrelation plots should cross the 0.05 benchmark line at least once for each parameter, for a given n-between. This appears to be the case for all parameters where n-between n_{between}= 500.

Parameters of the level 2 covariance matrix (Covariance u) converged quickly to the distribution and stayed well within the [-0.05; 0.05] bounds for autocorrelation. In general, the main covariances of interest are the variances and the covariances involving the outcomes of the analysis models (walking to school, walking for leisure and outdoor physical activity at each wave). All those parameters had very good convergence as exemplified by the covariance of outdoor physical activity in boys at wave 1 (Figure 6.6)

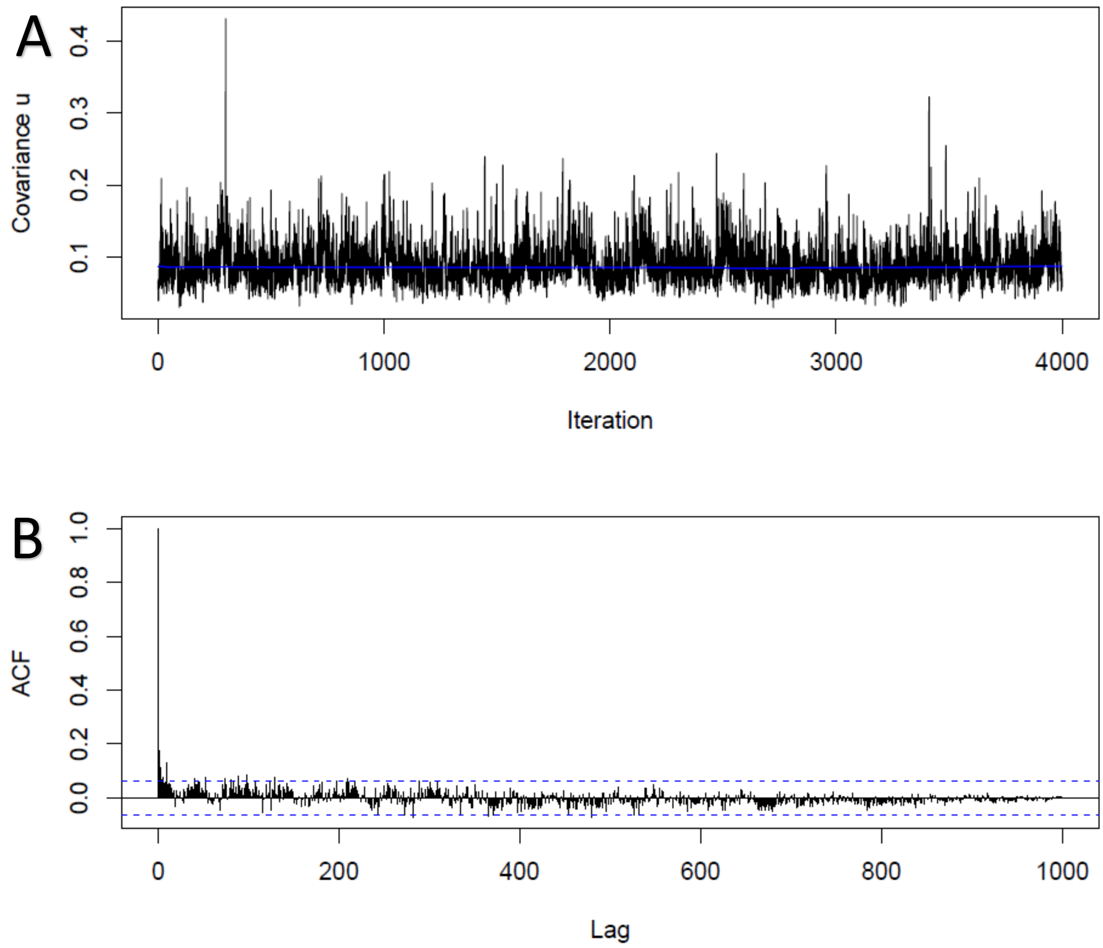


Figure 6.6 Example of time series plot (A) and autocorrelation plot (B) of a level 2 Covariance u parameter with excellent convergence in Model 4. The parameter of this example corresponds to the level 2 variance of outdoor physical activity at wave 1 in the model for boys (Covariance u 16 16). Results are from the multilevel imputation Model 4 (fixed effects approach with school as a cluster). The autocorrelation plot starts at iteration 3,000. ACF – Autocorrelation Function

Graphs for the level 1 covariances indicate, especially for boys, that presumably no optimal acceptance ratio was found because once a stationary distribution is reached, there is limited variation around it (see Figure 6.7 for an example and Figure 6.8 for a better converging parameter). These results are not optimal. However, given that the purpose of this analysis is not to conduct a fully Bayesian analysis, the impact of this on the quality of the imputed values is likely to be negligible. In general, convergence diagnoses indicate that Model 4 could be used to impute the data with sufficient confidence.

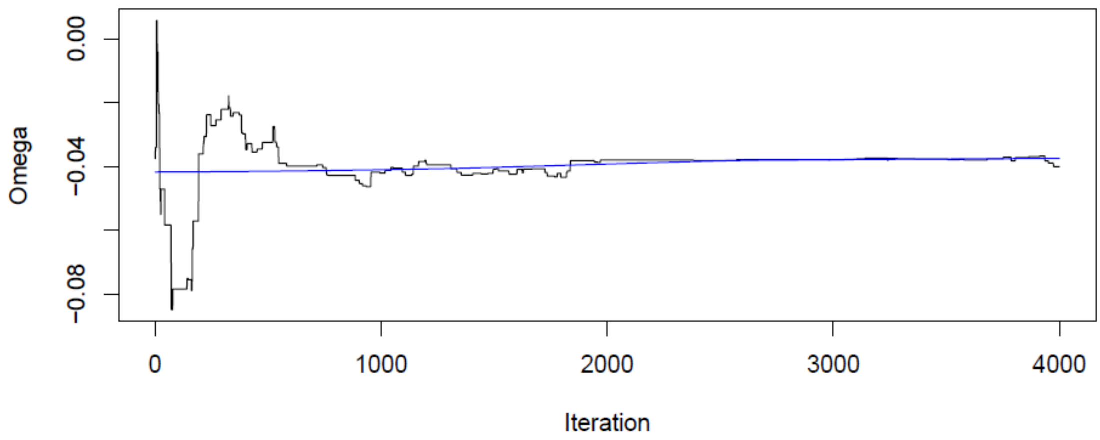


Figure 6.7 Example of time series plot with little variation around the average of a level 1 covariance parameter Omega updated with a Metropolis-Hastings step. Results are from the multilevel imputation Model 4 (fixed effects approach with school as a cluster).

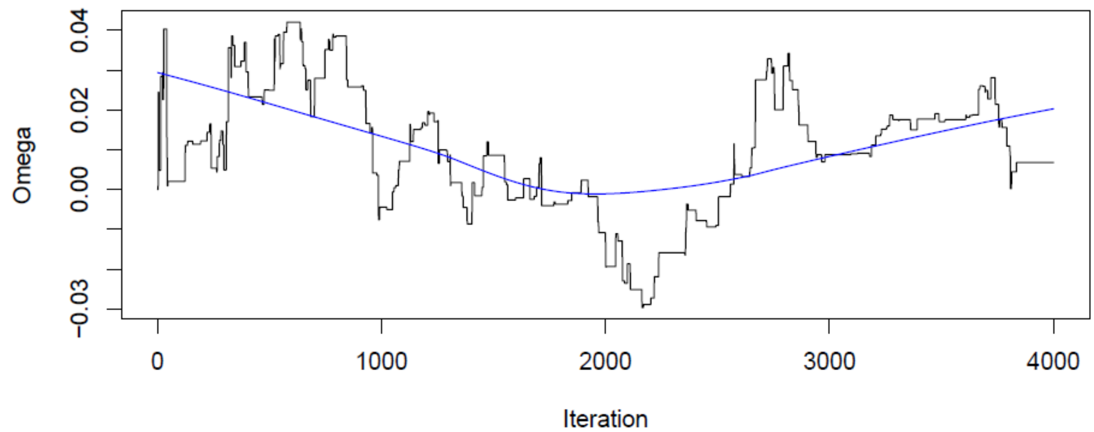


Figure 6.8 Example of time series plots with good mixing of level 1 covariance Omega parameter updated with a Metropolis-Hastings step. Results are from the multilevel imputation Model 4 for girls (fixed effects approach with school as a cluster).

6.4.1.3. Final imputation model

Model 4 is employed as the final imputation model in order to produce 20 imputed datasets each for boys and girls. A burn-in of n_{burn} =3,050 was used for boys and n_{burn} =4,050 for girls, and an n-between of n_{between} =500 was used for both models. The random seed 1,523 was used for replication purposes. The models took c.7 days each to complete the burn-in and impute the data. The boy and girl sets of 20 imputed datasets were merged and transformed back into long format for analysis. The analysis models were run on each imputed dataset and results were combined for final inference using Rubin’s rules (Carpenter & Kenward 2012).

6.4.2. Longitudinal associations between perceptions of the neighbourhood environment and physical activity

In this section, I analyse the 20 imputed datasets to answer the research questions (section 6.2.). These are, first, are the five measures of neighbourhood perceptions (perceived proximity to nearest bus stop, traffic safety, street connectivity, enjoyment of the neighbourhood for walking/cycling and personal safety) longitudinally associated with three common forms of physical activity (walking to school, walking for leisure, and outdoor physical activity) across all measurements? Second, do these perceptions of the neighbourhood have a cumulative influence on physical activity? Third, do trajectories of these perceptions of the neighbourhood relate to changes in physical activity? For each research question, I also explored whether the associations differ for boys and girls.

Analyses were conducted using logistic regression models estimated with GEE to account for clustering at individual-level (longitudinal analyses; questions 1.1. and 1.3.) and to account for clustering at school-level (cross-sectional analyses for accumulation of exposure; question 1.2.). Parameters of the pooled longitudinal models (question 1.1.) are interpreted either as cross-sectional or in terms of within individual change over time (cf. section 4.4.3.1.). Associations from other models (questions 1.2. and 1.3.) are comparisons between respondents with different forms of exposure. Results are presented for each physical activity outcome in turn, starting with a description of the associations between the confounders and the outcomes.

6.4.2.1. Walking to school

Before exploring the longitudinal associations between the exposure variables and walking to school, Table 6.3 presents unadjusted and adjusted associations between socio-demographic variables and walking to school. After adjustment for all socio-demographic variables, there is no indication that walking to school differs by gender (adjusted OR = 1.10 (95% CI: 0.94-1.29); p-value = 0.235). There is however strong evidence that it varies by ethnic group (adjusted p-value < 0.001). Compared to adolescents identifying as White UK, the odds of walking to school are much lower among the White Mixed, Black African and Black Caribbean groups (adjusted ORs are 0.60 (95% CI: 0.43-0.84), 0.60 (95% CI: 0.45-0.80) and 0.42 (95% CI: 0.29-0.60) respectively) and highest among the Bangladeshi and Indian adolescents (adjusted ORs are 1.34 (95% CI: 0.98-1.83) and 1.16 (95% CI: 0.72-1.87), respectively).

Table 6.3 Odds ratios (OR) of walking to school vs. not by potential socio-demographic and health confounders (3-wave balanced panel of the ORiEL study, n=2,260)

Potential confounder		**Unadjusted OR**	**Adjusted OR[1]**	**95%CI**	**P-value parameter**	**P-value unadjusted**	**P-value adjusted[1]**
Gender	Male	1.00	1.00			0.523	0.235
	Female	1.05	1.10	[0.94,1.29]	0.235		
Ethnicity	White: UK	1.00	1.00			<0.001	<0.001
	White: Mixed	0.62	0.60	[0.43,0.84]	0.002		
	Asian: Indian	1.13	1.16	[0.72,1.87]	0.550		
	Asian: Pakistani	0.87	0.89	[0.56,1.42]	0.621		
	Asian: Bangladeshi	1.32	1.34	[0.98,1.83]	0.069		
	Black: Caribbean	0.43	0.42	[0.29,0.60]	<0.001		
	Black: African	0.59	0.60	[0.45,0.80]	<0.001		
	Other	0.71	0.71	[0.57,0.90]	0.005		
Health	no condition	1.00	1.00			0.076	0.077
	1+ condition(s)	1.13	1.13	[0.99,1.30]	0.077		
Family affluence	Low	1.00	1.00			0.198	0.230
	Moderate	0.82	0.84	[0.66,1.07]	0.157		
	High	0.87	0.91	[0.70,1.17]	0.447		
Take free school	No	1.00	1.00			0.306	0.235
meals at W1	Yes	1.09	1.10	[0.94,1.30]	0.235		
Time		0.96	0.96	[0.91,1.02]	0.168	0.137	0.168

Results are from logistic regression models estimated with Generalised Estimating Equations to account for the dependency across repeated measurements (unstructured working correlation matrix).[1] Adjusted for all other variables of the table.

Family affluence and free school meal status indicate that lower socio-economic background might be associated with higher odds of walking to school, but none of the associations reached statistical significance (adjusted p-values=0.230 and 0.235). There is weak evidence that those reporting a health condition are more likely to walk to school (adjusted OR 1.13 (95% CI: 0.99-1.30); p-value=0.077). As shown in the data chapter (section 3.5.1.3.), the modelled time coefficient reveals no support for a decline in walking to school over the study period (adjusted OR 0.96 (95% CI: 0.91-1.02); p-value=0.168).

General association (pooled longitudinal models)

Results for the general associations between perceptions of the neighbourhood and walking to school estimated with pooled longitudinal models are presented in Table 6.4 (question 1.1.). The results give no evidence of an association between any of the five measures of perceptions and walking to school. Adjusted and unadjusted OR are of the same magnitude and parameters are in the expected direction; yet none of them reaches statistical significance (all adjusted p-values>=0.177). Those reporting living close to bus stops have a slightly lower chance of walking to school (adjusted OR = 0.90 (95% CI: 0.78-1.05); p-value=0.177). Adolescents with positive perceptions of traffic safety (medium and high) have 1.13 (95% CI: 0.94-1.36; p-value=0.201) and 1.14 (95% CI: 0.94-1.38; p-value=0.177) times higher odds of walking to school compared to those with worse perception (i.e. low traffic safety). Those perceiving their neighbourhood as highly connected have 1.16 (95% CI: 0.97-1.40; p-value=0.102) times higher odds of walking to school compared to those with a bad perception. Those perceiving their neighbourhood as enjoyable for walking/cycling have slightly lower odds of walking to school, compared to others (adjusted OR=0.89 (95% CI: 0.75-1.05); p-value=0.156). Adolescents feeling very or somewhat unsafe/safe have higher chance of walking to school compared to those who feel very unsafe (adjusted ORs are 1.14 (95% CI: 0.91-1.42; p-value=0.260) for slightly disagree; 1.02 (95% CI: 0.83-1.27; p-value=0.833) for neither agree nor disagree; 1.07 (95% CI: 0.85-1.34; p-value=0.560) for slightly agree; and 1.11 (95% CI: 0.89-1.40; p-value=0.355) for strongly agree).

The inclusion of interaction terms between gender and each measure of perception indicates no evidence that gender moderates the associations between perceptions of the environment and walking to school (all p-values>=0.456).

Overall, the results provide no indication of concurrent association between the fives measures of neighbourhood perceptions and walking to school. This concurrent association could have come either from two different adolescents with different exposure at one measurement point, or the same individual across different measurement points.

Table 6.4 Odds ratios (OR) of walking to school vs. not by perception of the neighbourhood environment , adjusting for potential confounders **(3-wave balanced panel of the ORiEL study, n=2,260)**

Exposure		**Unadjusted OR**	**Adjusted OR[1]**	**95%CI**	**P-value parameter**	**P-value unadjusted**	**P-value adjusted[1]**	**Gender interaction (p-value) [2]**
Perceived bus stop proximity	Further away	1.00	1.00			0.140	0.177	0.890
	1-5 minutes	0.89	0.90	[0.78,1.05]	0.177			
Perceived traffic safety	Low	1.00	1.00			0.505	0.369	0.501
	Medium	1.11	1.13	[0.94,1.36]	0.201			
	High	1.10	1.14	[0.94,1.38]	0.177			
Perceived street connectivity	Low	1.00	1.00			0.303	0.245	0.863
	Medium	1.10	1.10	[0.95,1.28]	0.184			
	High	1.14	1.16	[0.97,1.40]	0.102			
Enjoyment of neighbourhood for walking/cycling	Strongly/slightly disagree	1.00	1.00			0.446	0.189	0.456
	Slightly agree	1.02	1.00	[0.86,1.17]	0.968			
	Strongly agree	0.94	0.89	[0.75,1.05]	0.156			
Feeling safe (personal safety)	Strongly disagree	1.00	1.00			0.770	0.700	0.841
	Slightly disagree	1.14	1.14	[0.91,1.42]	0.260			
	Neither agree nor disagree	1.04	1.02	[0.83,1.27]	0.833			
	Slightly agree	1.06	1.07	[0.85,1.34]	0.560			
	Strongly agree	1.08	1.11	[0.89,1.40]	0.355			

Results are from logistic regression models estimated with Generalised Estimating Equations to account for the dependency across repeated measurements (unstructured working correlation matrix).[1] Adjusted for gender, ethnicity, health condition, family affluence, baseline free school meal status, time and the other perception variables of the table.[2] The adjusted model was replicated for each outcome with an additional interaction term between gender and exposure.

Cumulative perceptions

Results for the association between cumulative perceptions of the neighbourhood and walking to school at wave 3 are presented in Table 6.5 (question 1.2.). Both adjusted and unadjusted association indicate that cumulative perceptions are not associated with walking to school at the end of the study period. Cumulative perceived bus stop proximity indicates that a higher cumulative score decreased the odds of walking to school by 1.10(=1/0.91; 95%CI: 0.96-1.25) for every unit increase, but the association does not reach statistical significance (adjusted p-value = 0.169). There is even less evidence that cumulative perceived traffic safety, favourable street connectivity, enjoyment of the neighbourhood for walking/cycling and personal safety are associated with walking to school at wave 3 (adjusted ORs are 1.04 (95% CI: 0.97-1.13; p-value=0.278), 1.04 (95% CI: 0.96-1.13; p-value=0.315), 0.96 (95% CI: 0.88-1.04; p-value=0.295) and 0.99 (95% CI: 0.95-1.03; p-value=0.699), respectively).

The inclusion of interaction terms between gender and each measure of cumulative perception of the neighbourhood indicates no evidence that gender moderates the associations between cumulative perceptions of the neighbourhood and walking to school at wave 3 (all p-values >= 0.647).

Table 6.5 Odds ratios (OR) of walking to school vs. not at wave 3 by cumulative perceptions of the neighbourhood environment over the 3 waves , adjusting for potential confounders (3-wave balanced panel of the ORiEL study, n=2,260)

Exposure	Unadjusted OR	Adjusted OR[1]	95%CI	P-value unadjusted	P-value adjusted[1]	Gender interaction (p-value) [2]
Cumulative bus stop proximity	0.92	0.91	[0.80,1.04]	0.171	0.169	0.857
Cumulative traffic safety	1.01	1.04	[0.97,1.13]	0.772	0.278	0.938
Cumulative favourable street connectivity	1.03	1.04	[0.96,1.13]	0.514	0.315	0.647
Cumulative enjoyment of neighbourhood for walking/cycling	0.97	0.96	[0.88,1.04]	0.359	0.295	0.849
Cumulative personal safety	0.98	0.99	[0.95,1.03]	0.324	0.699	0.867

Results are from logistic regression models estimated with Generalised Estimating Equations to account for the clustering of individuals within schools (exchangeable working correlation matrix). The cumulative exposure are continuous variables constructed as the sum of scores of each exposure over the 3 waves. A higher score indicates a perception of supportive environment for the specific exposure. [1] Adjusted for gender, ethnicity, health condition (at wave 3), family affluence (at wave 3), baseline free school meal status and the other perception variables of the table. [2] The adjusted model was replicated for each outcome with an additional interaction term between gender and exposure.

Trajectories of perceptions

The analyses that investigate the association between trajectories of perceptions measured as changes between wave 3 and wave 1 and trajectory of walking to school are summarised in Table 6.6 (question 1.3.). The main parameters of interests are the time*trajectory in perception interaction terms because they indicate whether an improvement/decrease in perception between wave 1 and wave 3 is associated with changes in the probability of walking to school during the study period. Overall, unadjusted and adjusted ORs are of similar magnitude for all measured perceptions and indicate an absence of evidence of time*trajectory interactions. The estimates for change in bus stop proximity indicate that a positive change in perception is associated with an increased probability of walking to school over time (adjusted OR=1.07; 95% CI: 0.94-1.23), yet these results are not statistically significant (p-value=0.319). The time*trajectory interactions indicate ORs close to one for traffic safety (adjusted OR = 0.97 (95% CI: 0.89-1.06); p-value = 0.496), favourable street connectivity (adjusted OR = 1.02 (95% CI: 0.99-1.11); p-value = 0.716), and personal safety (adjusted OR = 1.00 (95% CI: 0.95-1.04); p-value = 0.890). An improvement in the perception of the neighbourhood as enjoyable for cycling/walking is estimated to decrease the probability of walking to school, without being statistically significant (adjusted OR = 0.96 (95% CI: 0.89-1.03); p-value = 0.240).

In order to assess whether gender moderates the time*trajectory interactions, two- and three-ways interaction terms were included in each model. These additional models indicate no evidence that the three-ways interaction terms were significant (all p-values > 0.365). In other words, it is unlikely that gender moderates the association between trajectories of perceptions and trajectories of walking to school.

Table 6.6 Odds ratios (OR) of walking to school vs. not by trajectory of perception of the neighbourhood environment , adjusting for potential confounders **(3-wave balanced panel of the ORiEL study, n=2,260)**

Exposure	Unadjusted OR	Adjusted OR[1]	95% CI	P-value unadjusted	P-value adjusted	Gender interaction (p-value) [2]
Trajectory: Bus stop proximity	0.87	0.85	[0.61 , 1.19]	0.419	0.353	0.905
Trajectory: Traffic safety	1.10	1.09	[0.88 , 1.35]	0.344	0.436	0.917
Trajectory: Favourable street connectivity	0.96	0.96	[0.78 , 1.19]	0.703	0.714	0.873
Trajectory: Enjoyment of neighbourhood for walking/cycling	1.10	1.12	[0.92 , 1.37]	0.290	0.257	0.514
Trajectory: Personal safety	0.99	0.97	[0.86 , 1.09]	0.822	0.600	0.911
Time*trajectory interaction: Bus stop proximity	1.06	1.07	[0.94 , 1.23]	0.367	0.319	0.956
Time*trajectory interaction: Traffic safety	0.96	0.97	[0.89 , 1.06]	0.323	0.496	0.365
Time*trajectory interaction: Favourable street connectivity	1.01	1.02	[0.93 , 1.11]	0.828	0.716	0.862
Time*trajectory interaction: Enjoyment of neighbourhood for walking/cycling	0.96	0.96	[0.89 , 1.03]	0.196	0.240	0.605
Time*trajectory interaction: Personal safety	0.99	1.00	[0.95 , 1.04]	0.606	0.890	0.944

Results are from logistic regression models estimated with Generalised Estimating Equations to account for the dependency across repeated measurements (unstructured working correlation matrix). Each exposure variable measures change since baseline on a continuous scale. Each unit represents an average change in exposure by one category between the baseline and the end of the study (+1 = improvement of the neighbourhood by one category on average). The time*trajectory interaction assesses whether exposure trajectory is associated with different trajectory of change in the outcome. [1] Adjusted for time, gender, ethnicity, health condition, family affluence and baseline free school meal status. [2] The adjusted models were replicated with the addition of two- and three- ways interactions between gender, change and time.

6.4.2.2. Walking for leisure

Before exploring the longitudinal associations between the exposure variables and walking for leisure, Table 6.7 presents unadjusted and adjusted associations between socio-demographic variables and walking for leisure. Walking for leisure is more frequent amongst girls than boys (adjusted OR=1.60 (95% CI: 1.40-1.83); p-value <0.001). As with walking to school, there is strong evidence of ethnic differences in walking for leisure: the odds are much lower in all groups compared to the White UK group, with particularly lower odds in the Bangladeshi adolescents (adjusted OR= 0.36; 95% CI: 0.29-0.45; p-value <0.001). There is no evidence that health, family affluence or free school meal status are significantly associated with walking for leisure (adjusted p-values=0.441, 0.126 and 0.150 respectively). Whereas the unadjusted estimates for the socio-economic conditions indicate no clear direction of associations, adjusted estimates suggest that family affluence might increase the odds of walking for leisure (adjusted OR for high vs. low=1.19 (95% CI: 0.94-1.51); p-value=0.141), and not taking free school meal decrease the odds of walking for leisure (adjusted OR of taking free school meal=1.10 (95% CI: 0.96-1.26); p-value=0.150). As shown in the data chapter of the thesis (section 3.5.1.4.), the modelled time coefficient confirms that the odds of walking for leisure decrease every year by a factor of 0.79 (95% CI: 0.74-0.84); p-value<0.001).

General association (pooled longitudinal models)

Results for the general associations between perceptions of the neighbourhood and walking for leisure estimated with pooled longitudinal models are presented in Table 6.8 (question 1.1.). Unadjusted and adjusted estimates are similar and there is some indication of general association between some exposure variables and walking for leisure. Similar to walking to school, perception of bus stop proximity is associated with more walking for leisure (adjusted OR=1/0.89=1.12; 95% CI: 0.98-1.28), yet evidence for the significance of the association is weak (unadjusted p-value=0.050, adjusted p-value=0.086). Despite the absence of significant evidence, the direction of the associations suggests that improved perceived traffic safety might lead to less walking for leisure (adjusted OR of high vs. low traffic safety=0.86 (95% CI: 0.71-1.04); p-value=0.123) and better perceived street connectivity might lead to more walking for leisure (adjusted OR of high vs. low street connectivity=1.09 (95% CI: 0.91-1.31); p-value=0.360).

However, the tests for the overall associations of these variables did not reach statistical significance (adjusted p-values=0.298 and 0.267 respectively).

Table 6.7 Odds ratios (OR) of walking for leisure vs. not by potential socio-demographic and health confounders **(3-wave balanced panel of the ORiEL study, n=2,260)**

Potential confounder		Unadjusted OR	Adjusted OR[1]	95%CI	P-value parameter	P-value unadjusted	P-value adjusted[1]
Gender	Male	1.00	1.00			<0.001	<0.001
	Female	1.60	1.60	[1.40,1.83]	<0.001		
Ethnicity	White: UK	1.00	1.00			<0.001	<0.001
	White: Mixed	0.70	0.67	[0.51,0.88]	0.003		
	Asian: Indian	0.53	0.53	[0.37,0.76]	0.001		
	Asian: Pakistani	0.49	0.51	[0.36,0.72]	<0.001		
	Asian: Bangladeshi	0.35	0.36	[0.29,0.45]	<0.001		
	Black: Caribbean	0.45	0.42	[0.30,0.59]	<0.001		
	Black: African	0.42	0.43	[0.33,0.55]	<0.001		
	Other	0.58	0.57	[0.47,0.69]	<0.001		
Health	no condition	1.00	1.00			0.214	0.441
	1+ conditions(s)	1.08	1.05	[0.93,1.18]	0.441		
Family affluence	Low	1.00	1.00			0.173	0.126
	Moderate	0.96	1.07	[0.86,1.33]	0.553		
	High	1.07	1.19	[0.94,1.51]	0.141		
Take free school	No	1.00	1.00			0.875	0.150
meal at W1	Yes	1.01	1.10	[0.96,1.26]	0.150		
Time		0.80	0.79	[0.74,0.84]	<0.001	<0.001	<0.001

Results are from logistic regression models estimated with Generalised Estimating Equations to account for the dependency across repeated measurements (unstructured working correlation matrix).[1] Adjusted for all other variables of the table.

Table 6.8 Odds ratios (OR) of walking for leisure vs. not by perception of the neighbourhood environment , adjusting for potential confounders **(3-wave balanced panel of the ORiEL study, n=2,260)**

Exposure		**Unadjusted OR**	**Adjusted OR[1]**	**95%CI**	**P-value parameter**	**P-value unadjusted**	**P-value adjusted[1]**	**Gender interaction (p-value) [2]**
Perceived bus stop proximity	Further away	1.00	1.00			0.050	0.086	0.760
	1-5 minutes	0.88	0.89	[0.78,1.02]	0.086			
Perceived traffic safety	Low	1.00	1.00			0.372	0.298	0.709
	Medium	0.90	0.90	[0.75,1.09]	0.292			
	High	0.88	0.86	[0.71,1.04]	0.123			
Perceived street connectivity	Low	1.00	1.00			0.149	0.267	0.964
	Medium	1.15	1.13	[0.97,1.32]	0.117			
	High	1.10	1.09	[0.91,1.31]	0.360			
Enjoyment of neighbourhood for walking/cycling	Strongly/slightly disagree	1.00	1.00			0.360	0.534	0.353
	Slightly agree	1.02	1.02	[0.88,1.18]	0.796			
	Strongly agree	1.10	1.09	[0.92,1.29]	0.335			
Feeling safe (personal safety)	Strongly disagree	1.00	1.00			0.068	0.034	0.881
	Slightly disagree	1.28	1.28	[1.02,1.62]	0.033			
	Neither agree nor disagree	1.09	1.09	[0.87,1.36]	0.460			
	Slightly agree	1.24	1.31	[1.04,1.65]	0.020			
	Strongly agree	1.11	1.18	[0.93,1.49]	0.180			

Results are from logistic regression models estimated with Generalised Estimating Equations to account for the dependency across repeated measurements (unstructured working correlation matrix).[1] Adjusted for gender, ethnicity, health condition, family affluence, baseline free school meal status, time and the other perception variables of the table.[2] The adjusted model was replicated for each outcome with an additional interaction term between gender and exposure.

There is no evidence of association between perception of the neighbourhood as enjoyable for walking/cycling and walking for leisure (all adjusted ORs are close to 1.00 and overall p-value=0.534). Finally, both adjusted and unadjusted models indicate some evidence that increased personal safety is associated with more walking for leisure (unadjusted p-value = 0.068, adjusted p-value=0.034). In particular, adolescents who feel very unsafe (i.e. strongly disagree) had lower odds of walking for leisure compared to the other groups. The adjusted OR of slightly disagree vs. strongly disagree is 1.28 (95% CI: 1.02-1.62; p-value=0.033) and the OR of slightly agree vs. strongly disagree is 1.31 (95% CI: 1.04-1.65; p-value=0.020).

The inclusion of interaction terms between gender and each measure of perception indicates no evidence that gender moderates the associations between perceptions of the environment and walking for leisure (all p-values >= 0.353).

Cumulative perceptions

Results for the association between cumulative perceptions of the neighbourhood and walking for leisure at wave 3 are presented in Table 6.9 (question 1.2.). Both unadjusted and adjusted models indicate that cumulative perceptions are not associated with walking for leisure at wave 3. Unadjusted and adjusted ORs all have estimates close to 1 and all the p-values >0.3. Cumulative favourable street connectivity has the strongest association with an adjusted OR of 1.05 (95% CI: 0.95-1.15; p-value=0.379). If statistically significant, this association would mean that those with a greater cumulative perception favourable street connectivity in the neighbourhood have slightly higher odds of walking for leisure at wave 3.

The inclusion of interaction terms between gender and each measure of cumulative perception of the neighbourhood indicates no evidence that gender moderates the associations between cumulative perception of the neighbourhood and walking for leisure at wave 3 (all p-values >= 0.471).

Table 6.9 Odds ratios (OR) of walking for leisure vs. not at wave 3 by cumulative perception of the neighbourhood environment over the 3 waves , adjusting for potential confounders **(3-wave balanced panel of the ORiEL study, n=2,260)**

Exposure	Unadjusted OR	Adjusted OR[1]	95%CI	P-value unadjusted	P-value adjusted[1]	Gender interaction (p-value)[2]
Cumulative bus stop proximity	1.00	0.98	[0.86,1.12]	0.939	0.798	0.844
Cumulative traffic safety	1.02	1.04	[0.95,1.13]	0.596	0.384	0.761
Cumulative favourable street connectivity	1.04	1.05	[0.95,1.15]	0.379	0.354	0.471
Cumulative enjoyment of neighbourhood for walking/cycling	0.99	1.00	[0.92,1.08]	0.721	0.943	0.829
Cumulative personal safety	0.98	1.00	[0.96,1.04]	0.319	0.827	0.918

Results are from logistic regression models estimated with Generalised Estimating Equations to account for the clustering of individuals within schools (exchangeable working correlation matrix). The cumulative exposure are continuous variables constructed as the sum of scores of each exposure over the 3 waves. A higher score indicates a perception of supportive environment for the specific exposure. [1] Adjusted for gender, ethnicity, health condition (at wave 3), family affluence (at wave 3) and baseline free school meal status.[2] The adjusted model was replicated for each outcome with an additional interaction term between gender and exposure.

Trajectories of perceptions

The analyses that investigate the association between trajectories of perceptions measured as changes between wave 3 and wave 1 and trajectory of walking for leisure are summarised in Table 6.10 (question 1.3.). Unadjusted and adjusted results indicate some evidence that an increase in the perception of bus stop proximity is associated with a decrease in walking for leisure, as indicated by the time*trajectory interaction term for bus stop proximity (adjusted OR=0.86 (95% CI: 0.74-1.00); p-value = 0.049). This result is in line with what was observed in Table 6.8, although the level of evidence seems to have increased in the model using time*trajectory interaction terms. The time*trajectory interaction terms have estimates close to one for the remaining measures of perceptions, i.e. traffic safety (adjusted OR=0.98 (95% CI: 0.90-1.08); p-value=0.707), favourable street connectivity (adjusted OR=1.00 (95% CI: 0.99-1.10); p-value=0.971), enjoyment of the neighbourhood for cycling/walking (adjusted OR=1.02 (95% CI: 0.95-1.11); p-value=0.583), and personal safety (adjusted OR=1.00 (95% CI: 0.95-1.05); p-value=0.942).

There is no evidence that gender moderated the associations between trajectories of perceptions of the neighbourhood and trajectory in walking for leisure (all p-values>0.240).

Table 6.10 Odds ratios (OR) of walking for leisure vs. not by change in perception of the neighbourhood environment since the baseline , adjusting for potential confounders **(3-wave balanced panel of the ORiEL study, n=2,260)**

Exposure	Unadjusted OR	Adjusted OR[1]	95% CI	P-value unadjusted	P-value adjusted	Gender interaction (p-value) [2]
Trajectory: Bus stop proximity	1.13	1.17	[0.85 , 1.61]	0.428	0.349	0.583
Trajectory: Traffic safety	0.99	1.00	[0.81 , 1.22]	0.921	0.963	0.271
Trajectory: Favourable street connectivity	1.01	1.01	[0.82 , 1.24]	0.941	0.947	0.627
Trajectory: Enjoyment of neighbourhood for walking/cycling	0.95	0.95	[0.80 , 1.14]	0.575	0.581	0.239
Trajectory: Personal safety	1.00	1.02	[0.91 , 1.14]	0.986	0.717	0.440
Time*trajectory interaction: Bus stop proximity	0.87	0.86	[0.74 , 1.00]	0.053	0.049	0.932
Time*trajectory interaction: Traffic safety	0.98	0.98	[0.90 , 1.08]	0.725	0.707	0.334
Time*trajectory interaction: Favourable street connectivity	1.00	1.00	[0.91 , 1.10]	0.962	0.971	0.240
Time*trajectory interaction: Enjoyment of neighbourhood for walking/cycling	1.02	1.02	[0.95 , 1.11]	0.665	0.583	0.260
Time*trajectory interaction: Personal safety	1.00	1.00	[0.95 , 1.05]	0.994	0.942	0.992

Results are from logistic regression models estimated with Generalised Estimating Equations to account for the dependency across repeated measurements (unstructured working correlation matrix). Each exposure variable measures change since baseline on a continuous scale. Each unit represents an average change in exposure by one category between the baseline and the end of the study (+1 = improvement of the neighbourhood by one category on average). The time*trajectory interaction assesses whether exposure change is associated with different trajectory of change in the outcome. [1] Adjusted for time, gender, ethnicity, health condition, family affluence and baseline free school meal status. [2] The adjusted models were replicated with the addition of two- and three- ways interactions between gender, change and time.

6.4.2.3. Outdoor physical activity

Before exploring the longitudinal associations between the exposure variables and walking for leisure, Table 6.11 presents unadjusted and adjusted associations between socio-demographic variables and outdoor physical activity. Unadjusted and adjusted models indicate that outdoor physical activity was associated with most of the socio-demographic variables considered. Whereas walking for leisure was shown to be more prevalent in girls, other outdoor physical activities are more often reported by boys (adjusted OR=0.23 (95% CI: 0.19-0.27); p-value <0.001). Ethnic disparities are observed (adjusted p-values <0.001): outdoor physical activity is less prevalent in the White UK, Black Caribbean and Bangladeshi groups as compared to all other ethnic groups (adjusted OR are respectively 1.00 (reference category), 1.05 (95% CI: 0.73-1.52) and 1.10 (95% CI: 0.84-1.43)). The odds of outdoor physical activity are 1.58 (95% CI: 1.18-2.12) times higher amongst the Black African and 1.91 (95% CI: 1.21-3.01) times higher amongst the Pakistani adolescents compared to the White UK adolescents. There is also evidence that family affluence is positively associated with outdoor physical activity (adjusted p-value=0.004). Adolescents from the most affluent families are 1.46 (95% CI: 1.11-1.91) times more likely to report outdoor physical activity compared to the least affluent. Free school meals seems to indicate an opposite relationship, both in the adjusted and unadjusted models, but does not reach statistical significance (adjusted p-value = 0.159). Health status is not associated with outdoor physical activity (adjusted OR=0.95 (95% CI: 0.82-1.09); p-value=0.444). The modelled time coefficient reveals a decline in outdoor physical activity over the study period (adjusted OR=0.75 (95% CI: 0.70-0.80)).

General association (pooled longitudinal models)

Results for the general associations between perceptions of the neighbourhood and outdoor physical activity estimated with pooled longitudinal models are presented in Table 6.12 (question 1.1.). Perceived bus stop proximity is not associated at all with outdoor physical activity (adjusted OR = 0.99 (95% CI: 0.83-1.19); p-value=0.946). Adolescents with higher perception of traffic safety are estimated to have slightly lower odds of outdoor physical activity (adjusted OR=0.90 (95% CI: 0.71-1.14)), yet neither the specific parameter test (p-value=0.366) nor the overall test of association (p-value=0.182) provide evidence that this estimation can be generalised beyond the sample. In the adjusted model, unlike the unadjusted model, there is weak evidence that better perception of street connectivity increases the odds of outdoor physical activity (adjusted p-value=0.077). The odds of outdoor physical activity for those with high perception of street connectivity are 1.27 (95% CI: 1.03-1.57; p-value=0.024) times higher compared to those with low perception.

Table 6.11 Odds ratios (OR) of reporting at least one outdoor physical activity vs. not by potential socio-demographic and health confounders* **(3-wave balanced panel of the ORiEL study, n=2,260)**

Potential confounder		**Unadjusted OR**	**Adjusted OR[1]**	**95%CI**	**P-value parameter**	**P-value unadjusted**	**P-value adjusted[1]**
Gender	Male	1.00	1.00			<0.001	<0.001
	Female	0.23	0.23	[0.19,0.27]	<0.001		
Ethnicity	White: UK	1.00	1.00			0.002	0.012
	White: Mixed	1.16	1.31	[0.96,1.80]	0.092		
	Asian: Indian	1.42	1.45	[0.95,2.23]	0.087		
	Asian: Pakistani	2.04	1.91	[1.21,3.01]	0.005		
	Asian: Bangladeshi	1.18	1.10	[0.84,1.43]	0.482		
	Black: Caribbean	0.86	1.05	[0.73,1.52]	0.789		
	Black: African	1.59	1.58	[1.18,2.12]	0.002		
	Other	1.26	1.30	[1.04,1.63]	0.020		
Health	no condition	1.00	1.00			0.179	0.444
	1+ conditions(s)	0.91	0.95	[0.82,1.09]	0.444		
Family affluence	Low	1.00	1.00			0.008	0.004
	Moderate	1.12	1.21	[0.94,1.56]	0.142		
	High	1.33	1.46	[1.11,1.91]	0.006		
Take free school meal at W1	No	1.00	1.00			0.111	0.159
	Yes	1.13	1.12	[0.96,1.32]	0.159		
Time		0.78	0.75	[0.70,0.80]	<0.001	<0.001	<0.001

Results are from logistic regression models estimated with Generalised Estimating Equations to account for the dependency across repeated measurements (unstructured working correlation matrix). [1] Adjusted for all other variables of the table. * Outdoor physical activities include: basketball (or volleyball), blading, cricket, football, rounders, rugby and roller skating.

Table 6.12 Odds ratios (OR) of reporting at least one outdoor physical activity vs. not by perception of the neighbourhood environment , adjusting for potential confounders* **(3-wave balanced panel of the ORiEL study, n=2,260)**

Exposure		**Unadjusted OR**	**Adjusted OR[1]**	**95%CI**	**P-value parameter**	**P-value unadjusted**	**P-value adjusted[1]**	**Gender interaction (p-value) [2]**
Perceived bus stop proximity	Further away	1.00	1.00			0.639	0.946	0.674
	1-5 minutes	0.96	0.99	[0.83,1.19]	0.946			
Perceived traffic safety	Low	1.00	1.00			0.490	0.182	0.012
	Medium	0.99	1.02	[0.82,1.29]	0.840			
	High	0.92	0.90	[0.71,1.14]	0.366			
Perceived street connectivity	Low	1.00	1.00			0.222	0.077	0.719
	Medium	1.05	1.15	[0.97,1.36]	0.116			
	High	1.18	1.27	[1.03,1.57]	0.024			
Enjoyment of neighbourhood for walking/cycling	Strongly/slightly disagree	1.00	1.00			0.042	0.270	0.809
	Slightly agree	0.93	0.95	[0.81,1.11]	0.509			
	Strongly agree	1.10	1.07	[0.89,1.29]	0.466			
Feeling safe (personal safety)	Strongly disagree	1.00	1.00			0.324	0.507	0.697
	Slightly disagree	1.06	1.12	[0.86,1.46]	0.399			
	Neither agree nor disagree	0.95	0.96	[0.75,1.23]	0.747			
	Slightly agree	1.06	1.09	[0.84,1.41]	0.506			
	Strongly agree	1.13	1.09	[0.85,1.39]	0.508			

Results are from logistic regression models estimated with Generalised Estimating Equations to account for the dependency across repeated measurements (unstructured working correlation matrix). [1] Adjusted for gender, ethnicity, health condition, family affluence, baseline free school meal status, time and the other perception variables of the table. [2] The adjusted model was replicated for each outcome with an additional interaction term between gender and exposure. * Outdoor physical activities include: basketball (or volleyball), blading, cricket, football, rounders, rugby and roller skating.

Perceiving the neighbourhood as enjoyable for walking/cycling is not associated with outdoor physical activity in the adjusted model, despite some indication of association in the unadjusted model (unadjusted p-value=0.042 ; adjusted p-value=0.270). Point estimates for that variable indicated no clear pattern of associations (i.e. adjusted OR for slightly agree vs. disagree=0.95 and OR for strongly agree vs. disagree = 1.07). Finally, personal safety indicated similar patterns of associations as for walking for leisure, yet the estimated OR are all close to zero and the overall association did not reach statistical significance (adjusted p-value=0.507).

The inclusion of interaction terms between gender and each measure of perception of the neighbourhood indicates strong evidence that gender moderates the associations between perceptions of traffic safety and outdoor physical activity (p-value=0.012). There is no evidence that gender moderates any other association (all remaining p-values >0.674).

Gender-specific results presented in Table 6.13 indicate that boys with medium or high perception of traffic safety have higher odds of outdoor physical activity compared to those with low perception of traffic safety (ORs=1.53 (95% CI: 1.10-2.11) and 1.21 (95% CI: 0.89 - 1.64) respectively). In girls, the association takes the opposite direction: the odds of outdoor physical activity are lower if the perception of street connectivity is medium (OR=0.79 (95% CI: 0.56-2. 1.03)) or high (OR=0.74 (95% CI: 0.52-0.96)) compared to low perception.

Table 6.13 Gender-specific odds ratios (OR) of reporting at least one outdoor physical activity* vs. not by perceived traffic safety , adjusting for potential confounders **(3-wave balanced panel of the ORiEL study, n=2,260)**

Perceived traffic safety	Adjusted OR[1]	95% CI	P-value adjusted[1]
Boys			
Low	1.00		
Medium	1.53	[1.10 , 2.11]	0.011
High	1.21	[0.89 , 1.64]	0.232
Girls			
Low	1.00		
Medium	0.79	[0.56 , 1.03]	<0.001
High	0.74	[0.52 , 0.96]	<0.001

Results are from logistic regression models estimated with Generalised Estimating Equations to account for the dependency across repeated measurements (unstructured working correlation matrix). [1] Adjusted for bus stop proximity, perceived street connectivity, enjoyment of the neighbourhood for walking/cycling, personal safety, ethnicity, self-rated health, family affluence and baseline free school meal status. * Outdoor physical activities include: basketball (or volleyball), blading, cricket, football, rounders, rugby and roller skating.

Cumulative perceptions

Results for the association between cumulative perceptions of the neighbourhood and outdoor physical activity at wave 3 are presented in Table 6.14 (question 1.2.). Overall, results are comparable to those of other physical activity outcomes: there is no evidence of association with any of the cumulative perception scores. Cumulative perceived bus stop proximity indicates that an increase in cumulative perception by one unit leads to a reduction in the odds of outdoor physical activity by 0.94 (95% CI: 0.83-1.07); yet, the association does not reach statistical significance (adjusted p-value=0.331). There is even less evidence that cumulative perceived traffic safety, favourable street connectivity, enjoyment of the neighbourhood for walking/cycling, and personal safety are associated with outdoor physical activity at wave 3, given that all adjusted ORs are close to 1.00. Adjusted ORs are 1.00 for traffic safety (95% CI: 0.93-1.08; p-value=0.988), 1.03 for favourable street connectivity (95% CI: 0.96-1.11; p-value=0.398), 1.01 for enjoyment of the neighbourhood for walking/cycling (95% CI: 0.95-1.08; p-value=0.730) and 1.02 for personal safety (95% CI: 0.98-1.07; p-value=0.278).

Table 6.14 Odds ratios (OR) of reporting at least one outdoor physical activity* vs. not at wave 3 by cumulative perception of the neighbourhood environment over the 3 waves , adjusting for potential confounders **(3-wave balanced panel of the ORiEL study, n=2,260)**

Exposure	Unadjusted OR	Adjusted OR[1]	95%CI	P-value unadjusted	P-value adjusted[1]	Gender interaction (p-value)[2]
Cumulative bus stop proximity	0.95	0.94	[0.83,1.07]	0.377	0.331	0.900
Cumulative traffic safety	1.03	1.00	[0.93,1.08]	0.332	0.988	0.535
Cumulative favourable street connectivity	0.99	1.03	[0.96,1.11]	0.873	0.398	0.816
Cumulative enjoyment of neighbourhood for walking/cycling	1.03	1.01	[0.95,1.08]	0.165	0.730	0.510
Cumulative personal safety	1.05	1.02	[0.98,1.07]	0.006	0.278	0.825

Results are from logistic regression models estimated with Generalised Estimating Equations to account for the clustering of individuals within schools (exchangeable working correlation matrix).
The cumulative exposure are continuous variables constructed as the sum of scores of each exposure over the 3 waves. A higher score indicates a perception of supportive environment for the specific exposure. [1] Adjusted for gender, ethnicity, health condition (at wave 3), family affluence (at wave 3) and baseline free school meal status. [2] The adjusted model was replicated for each outcome with an additional interaction term between gender and exposure. * Outdoor physical activities include: basketball (or volleyball), blading, cricket, football, rounders, rugby and roller skating.

It could be noted that unadjusted results for personal safety indicate that an increase of the cumulative score by one unit increases the odds of outdoor physical activity by 1.05 (p-value = 0.006), but the association appears to be confounded, as indicated by the attenuation of the adjusted estimate to 1.02.

The inclusion of interaction terms between gender and each measure of cumulative perception of the neighbourhood indicates no evidence that gender moderates the associations with outdoor physical activity at wave 3 (all p-values >= 0.510).

Trajectories of perceptions

The analyses that investigate the association between trajectories of perceptions measured as changes between wave 3 and wave 1 and trajectory of outdoor physical activity are summarised in Table 6.15 (question 1.3.). As for other outcomes, the focus of this analysis is on the time*trajectory interaction terms for each measure of perception and outdoor physical activity. Unadjusted and adjusted ORs are of similar magnitude for all measures and indicate an absence of evidence of time*trajectory interaction. The estimate for change in perceived bus stop proximity indicates that a positive change in perception is associated with an increased probability of outdoor physical activity over time (adjusted OR=1.11; 95% CI: 0.93-1.32), yet the confidence interval is wide and the results are not statistically significant (p-value=0.248). Although not statistically significant, an improvement in the perception of the traffic safety is estimated to decrease the probability outdoor physical activity (adjusted OR = 0.94 (95% CI: 0.84-1.04); p-value = 0.222). Conversely, an improvement in the perception of street connectivity is estimated to increase that probability, but again without being statistically significant (adjusted OR = 1.07 (95% CI: 0.97-1.19); p-value = 0.172). The time*trajectory interactions indicate ORs close to one for enjoyment of the neighbourhood for walking/cycling (adjusted OR = 1.05 (95% CI: 0.93-1.11); p-value = 0.737) and personal safety (adjusted OR = 1.01 (95% CI: 0.96-1.07); p-value = 0.734).

Additional analyses that assessed whether gender moderates these associations indicate very weak evidence that perceived bus stop proximity and street connectivity trajectories were differently associated with changes in outdoor physical activity for boys and for girls (p-values = 0.095 and 0.091, respectively). The stratum specific results were not presented because they did not indicate any significant results within stratum. Other gender interaction terms did not reach statistical significance (other three-ways interaction p-values were 0.828, 0.527 and 0.956).

Table 6.15 Odds ratios (OR) of reporting at least one outdoor physical activity* vs. not by change in perception of the neighbourhood environment since the baseline , adjusting for potential confounders **(3-wave balanced panel of the ORiEL study, n=2,260)**

Exposure	**Unadjusted OR**	**Adjusted OR[1]**	**95% CI**	**P-value unadjusted**	**P-value adjusted**	**Gender interaction (p-value) [2]**
Trajectory: Bus stop proximity	0.86	0.82	[0.53 , 1.26]	0.457	0.366	0.045
Trajectory: Traffic safety	1.11	1.11	[0.85 , 1.45]	0.383	0.448	0.601
Trajectory: Favourable street connectivity	0.79	0.78	[0.61 , 1.01]	0.043	0.055	0.427
Trajectory: Enjoyment of neighbourhood for walking/cycling	0.99	1.00	[0.82 , 1.23]	0.955	0.977	0.837
Trajectory: Personal safety	1.01	1.02	[0.89 , 1.16]	0.802	0.816	0.759
Time*trajectory interaction: Bus stop proximity	1.11	1.11	[0.93 , 1.32]	0.192	0.248	0.095
Time*trajectory interaction: Traffic safety	0.94	0.94	[0.84 , 1.04]	0.230	0.222	0.828
Time*trajectory interaction: Favourable street connectivity	1.08	1.07	[0.97 , 1.19]	0.112	0.172	0.091
Time*trajectory interaction: Enjoyment of neighbourhood for walking/cycling	1.02	1.02	[0.93 , 1.11]	0.622	0.737	0.527
Time*trajectory interaction: Personal safety	1.01	1.01	[0.96 , 1.07]	0.640	0.734	0.956

Results are from logistic regression models estimated with Generalised Estimating Equations to account for the dependency across repeated measurements (unstructured working correlation matrix). Each exposure variable measures change since baseline on a continuous scale. Each unit represents an average change in exposure by one category between the baseline and the end of the study (+1 = improvement of the neighbourhood by one category on average). The time*trajectory interaction assesses whether exposure change is associated with different trajectory of change in the outcome. [1] Adjusted for time, gender, ethnicity, health condition, family affluence and baseline free school meal status. [2] The adjusted models were replicated with the addition of two- and three- ways interactions between gender, change and time. * Outdoor physical activities include: basketball (or volleyball), blading, cricket, football, rounders, rugby and roller skating.

6.4.2.4. Sensitivity analyses

A series of sensitivity analyses were conducted. Analyses were replicated using different specifications of the working correlation structure in the GEE estimation process (Appendix E section E.4). Results from these additional analyses were only marginally different from the main results presented in the text and all interpretations and conclusions are unaffected.

Finally, I compared the results obtained from the imputed datasets with those from a 'naive' complete case analysis (Appendix E section E.5). Results indicate that point estimates tend to be slightly over-estimated in the complete case analysis. The analysis of the complete cases confirms the results from the analysis of missingness, which suggested that coefficients from the complete case analysis would be slightly biased (Appendix E section E.1). Despite the bias and the loss of efficiency, however, the general conclusions about the directions of the main associations are not seriously affected in the complete case analysis.

6.5. Summary

In this chapter, I have investigated the longitudinal associations between five measures of perceptions of the neighbourhood environment (perceived bus stop proximity, traffic-related safety, street connectivity, enjoyment of the neighbourhood for walking/cycling and personal safety) and three physical activity outcomes (walking to school, walking for leisure and outdoor physical activity). I explored whether each of the variables was associated with the outcomes using pooled longitudinal models to obtain general measures of association (question 1.1.); models for associations between the accumulation of exposure and the outcome at a later stage (question 1.2.); and models for the associations between individual trajectories of exposures and outcomes (question 1.3.). I also tested whether the observed associations differed for boys and girls (question 1.4.).

To do so, I used the ORiEL 3-wave balanced panel. I first explored the extent of missingness in order to better understand whether the use of the complete cases, which is common in the field, might lead to bias. I used newly available tools for multilevel multiple imputation in order to handle missing data, based on a MAR assumption. These analyses have evidenced that these tools were appropriate and suitable for imputation purposes in the ORiEL study which features a mix of continuous and discrete variables, a 3-level structure (repeated measurements, individuals, schools), and interaction terms. Yet, the difficulty of finding an adequate imputation model suggests that multilevel multiple imputation may become even more challenging with larger multilevel datasets or with datasets having more waves of data collection.

Using 20 imputed datasets, I have shown that there is little evidence of general association (i.e. across all measurement occasions) between the five measures of neighbourhood perceptions and the three physical activity outcomes (question 1.1.). There is some evidence that, either when comparing different adolescents or the same adolescent over time, feeling very unsafe and perceiving a bus stop as proximal lead to less walking for leisure. There is also some indication that a high perceived street connectivity leads to more outdoor physical activity.

Models for the cumulative influence of perceptions on physical activity at a later stage indicated no support for such associations in any of the adjusted models (question 1.2.). The examination of the associations between trajectories of perceptions and physical activity outcomes over time also indicated that adolescents' perceptions poorly predict physical activity (question 1.3.). A similar association between perceived bus stop proximity and walking for leisure was observed. Adolescents who changed their perception of proximity over time and reported that their closest bus stop became closer, were less likely to report walking for leisure at follow-ups.

Despite evidence that physical activity outcomes and perceptions differ by gender, there was very little evidence that the associations between perceptions of the neighbourhood and physical activity differed by gender (question 1.4.). This result is not surprising given the limited overall evidence of association between the exposures and the outcomes.

Overall, the longitudinal analyses of this chapter have shown that the five measures of perceptions of the environment studied in this chapter are poorly associated with physical activity despite evidence that physical activity is strongly patterned by socio-demographic variables, in particular gender and ethnicity. These robust associations suggest that the neighbourhood socio-cultural environment might nevertheless have a role in explaining physical activity patterns. Accordingly, in the next chapter, I will investigate the role of ethnic density in predicting physical activity behaviours. In chapter 8, I will finally explore whether other aspects of the social environment not captured so far – namely social capital and social support – might contribute to explaining differences in physical activity.

Chapter 7: Associations between own-group ethnic density and physical activity

7.1. Introduction

In this chapter, I present an analysis of the associations between own-group ethnic density and three physical activity outcomes. Results from chapter 6 indicate that the likelihood of being physically active differs by ethnic group (cf. also section 3.5.1.). In the ORiEL study, walking to school is more prevalent amongst the White UK and Bangladeshi adolescents; walking for leisure amongst the White UK adolescents; and outdoor physical activity is predominantly prevalent in the Black African and Pakistani adolescents. Ethnic differences in physical activity have been previously documented in the UK (Fischbacher et al. 2004, Griffiths et al. 2013, Owen et al. 2012). However, the use of broader ethnic categories such as 'South Asians', veiled some of the ethnic differences described in this thesis. To explain ethnic differences in health, several theoretical perspectives were proposed in the literature (Nazroo 1998). One strand of research has focused on the broader socio-economic context and the neighbourhood environment because ethnic minorities tend to concentrate in places which are often more deprived than the average (Karlsen et al. 2002). In spite of a disadvantage in terms of neighbourhood deprivation, it has been suggested that individuals living in areas with a high concentration of people from the same ethnic group as themselves or 'ethnic density' may confer a protective benefit on health (Pickett & Wilkinson 2008), and by extension health behaviours (Bécares et al. 2011).

As indicated in the background chapter (section 2.4.2.), the evidence supporting the ethnic density hypothesis for mental and physical health has been mixed in the UK (Bécares et al. 2012b, Shaw et al. 2012). Most studies reported that ethnic density was protective for at least some ethnic minorities, but the associations were not consistent across ethnic groups. With respect to health behaviours, a protective effect on alcohol consumption was found for all ethnic minorities (Bécares et al. 2011), while the probability of smoking was shown to decline as ethnic density increased for minorities where smoking was not the norm (Mathur et al. 2017, Uphoff et al. 2016). As described in section 2.4.2., these results offer insight into the relevance of cultural identity and social norms as moderators of the associations between ethnic density and health behaviours.

In spite of these promising results, research on the ethnic density hypothesis is still in its infancy and knowledge gaps remain. To my knowledge, no study has investigated the association between ethnic density and physical activity in the UK, and there are few investigations in adolescents. Exploring the ethnic density hypothesis in adolescents may help shed light on the relative importance of ethnic density in the residential and school settings (Astell-Burt et al. 2012). Teasing out the independent contributions of neighbourhood deprivation and ethnic density also remains an issue, given the correlation between the processes of ethnic and economic segregations (Karlsen & Nazroo 2002). Focusing on homogeneously deprived but ethnically diverse areas might help better capture the ethnic density 'effect' itself (Uphoff et al. 2016).

From a statistical point of view, most studies of ethnic density have ignored bias and loss of information due to missing data. The few studies that have attempted to account for the missing data mechanism ignore the multilevel nature of the data in the imputation models used (e.g. Astell-Burt et al. (2012)), which is likely to cause bias (Carpenter & Kenward 2012).

In this chapter, I use the 3-wave balanced panel from the ORiEL study to test whether own-group ethnic densities measured at school and neighbourhood levels predict three common forms of physical activity: walking to school, walking for leisure and a composite measure of outdoor physical activity. These three dimensions were chosen to be consistent with results reported in chapter 6 and because they are most likely to be influenced by the neighbourhood environment (Evenson et al. 2012, Kerr et al. 2015). Similar to chapter 6, I handle item non-response using multilevel multiple imputation, and specify a distinct imputation model for the data used and research questions posed in this chapter. Analyses are restricted to the four main ethnic groups of the ORiEL study.

7.2. Research questions

Question 1: Is own-group ethnic density associated with physical activity in the ORiEL study and does this vary by ethnicity?

More specifically:

1.1. Is school-level own-group ethnic density associated with forms of physical activity (walking to school; walking for leisure; outdoor physical activity) and does this vary by ethnicity?

1.2. Is neighbourhood-level own-group ethnic density associated with forms of physical activity (walking to school; walking for leisure; outdoor physical activity) and does this vary by ethnicity?

1.3. Which of school-level or neighbourhood level own-group ethnic density best predicts forms of physical activity (walking to school; walking for leisure; outdoor physical activity)?

7.3. Methods

To explore the association between physical activity and ethnic density, I estimated pooled longitudinal analyses with GEE using imputed datasets. The data and methods used are outlined below.

7.3.1. Analytical sample

The final sample used for these analyses was constructed as described in section 3.3., by excluding ORiEL respondents that did not participate in all three waves (3-wave balanced panel). In this chapter, analyses are further restricted to the four most prevalent ethnic groups – White UK, White Mixed, Bangladeshi and Black African – to ensure sufficient power to detect ethnic-specific effects and to guarantee reliable estimations of the analysis models and of the imputation models[25]. This analytical sample was defined as the 'main ethnic groups 3-wave balanced panel' in section 3.3. It includes 1,160 participants and 3,480 observations.

[25] A conservative rule of thumb (Peduzzi et al. 1996) requires 10 events per parameter in a logistic regression model. This corresponds to 366 individuals in a logistic regression with 11 parameters and an outcome with 30% prevalence (i.e. the prevalence of walking for leisure). A less conservative rule requires 10 observations per parameter, which corresponds to 110 observations for a similar logistic regression model. Given that I use three waves of data with individual-level clustering, I expect to gain further information from repeated measurements. I assume that estimates from the Black Caribbean group (111 individuals) carry a too high risk of being unreliable after exploratory analyses indicated a lack of power to detect significant differences in that group. The White Mixed group (190 individuals) would allow reliable estimates if repeated observations provide at least 1.5 times the equivalent of information available in one wave, which seems reasonable to assume. The other groups retained had 382, 337 and 251 individuals and were judged unproblematic.

7.3.2. Variables

The variables summarised in Table 7.1 and outlined in the data chapter and were used for the analyses presented in this chapter. These include three binary physical activity outcomes, two measures of own-group ethnic density, a measure of ethnicity, a set of potential confounders, and cluster variable. These are described below.

Table 7.1 Variable definitions and item missingness at each wave for the main ethnic groups 3-wave balanced panel (n = 1,160; 3,480 measurements)

Variable	Variable type and use in the analysis	% missing W1	W2	W3
Outcomes				
Walking to school	Ordinal (almost count), 4 categories, non-Normal; binary version used	8.4	2.5	2.4
Walking for leisure	Ordinal (almost count), 4 categories, non-Normal; binary version used	17.0	6.0	5.5
Outdoor physical activity	Count (0-7), non-Normal; binary version used	22.2	10.3	8.6
Exposures				
School-level ethnic density	Continuous, non-Normal	Fully observed		
Neighbourhood-level ethnic density	Continuous, approximately Normal	7.6	7.9	9.7
Potential confounders				
Gender	Binary	Fully observed		
Ethnicity	Nominal variable with 4 categories	Fully observed		
Health condition	Count score of 9 binary items* (0-9), skewed; binary version used (0/1+)	2.9	14.2	14.0
Family affluence	Count score of 3 items (0-9), approximately Normal; categorised in 3 groups	4.6	3.2	3.3
Baseline free school meal status	Binary: Yes/No	1.7		
Household composition	Nominal, 4 categories, binary version used (both parents vs. not)	1.5	0.4	0.8
Time lived in neighbourhood	Ordinal, 5 categories, binary version used	15.1	5.1	4.1
Distance to school	Continuous, approximately log Normal	7.7	8.1	9.8
Cluster variable				
School	Assumed to be time invariant (W1 value used for those changing school)	Fully observed		
Auxiliary variables				
Total physical activity	Continuous, approximately log Normal	3.0	0.5	0.6
Country of birth	Binary (UK/non-UK)	1.9		
Language spoken at home	Binary (English/Other)	0.7		
Mental health (WEMWBS)	Continuous, approximately square Normal	3.1	1.7	2.4
BMI (BMI z score)	Continuous, Normal	8.7	8.1	6.9
Self-rated health	Ordinal variable with 3 categories	1.5	0.9	0.9

*requirement that at least five items are completed to get a score because the interest is in whether any condition is reported.

7.3.2.1. Outcomes

Three common forms of physical activity hypothesised to be associated with measures of ethnic density in the ORiEL study are examined: walking to school, walking for leisure (dog/exercise) and outdoor physical activity. As described in the data chapter (section 3.5.), each binary physical activity outcome captures whether adolescents reported having participated in the activity over the past week. The outdoor physical activity outcome combines participation in any of the following activities: basketball/volleyball, blading, cricket, football, rounders, rugby and roller skating.

7.3.2.2. Exposures

The two exposure variables are neighbourhood-level own-group ethnic density (referred to as neighbourhood-level ethnic density) and school-level own-group ethnic density (referred to as school-level ethnic density). Ethnic densities were calculated as the percentage of adolescents, either in the relevant school or neighbourhood, defined as the lower layer super output area (LSOA) of their home-address, who were of the same ethnic group. School-level ethnic density was treated as time-invariant, owning to only marginal changes observed over the study period in the annual school ethnic composition reported by the Department for Education (Department for Education 2012, 2013, 2014). Neighbourhood-level ethnic density was based on 2011 UK Census of population data and hence treated as time-invariant, except for those who reported change in the home-address. Both ethnic density variables were treated as continuous. Results were presented as change per 10 percentage points. Construction of the ethnic density variables is further described in section 3.5.2.2.

Ethnicity was treated as a moderator throughout this chapter. Analyses were presented separately for the White UK, White Mixed, Bangladeshi and Black African groups.

7.3.2.3. Potential confounders

The following potential confounders were included in adjusted models: gender, family affluence (3 categories derived from the family affluence scale), health condition (no condition vs. 1+ condition(s)), free school meal status, household composition (living with both parents vs. not), and time resident in the neighbourhood (less than 5 years vs. more). Gender and free school meal status were considered to be time-invariant. Baseline free school meal status was used following preliminary analysis of the reliability of the item (cf. section 3.5.3.4.). The other variables were treated as time-varying. Network distance to school was also included as a confounder in the models with walking to school as an outcome.

Measures of acculturation, such as country of birth and language spoken at home, were not included as confounders because they were not associated with any of the physical activity outcomes in the three ethnic minority groups studied (p>0.2), and therefore did not qualify as potential confounders.

7.3.2.4. School

School was considered to be time-invariant for ease of modelling (see below). During the study period, n=4 adolescents of the relevant ethnic groups moved within the surveyed school sample. Baseline-school was used for these adolescents in the imputation model and for the creation of school-level ethnic density measures. This simplification is highly unlikely to have any impact on the interpretation of the results.

7.3.3. Analytical strategy used in this chapter

As detailed in the methods chapter (chapter 4), the analytical strategy for the longitudinal analyses is twofold; it involves the handling of missing data with multilevel multiple imputation and the specification of models used to answer the research questions, known as analysis models (or models of interest). The specific models used in this chapter are presented in this section.

7.3.3.1. Handling missing data with multilevel multiple imputation

I handled missing data using multilevel multiple imputation (MI) models. I first described the extent of missingness in each variable of interest and explored the plausibility of different missing data mechanisms. As in chapter 6, preliminary analyses of the variables of interest revealed that a complete case analysis was likely to be invalid and to generate bias (Appendix F section F.1).

MI was therefore used to handle item non-response under the missing at random assumption (MAR). To increase the plausibility of the MAR assumption, reduce bias and improve efficiency (Carpenter & Kenward 2012), I included the following auxiliary variables in the imputation models: log of total physical activity (centred), country of birth, language spoken at home, squared WEMWBS score for positive mental wellbeing (centred), BMI z-score (centred) and self-rated health. The selection process of these auxiliary variables is reported in Appendix F (section F.1).

Building on the results of chapter 6, I explored Multilevel MI solutions within the joint modelling framework in order to account for the correlations implied by the 3-level hierarchical structure of the data (repeated measurements, individuals, schools). The analysis models include continuous variables, discrete variables and interaction terms between the exposure variables and ethnicity. Potential interactions were handled by imputing the data separately by ethnic group. Following recommendations from the literature (Rodwell et al. 2014), limited-range continuous variable (i.e. neighbourhood-level ethnic density) was imputed on the raw scale with no restrictions to the range[26], and with no post-imputation rounding. The imputation models were implemented using the R package 'jomo' (Quartagno et al. 2018), which is the latest package available to run complex multilevel MI models with unordered discrete variables. For comparison purposes, results of the complete case analysis are provided in Appendix F (section F.6).

7.3.3.2. Analysis models

To answer the research questions of this chapter, I estimated logistic regression models using generalised estimating equations (GEE) in Stata 15 ('xtgee') as detailed in the methods chapter (section 4.4.3.). Marginal models estimated with GEE have a convenient population-average interpretation of the parameters (Fitzmaurice et al. 2011), although current software implementations only allow for models with 2-level structures. In this chapter, I used GEE methods to account for the hierarchical structure of the data at individual level (measurements nested within individuals). Clustering at school-level could not be accounted for, but was expected to be limited as indicated previously (section 3.5.1.1.). Following results given in Appendix E (section E.3), unstructured working correlation structures were used to initiate the GEE estimation process. The models were replicated using an alternative specification of the working correlation to ensure that results were not sensitive to its specification (cf. Appendix F section F.3).

For each outcome, separate logistic models estimated with GEE were specified to test school-level and neighbourhood-level ethnic density effects by ethnic group using imputed datasets. To gain efficiency, I used general models that included interaction terms between ethnicity

[26] This implies that imputed percentages could take values <0 or >100.

and ethnic density as opposed to stratifying the results by ethnic group. Ethnic-specific inferences were obtained using an 'mi estimate' command equivalent of the 'lincom' command with imputed datasets in Stata. For each exposure variable, I fitted unadjusted models including time, exposure, ethnicity and ethnicity*exposure interaction terms. Partially adjusted models further included potential confounders. Finally, the fully adjusted models included time, ethnicity, confounders, the two exposures and their interaction with ethnicity. The model equations are given in Appendix F section F.2. For sensitivity analysis purposes, I also stratified the analyses by ethnic group and adjusted for confounders (Appendix F section F.4). Stratified results were also computed using ethnic density tertiles as opposed to continuous scores, which allowed deviation from linearity to be assessed (Appendix F section F.5).

Lowess smoothers were used in exploratory analyses to identify the functional shape of the association between the logit of physical activity and the measures of ethnic density. Lowess, which stands for 'locally weighted scatterplot smoothing', is a non-parametric regression method that creates smooth line through a scatter plot to help identify relationships between variables.(Cleveland 1979).

7.4. Results

This section presents the results of the analyses conducted to answer the research questions on the relationships between physical activity and ethnic density. The first part presents how item non-response is handled using a multilevel multiple imputation model, which is specific to the analyses presented in this chapter. The second part presents the results of the analysis models fitted to answer the research questions.

7.4.1. Missing data handling

7.4.1.1. Description of item missingness

Patterns of missingness for the four selected ethnic groups are very similar to those of the 3-wave balanced panel, and most of the variables used in this chapter were already described in chapter 6 (section 6.4.1.1.). Missingness is less frequent overall for the present analyses, compared to previous chapters as neighbourhood perceptions variables, which had high levels of missingness, are not included in the present analysis.

Table 7.1 indicates the proportion of missing data by wave for the variables of interest and potential auxiliary variables. All variables, except school, school-level ethnic density, gender and ethnicity are subject to some degree of non-response. Most variables have highest missingness at wave 1 and lowest at wave 3, except for the health condition questions, distance to school, and neighbourhood-level ethnic density. Missingness in the latter two variables rises over time due to an increase in refusal to report home-address (8% missing at waves 1-2 and 10% at wave 3). Missingness is highest for outdoor physical activity and walking for leisure, in which the proportion of missing values lies between 17% and 22% at wave 1, between 6% and 10% at wave 2 and between 5% and 9% at wave 3. It is slightly lower for walking to school (8% at wave 1, and 2% at waves 2-3). Outdoor physical activity has more missing data because it combines multiple items, with each item having missing values. Missingness for time-lived in the neighbourhood was 15% at wave 1, 5% at wave 2 and 4% at wave 3, and lies around 7-8% for the auxiliary variables BMI. Other variables had missingness below 5%.

7.4.1.2. Imputation model

I used the experience gained in chapter 6 (section 6.4.1.2.) to inform my imputation strategy in this chapter. I first split the data by ethnic group to allow for interaction terms between ethnicity and ethnic density measures. I transformed the data to wide format, used a fixed effects approach to account for clustering at individual level and included baseline school as a random effect.

Following the analysis of missingness (Appendix F section F.1), the initial imputation model of each ethnic group included the variables of the analysis models and the auxiliary variables of Table 7.1 (with the exception of the stratification variable, ethnicity). Normally distributed continuous variables were treated as outcomes and rescaled if necessary. School-level ethnic density was not normally distributed but could be included as a covariate given that it was fully observed (cf. section 3.5.2.2.). All discrete variables were treated as outcomes using the latent normal distribution approach described in section 4.3.2.2.

The initial 'full model', named Model 1 in Table 7.2 is quick to run but has very slow convergence. Therefore, an initial 30,000 iterations were obtained and analysed for each of the four subsets of the data. Overall, results indicate slow convergence, non-optimal mixing and relatively high auto-correlation. Over a long chain of iterations however, convergence seems acceptable, suggesting that a large burn-in $n_{\text{burn}} \approx$ 10,000 and a large n-between $n_{\text{between}} \approx$ 5,000 could be suitable.

Table 7.2 Summary of imputation models of chapter 7

Model	Data format	Cluster variable	Variables	Coefficients matrices	Computational time for 10 iterations	MCMC convergence
Model 1: final model for the White Mixed, Bangladeshi, and Black African groups	wide	school	normal transformation and centring of continuous variables school-level ethnic density as a covariate	Beta [2x 49] Cov u [49x49] Omega [49 x 49]	28 sec*	slow convergence, rather high auto-correlation; poor mixing for the Beta parameters associated with country of birth for White UK group. recommended burn-in of $n_{\text{burn}} \geq$ 10,000 and n-between of n_{between} = 5,000
Model 2: final model for the White UK group	wide	school	same as above country of birth excluded	Beta [2x 48] Cov u [48x48] Omega [48 x 48]	26 sec	slow convergence, rather high auto-correlation not optimal but acceptable mixing for the Beta parameters associated with language spoken at home recommended burn-in of $n_{\text{burn}} \geq$ 10,000 and n-between of n_{between} = 5,000

* Computational time for the White UK group in the initial model.

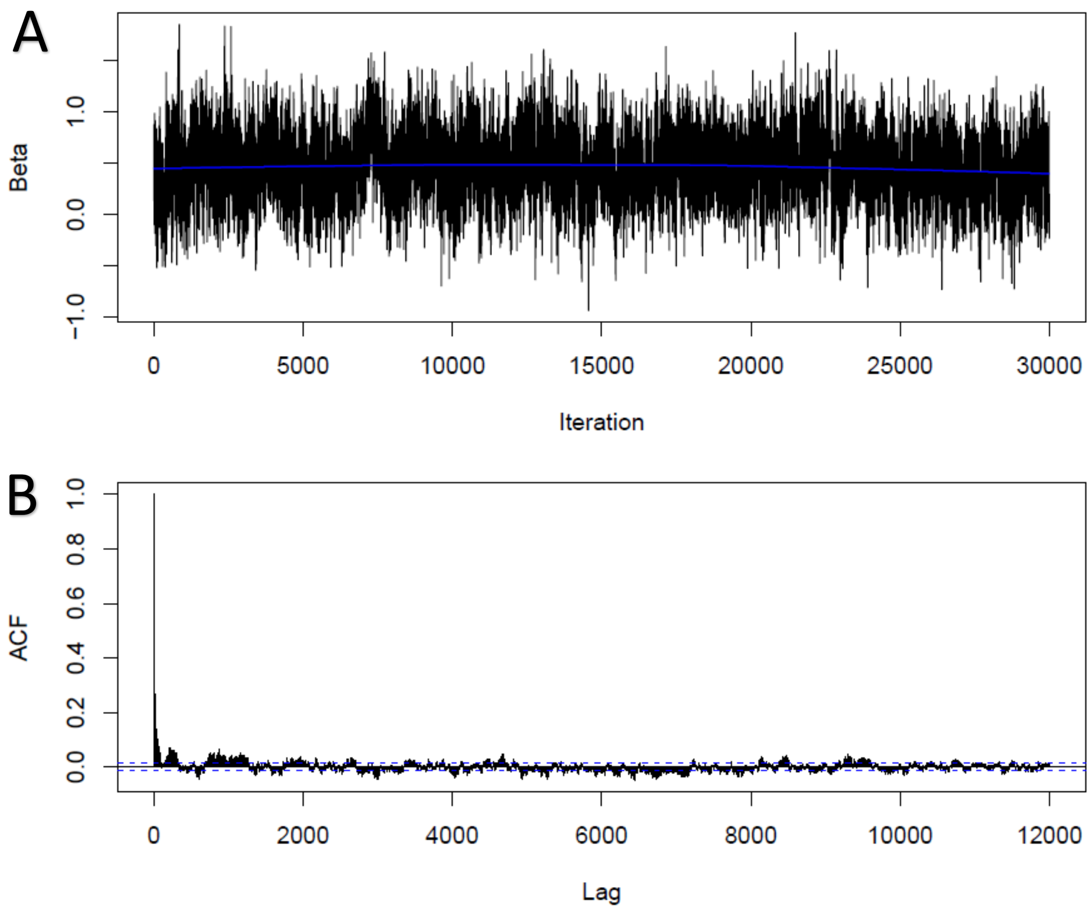


Figure 7.1 Example of time series plot (A) and autocorrelation plot (B) of a β parameter with good convergence in Model 1. The β parameter of this example corresponds to walking for leisure at wave 2 ($\beta_{1,21}$) for the Black African model. Results are from the multilevel imputation Model 1 (fixed effects approach with school as a cluster). The autocorrelation plot starts at iteration 10,000. ACF – Autocorrelation Function

Such a requirement is feasible because of the fast computational speed of the model. The total computational time for 20 imputations with such high burn-in and n-between values is estimated to be about 3 days for each model.

Most of the β coefficients of Model 1 have satisfactory convergence. Figure 7.1 gives an example of good convergence for one of the physical activity outcomes ($\beta_{1,21}$) in Black African adolescents. Other parameters (like $\beta_{1,23}$ in the White Mixed adolescents; not presented) had some autocorrelation with a lag above 5,000, indicating poor mixing. Parameters with such patterns are not a major concern however given that the usual rule of thumb was respected, i.e. the autocorrelation plots cross at least once the 0.05 benchmark for lags of 5,000.

Although results for the β coefficients are comparable and satisfactory across ethnic groups, Model 1 displays a convergence issue in the White UK subset. Indeed, the parameters associated with country of birth ($\beta_{1,48}$ and $\beta_{2,48}$) have poor mixing and very high-autocorrelation, even for lags of 10,000 (Figure 7.2).

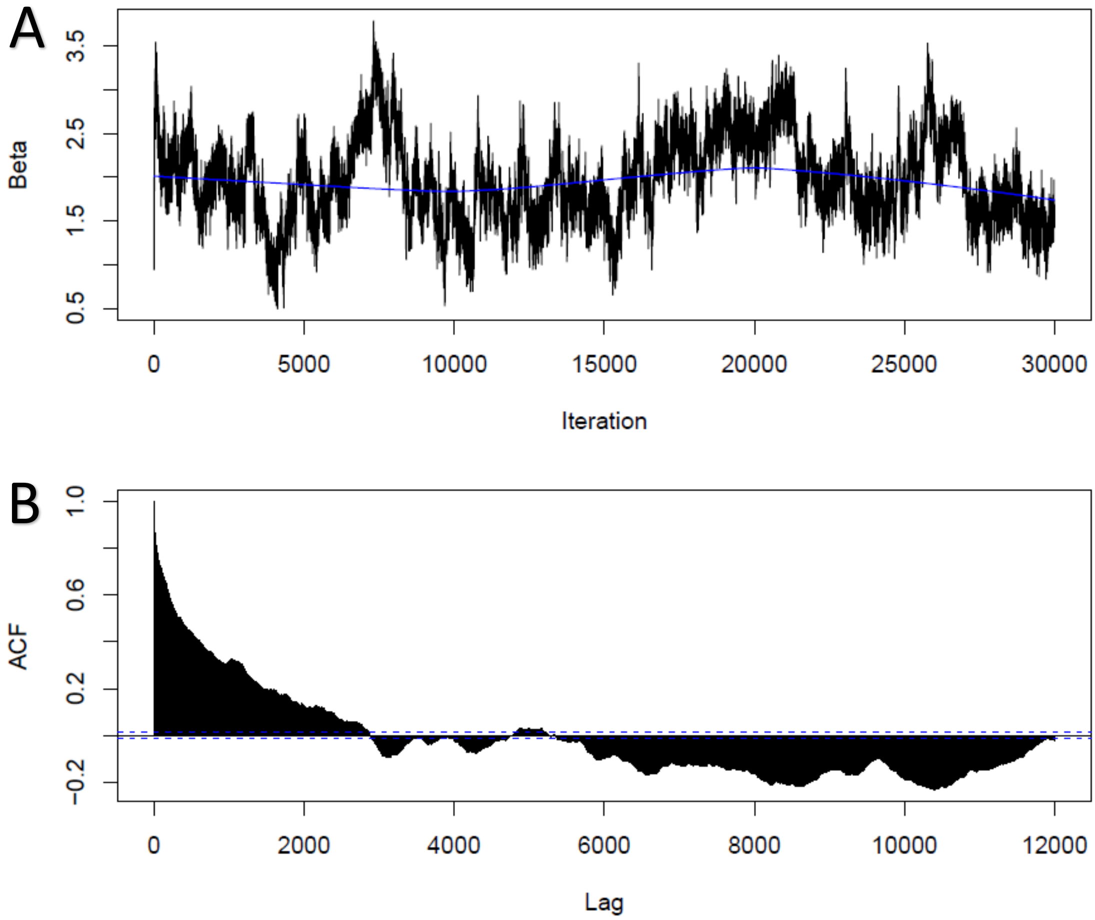


Figure 7.2 Time series plot (A) and autocorrelation plot (B) with of a β parameter with poor convergence in Model 1. The β parameter of this example corresponds to country of birth ($\beta_{1,48}$) for the White UK model. Results are from the multilevel imputation Model 1 (fixed effects approach with school as a cluster). The autocorrelation plot starts at iteration 10,000. ACF – Autocorrelation Function

The lack of variability in the country of birth for the White UK group is likely to be the problem. In a subsequent model (Model 2), the variable was excluded from the White UK model. Country of birth was retained for the other ethnic groups because of its potential to reduce bias and increase precision (Appendix F section F.1). In Model 2, β coefficients have good mixing overall. The parameters associated with language spoken at home ($\beta_{1,48}$ and $\beta_{2,48}$) still display some autocorrelation for large lag values.

In Model 1 and Model 2, parameters of the level 2 covariance matrix (Covariance u) generally have good convergence and usually stay well within the [-0.05; 0.05] bounds for autocorrelation. Most of the variances and the covariances involving the outcomes of the analysis models (walking to school, walking of leisure and outdoor physical activity at each wave) have good convergence. Some non-ideal convergences indicate remaining autocorrelation with large lags (see Figure 7.3 for an illustration). These would not be a problem using an n-between of $n_{\mathrm{between}} \geq 5{,}000$.

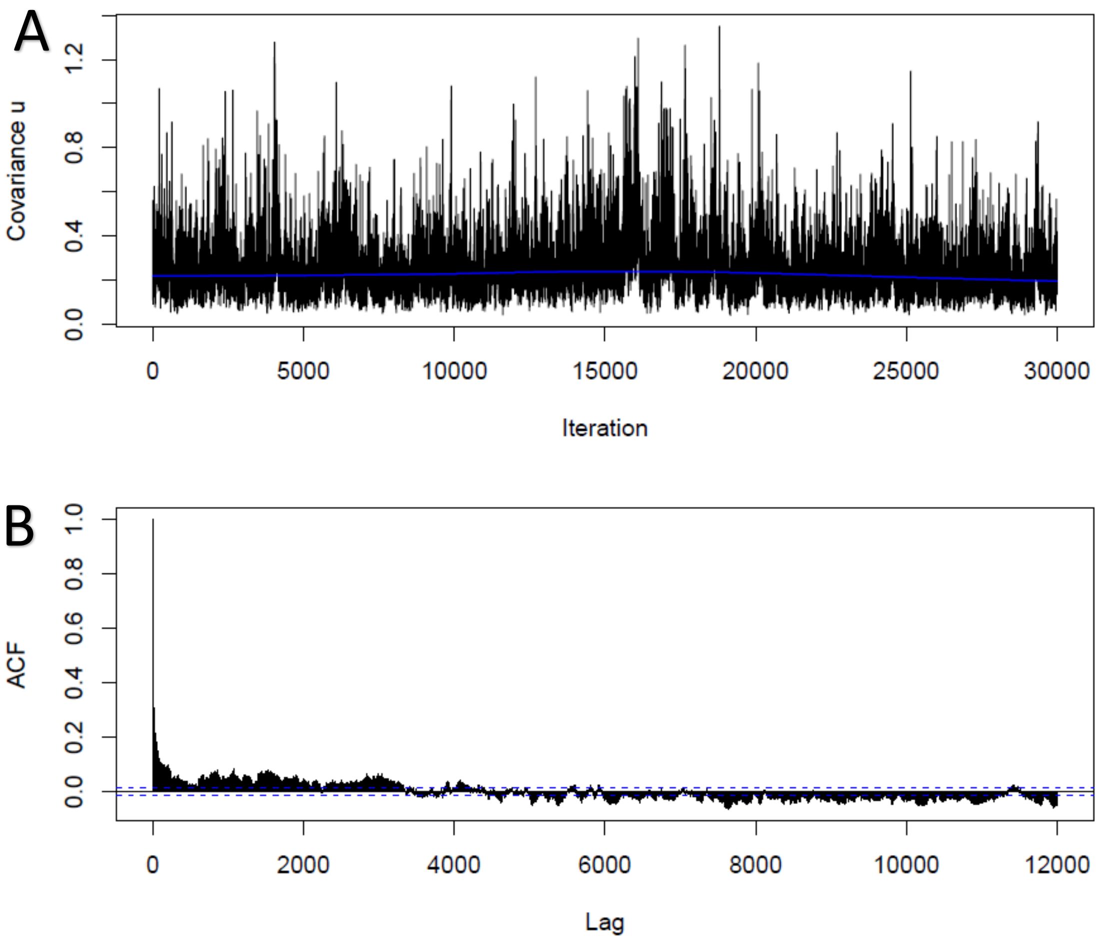


Figure 7.3 Example of time series plot (A) and autocorrelation plot (B) of a level 2 covariance parameter with small persistent autocorrelation in Model 1. The parameter of this example corresponds to the level 2 covariance associated with walking to school at wave 2 (Covariance u 17 17) for the White Mixed model. Results are from the multilevel imputation Model 1 (fixed effects approach with school as a cluster). The autocorrelation plot starts at iteration 5,000. ACF – Autocorrelation Function

Diagnosis outputs for the level 1 covariances indicate acceptable mixing when the Metropolis-Hastings algorithm is used (see Figure 7.4 for an example). Compared to chapter 6 (section 6.4.1.2.), convergence results of the level 1 covariances are generally better. Even so, the relatively low quality of mixing should not affect the results of the imputation if not followed by a full Bayesian analysis.

To summarise, the convergence analysis indicates that Model 1 is suitable to impute the data for the White Mixed, Bangladeshi and Black African samples with a large burn-in of $n_{\text{burn}} \geq$ 10,000 and an n-between of $n_{\text{between}} \geq$ 5,000. Model 2 seems appropriate for the White UK sample, with similar burn-in and n-between values. It should be stressed that the use of two imputation models for subsamples should not cause compatibility problems as the country of birth variable is not included in any of the analysis models (Carpenter & Kenward 2012).

Model 2 for White UK and Model 1 for other ethnic groups are employed as the final imputation models to produce 20 imputed datasets for each ethnic group. A burn-in of $n_{\text{burn}} =$

30,050 and an n-between of $n_{\text{between}} = 5{,}000$ were used. The random seed 1,523 was used for replication purposes. The models took c.5 days each to complete the burn-in and impute the data. The ethnic-specific 20 imputed datasets were merged and transformed back into long format for analysis. The analysis models were run on each imputed dataset and results were combined for final inference using Rubin's rules (Carpenter & Kenward 2012).

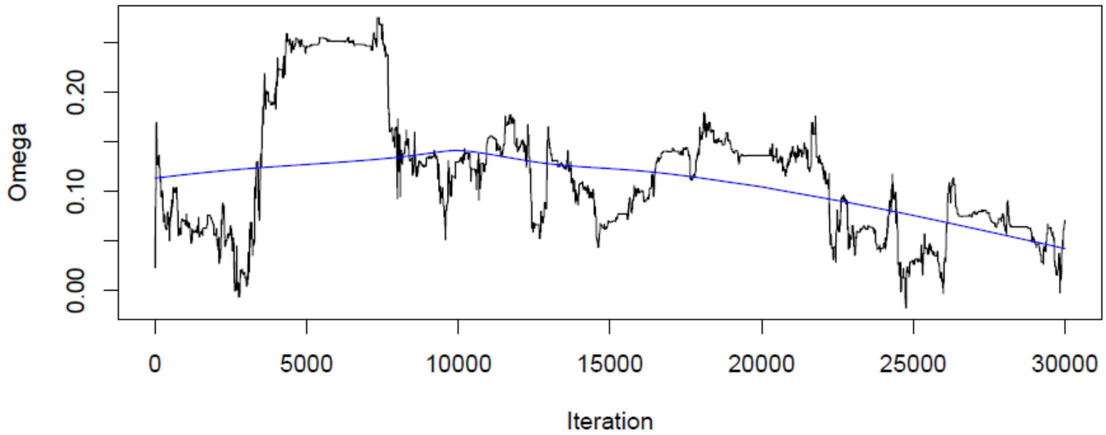


Figure 7.4 Example of time series plot with acceptable mixing of a level 1 covariance Omega parameter updated with a Metropolis-Hastings step in Model 1. Results are from the multilevel imputation Model 1 for the Bangladeshi group (fixed effects approach with school as a cluster).

7.4.2. Associations between ethnic densities and physical activity

In this section, I analyse the 20 imputed datasets to answer the established research questions (section 7.2.). Briefly, first, is school-level ethnic density associated with common forms of physical activity (walking to school; walking for leisure; outdoor physical activity) and does this vary by ethnicity? Second, is neighbourhood-level ethnic density associated with these forms of physical activity and does this vary by ethnicity? Third, which of school-level or neighbourhood-level own-group ethnic density best predicts these forms of physical activity?

Analyses were conducted using logistic regression models estimated with GEE. Unadjusted and partially adjusted models were fitted separately for school-level and neighbourhood-level ethnic densities (questions 1.1. and 1.2.). Fully adjusted models then included both measures of exposure and their interactions with ethnicity (question 1.3.). School-level ethnic density parameters are interpreted as in cross-sectional analysis because the exposure variable is time-invariant. Neighbourhood-level ethnic density varied for adolescents who changed LSOA during the study (amongst those who reported an address, 5.2% change LSOA at wave 2 and another 5.9% changed LSOA wave 3). Parameter estimates are therefore interpreted both as cross-sectional (comparing two individuals with different ethnic density values) and in terms of within individual change over time in ethnic density due to neighbourhood change. Results are presented for each physical activity outcome at a time, starting with some descriptive statistics and an analysis of the functional form of the relationship between the exposure and outcome variables.

7.4.2.1. Walking to school

Table 7.3 shows that walking to school at least once over the past week is most prevalent in the Bangladeshi group (84.5%) followed by the White UK (80.8%), White Mixed (72.4%) and Black African groups (71.4%). Compared to the White UK group, the odds of walking to school are statistically different and lower for the White Mixed and Black African groups, (OR are 0.62 (95% CI: 0.45-0.68) and 0.59 (95% CI: 0.44-0.79), respectively). Ethnic density measures also vary across ethnic groups (Table 7.3). At school-level, median ethnic density is 63.3% for the Bangladeshi adolescents, lies close to 20% for the White UK and Black African adolescents (22.7% and 19.3% respectively), and is 14.2% for the White Mixed adolescents. Large variations within the Bangladeshi group are observed, whereas variations were smallest for the White Mixed and Black African groups. At neighbourhood-level, patterns are very similar for the White Mixed and Black African groups, displaying low median values and limited variability (medians are 12.7% and 13.6%, respectively). For the White UK and Bangladeshi groups, neighbourhood-level densities are attenuated, yet still higher than in the other groups (medians are 40.5% and 22.3%, respectively), and notable within group variability is observed.

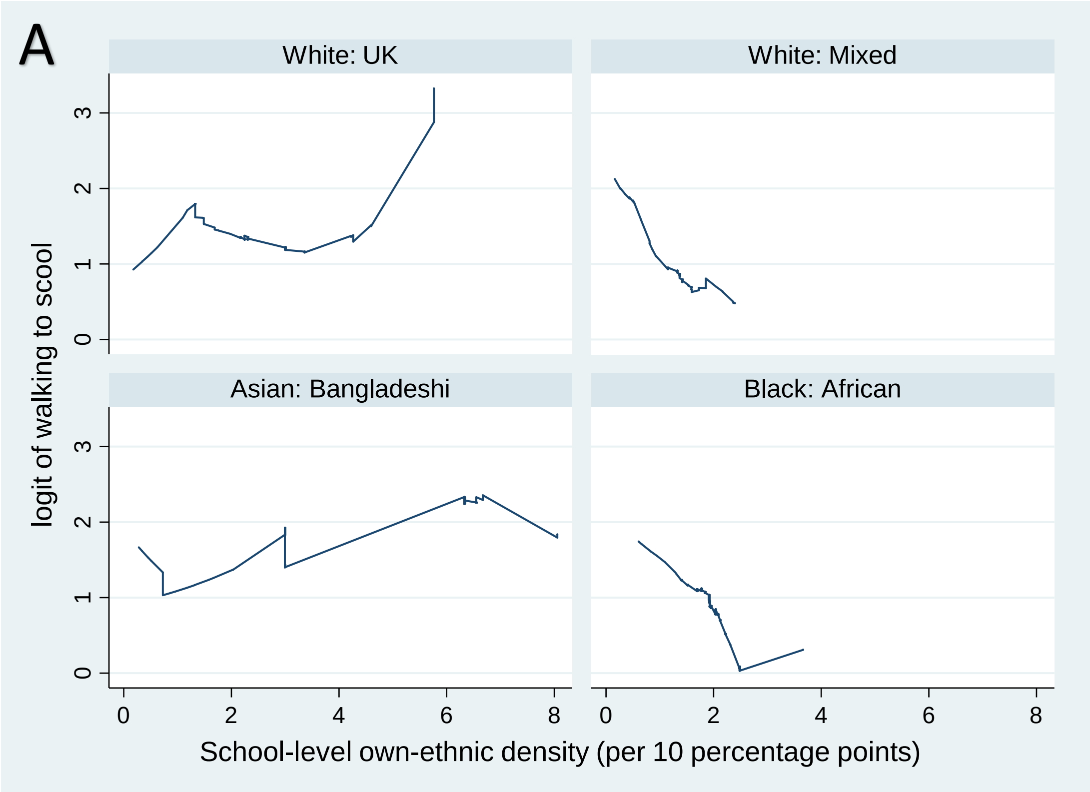
Functional form of the associations

To inform modelling decisions, I used the lowess smoother to explore the function form of the associations between each ethnic density measure and the outcome (Figure 7.5). I concentrate my interpretation to the areas of the ethnic density variables with most observations, focusing on the observations lying between the 10th and the 90th percentiles (Table 7.3). Figure 7.5 indicates that associations between the two ethnic density measures and walking to school are approximately linear on the logit scale. Results also indicate the need for caution with school-level exposure in the White UK group (Figure 7.5A), whose pattern of association with walking to school might not be well captured by a linear trend. As a result, sensitivity analyses using exposure definitions based on tertiles (Appendix F section F.5) will also be presented in this chapter. Any difference in results between ethnic density tertiles and continuous ethnic density variables will be emphasised.

Table 7.3 Descriptive statistics of the exposure and outcome variables by ethnic group (3 waves of the ORiEL Study, n=1,160)

	White: UK	**White: Mixed**	**Asian: Bangladeshi**	**Black: African**
N per wave	382	190	337	251
% walking to school	80.8	72.4	84.5	71.4
OR [95% CI] of walking to school[1]	1.00*	0.62 [0.45,0.86]	1.29 [0.95,1.76]	0.59 [0.44,0.79]
% walking for leisure	48.3	39.8	24.4	28.5
OR [95% CI] of walking for leisure[1]	1.00*	0.71 [0.55,0.92]	0.35 [0.28,0.43]	0.43 [0.33,0.55]
% reporting outdoor physical activity	71.4	75.1	74.8	80.1
OR [95% CI] of outdoor physical activity[1]	1.00*	1.23 [0.91,1.66]	1.21 [0.93,1.57]	1.64 [1.22,2.20]
Median [10^{th}- 90^{th} percentiles] school-level ethnic density	22.7 [13.2-57.6]	14.2 [4.4-21.7]	63.3 [7.5-80.6]	19.3 [9.5-24.8]
Median [10^{th}- 90^{th} percentiles] neighbourhood-level ethnic density	40.5 [19.7-63.1]	12.7 [6.3-22.2]	22.3 [4.5-53.2]	13.6 [4.0-23.5]

[1] Results are from logistic regression models estimated with Generalised Estimating Equations to account for the dependency across repeated measurements (unstructured working correlation matrix). *reference group.



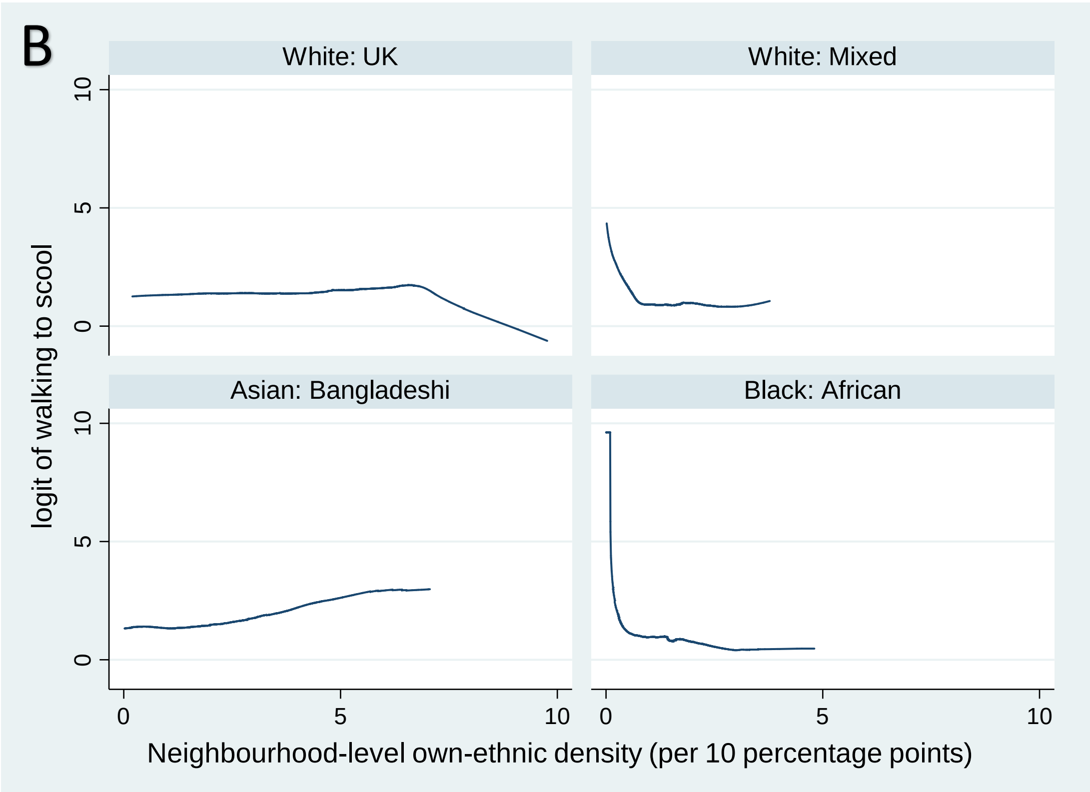


Figure 7.5 Exploration of the functional form of the association between the logit of walking to school and ethnic density measures using lowess smoother. School-level ethnic density is represented in A and neighbourhood-level ethnic density in B. All waves of the data are used and imputed density measures lower than 1.9 percent are excluded. Bandwidth of 0.8 is used.

School-level ethnic density

Table 7.4 shows that school-level ethnic density is associated with walking to school, after adjustment for potential confounders (p-value of the test for an 'overall' association in the partially adjusted model <0.001). A positive association is observed for the Bangladeshi group, indicating that an increase in school-level ethnic density by 10% increases the odds of walking to school by 1.20 (95% CI: 1.09-1.31). Negative significant associations are observed for the White Mixed and Black African groups (partially adjusted OR are 0.51 (95% CI: 0.35-0.76) and 0.58 (95% CI: 0.45-0.75), respectively), and a positive non-significant association is observed for the White UK group (partially adjusted OR = 1.08 (95% CI: 0.96-1.21)). The model using exposure tertiles (Appendix F Table F.10), indicates a U-shaped relationship for the White UK group (as expected from Figure 7.5A). The lowest odds of walking to school are observed for the 2^{nd} tertile of ethnic density (partially adjusted OR of 2^{nd} tertile vs. 1^{st} = 0.52 (95% CI: 0.32-0.83)) and there is no significant difference between the 1^{st} and the 3^{rd} tertiles (partially adjusted p-value=0.890).

Neighbourhood-level ethnic density

Table 7.4 also indicates significant associations between walking to school and neighbourhood-level ethnic density (overall test p-value in the partially adjusted model =0.003). Compared to school-level measures, coefficients have the same signs but are lower in magnitude. The only significant result is a strong positive association in the Bangladeshi group: an increase in neighbourhood-level ethnic density by 10% (interpreted either as a difference between two adolescents of the same ethnic group, or within the same adolescent over time) increases the odds of walking to school by 1.31 (95% CI: 1.14-1.51). Partially adjusted p-values for the other ethnic groups vary between 0.123 and 0.852.

School vs. neighbourhood

The fully adjusted model (Table 7.4) finally shows that, in the presence of the two ethnic density exposures and potential confounders, only school-level ethnic density remains statistically significant overall (overall test p-value is <0.001 for school-level ethnic density and 0.523 for neighbourhood-level ethnic density). Results indicate that an increase in school-level ethnic density by 10% would decrease the odds of walking to school by a factor of 2.27 (=1/0.44) for the White Mixed group and by 1.67 (=1/0.60) for the Black African group (95% CI: 1.43-3.57 and 1.27-2.22, respectively). In the White UK group, results from the tertiles analysis (Appendix F Table F.10) also show significantly lower odds of walking to school for the 2^{nd} tertile of school-level ethnic density (fully adjusted OR compared to the 1^{st} tertile = 0.49 (95% CI: 0.30-0.80)).

Table 7.4 Ethnic group specific odds ratios (OR) of walking to school vs. not by own-group ethnic density (3 waves of the ORiEL Study, n=1,160)*

Exposure	Unadjusted OR	Partially Adjusted OR[1]	95% CI	P-value	Fully Adjusted OR[2]	95% CI	P-value
School-level ethnic density				<0.001			<0.001
White: UK	1.08	1.08	[0.96 , 1.21]	0.195	1.10	[0.94 , 1.30]	0.230
White: Mixed	0.53	0.51	[0.35 , 0.76]	0.001	0.44	[0.28 , 0.70]	0.001
Asian: Bangladeshi	1.19	1.20	[1.09 , 1.31]	<0.001	1.13	[0.96 , 1.32]	0.140
Black: African	0.58	0.58	[0.45 , 0.75]	<0.001	0.60	[0.45 , 0.79]	<0.001
Neighbourhood-level ethnic density				0.003			0.523
White: UK	1.01	1.01	[0.88 , 1.16]	0.852	0.97	[0.81 , 1.15]	0.699
White: Mixed	0.95	0.94	[0.62 , 1.43]	0.772	1.33	[0.81 , 2.18]	0.262
Asian: Bangladeshi	1.32	1.31	[1.14 , 1.51]	<0.001	1.15	[0.91 , 1.46]	0.234
Black: African	0.80	0.80	[0.60 , 1.06]	0.123	0.91	[0.67 , 1.25]	0.576

Results are from logistic regression models estimated with Generalised Estimating Equations to account for the dependency across repeated measurements (unstructured working correlation matrix). Interaction terms between the own-group ethnic density variable and ethnicity were used and ethnic group specific ORs were obtained. *Own-group density assessed as change per 10 percentage points. [1] Adjusted for time, gender, health condition, family affluence, baseline free school meal status, household composition, time lived in the neighbourhood and distance to school. [2] Adjusted for time, gender, health condition, family affluence, baseline free school meal status, household composition, time lived in the neighbourhood, distance to school, the other ethnic density variable and its interaction with ethnicity.

In the Bangladeshi group, coefficients of school-level and neighbourhood-level ethnic densities are attenuated in the fully adjusted model (ORs=1.13 and 1.15, respectively) and are no longer significant (p-values are 0.140 and 0.234, respectively). This is likely to reflect an overlap between the two ethnic density measures for that group and the incapacity of the model to differentiate school from neighbourhood-level associations in this context.

7.4.2.2. Walking for leisure

Table 7.3 shows that walking for leisure at least once over the past week is most prevalent in the White UK group (48.3%) followed by the White Mixed (39.8%), Black African (28.5%) and Bangladeshi groups (24.4%) Compared to the White UK group, the odds are significantly different and lower for the White Mixed, Bangladeshi and Black African groups, (OR are 0.71 (95% CI: 0.55-0.92), 0.35 (95% CI: 0.28-0.43), and 0.43 (95% CI: 0.33-0.55) respectively).

Functional form of the associations

Figure 7.6 indicates that associations between the two ethnic density measures and walking for leisure are approximately linear on the logit scale in the parts of the distribution that contain the most observations. For example, in the Bangladeshi group, the increase in the logit only occurs for a small number of observations with very small school-level exposure values. Nonetheless, there is a particular need for caution with school-level exposure in the Black African group (Figure 7.6A), whose pattern of association with walking for leisure might not be well captured by a linear trend. The additional analyses using exposure tertiles, and presented in Appendix F (section F.5), will also be interpreted and reported if they diverge from the main results presented here.

School-level ethnic density

Table 7.5 shows that school-level ethnic density is not associated with walking for leisure for any ethnic group, after adjustment for potential confounders (overall test p-value in the partially adjusted model = 0.454). The estimated associations are close to null for the White UK group (partially adjusted OR=0.99; p-value=0.835), slightly negative for the White Mixed and Bangladeshi groups (respectively, partially adjusted ORs are 0.88 and 0.95; p-values 0.476 and 0.125), and slightly positive for the Black African group (partially adjusted OR= 1.14; p-value=0.375).

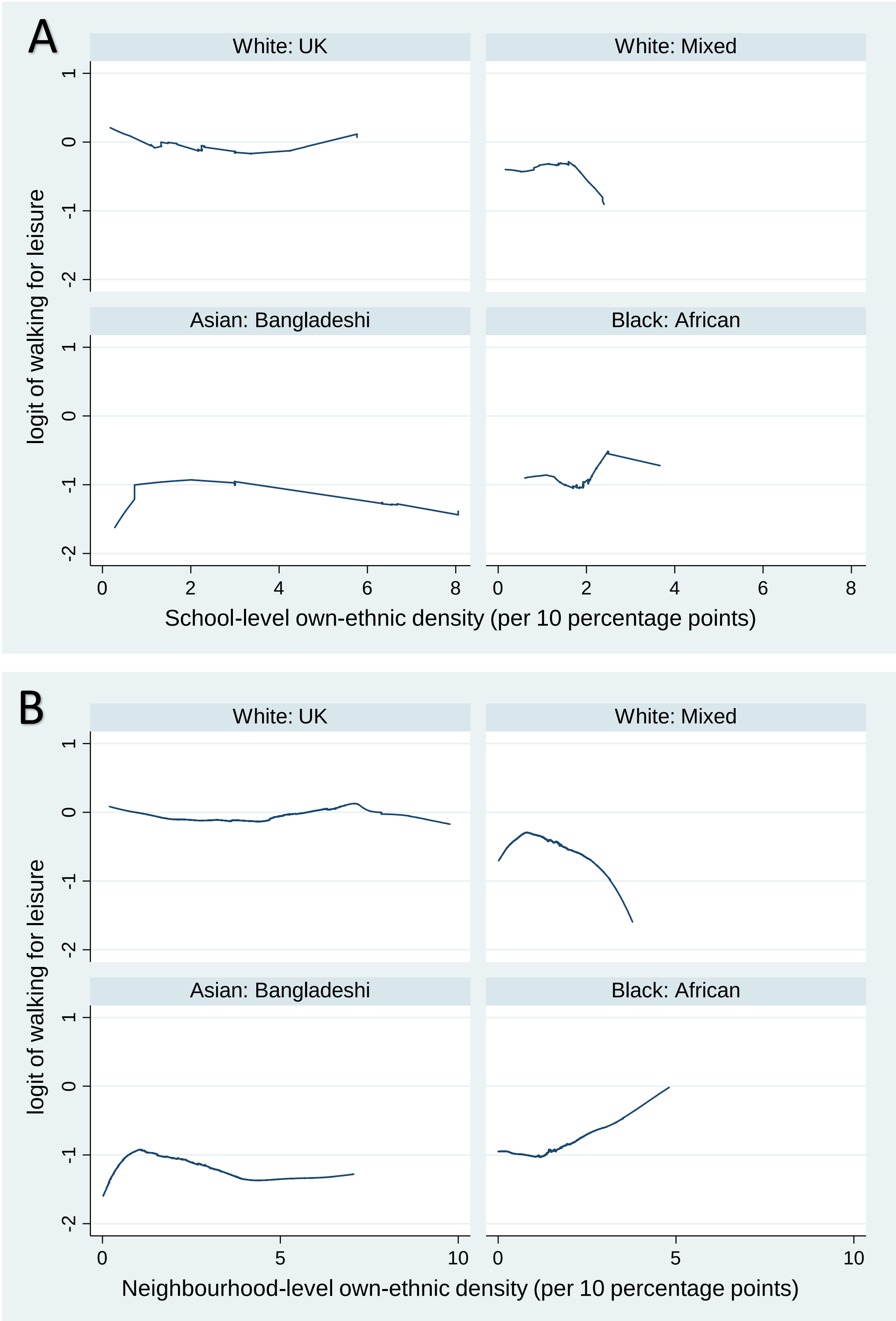


Figure 7.6 Exploration of the functional form of the association between the logit of walking for leisure and ethnic density measures using lowess smoother. School-level ethnic density is represented in A and neighbourhood-level ethnic density in B. All waves of the data are used and imputed density measures lower than 1.9 percent are excluded. Bandwidth of 0.8 is used.

Table 7.5 Ethnic group specific odds ratios (OR) of walking for leisure vs. not by own-group ethnic density (3 waves of the ORiEL Study, n=1,160)*

Exposure	Unadjusted OR	Partially Adjusted OR[1]	95% CI	P-value	Fully Adjusted OR[2]	95% CI	P-value
School-level ethnic density				0.454			0.899
White: UK	0.99	0.99	[0.89 , 1.10]	0.835	0.96	[0.86 , 1.08]	0.531
White: Mixed	0.92	0.88	[0.62 , 1.25]	0.476	0.96	[0.65 , 1.40]	0.814
Asian: Bangladeshi	0.94	0.95	[0.90 , 1.01]	0.125	0.97	[0.89 , 1.06]	0.488
Black: African	1.11	1.14	[0.86 , 1.51]	0.375	1.07	[0.78 , 1.47]	0.688
Neighbourhood-level ethnic density				0.318			0.622
White: UK	1.03	1.02	[0.94 , 1.12]	0.620	1.04	[0.94 , 1.15]	0.417
White: Mixed	0.83	0.82	[0.57 , 1.18]	0.286	0.84	[0.56 , 1.25]	0.385
Asian: Bangladeshi	0.92	0.93	[0.85 , 1.03]	0.182	0.97	[0.84 , 1.11]	0.626
Black: African	1.17	1.18	[0.91 , 1.54]	0.218	1.16	[0.86 , 1.55]	0.328

Results are from logistic regression models estimated with Generalised Estimating Equations to account for the dependency across repeated measurements (unstructured working correlation matrix). Interaction terms between the own-group ethnic density variable and ethnicity were used and ethnic group specific ORs were obtained. *Own-group density assessed as change per 10 percentage points. [1] Adjusted for time, gender, health condition, family affluence, baseline free school meal status, household composition and time lived in the neighbourhood. [2] Adjusted for time, gender, health condition, family affluence, baseline free school meal status, household composition, time lived in the neighbourhood, the other ethnic density variable and its interaction with ethnicity.

Results by tertile (Appendix F Table F.12) confirm the lack of association with school-level ethnic density, with the exception of the Bangladeshi group. Results indicate a possible dose-response relationship: as school-level ethnic density increases, the odds of walking for leisure decreases (overall p-value for the two parameters equals 0.085). In particular, the odds of walking for leisure in the 3rd tertile (i.e. high ethnic density) are 0.60 (95% CI: 0.37-0.96) time those of the 1st tertile (i.e. low ethnic density).

Neighbourhood-level ethnic density

Table 7.5 also shows no association between neighbourhood-level ethnic density and walking for leisure (overall test p-value in the partially adjusted model =0.318). Compared to school-level measures, coefficients have the same signs and are slightly stronger in magnitude, but remain non-significant. The associations are close to null for the White UK group (partially adjusted OR=1.02; p-value=0.620), slightly negative for the White Mixed and Bangladeshi groups (respectively, partially adjusted ORs are 0.82 and 0.93; p-values 0.286 and 0.182), and slightly positive for the Black African group (partially adjusted OR= 1.18; p-value=0.218).

Results by tertile (Appendix F Table F.13) are comparable to those observed for school-level exposure and confirm the lack of association with neighbourhood-level ethnic density. For the Bangladeshi group, there is some indication of a potentially decreasing dose-response relationship: as school-level ethnic density increases, the odds of walking for leisure decreases. The evidence on differences between tertiles is weak though (overall p-value for the two parameters equals 0.241). Nevertheless, the odds of walking for leisure in the 3rd tertile (i.e. high ethnic density) are 0.70 (95% CI: 0.47-1.06) times those of the 1st tertile (i.e. low ethnic density).

School vs. neighbourhood

The fully adjusted model (Table 7.5) finally confirms that, in the presence of the two exposures and potential confounders, none of the exposures are significant overall (overall test p-value in the fully adjusted model is 0.899 for school-level ethnic density and 0.622 for neighbourhood-level ethnic density). Point estimates are even closer to 1.00 for school-level ethnic density. For neighbourhood-level ethnic density, results are also not statistically significant, point estimates do not change dramatically, and p-values lie between 0.3 and 0.7.

In the models by tertile (Appendix F Table F.12), the Bangladeshi group indicates some weak evidence of difference in walking for leisure between the 1st and the 3rd tertile of school-level ethnic density (OR=0.65 (95% CI: 0.38-1.09); p-value=0.103). No significant association is observed in the fully adjusted models by tertile for neighbourhood-level ethnic density (Appendix F Table F.13).

7.4.2.3. Outdoor physical activity

Table 7.3 shows that having undertaken at least one bout of outdoor physical activity over the past week is most common in the Black African group (80.1%) followed by the White Mixed (75.1%), Bangladeshi (74.8%) and White UK groups (71.4%). The odds were significantly different and higher for the Black African group compared to the White UK group (OR =1.64 (95% CI: 1.22-2.20)).

Functional form of the associations

Figure 7.7 indicates that, for most of the ethnic groups, associations between the two ethnic density measures and outdoor physical activity are approximately linear on the logit scale in the parts of the distribution that contain the most observations. Caution is needed regarding linear interpretation in the White Mixed and Black African groups at school-level (Figure 7.7A) and neighbourhood-level of exposure (Figure 7.7B). The additional analyses using exposure tertiles, and presented in Appendix F section F.5, will also be interpreted and reported if they diverge from the main results presented here.

School-level ethnic density

Table 7.6 shows that there is weak evidence that school-level ethnic density is associated with outdoor physical activity, after adjustment for potential confounders (overall test p-value in the partially adjusted model =0.065). A negative significant association is observed for the White UK group, indicating that an increase in school-level ethnic density by 10% decreases the odds of outdoor physical activity by 1.16 (=1/0.86; 95% CI: 1.03-1.30). A negative association is also observed for the Black African group (OR=0.77 (95% CI: 0.58-1.04)) although the level of evidence is weak (p-value=0.087). The estimated associations are close to 1.00 for the White Mixed and Bangladeshi groups (partially adjusted OR are 1.05 (95% CI: 0.68-1.62), and 1.02 (95% CI: 0.95-1.10), respectively).

The model using exposure tertiles presented in Appendix F Table F.14, is consistent with the results, except for the Black African group. The non-linear association suggested in Figure 7.7A is confirmed: estimated odds of outdoor physical activity are highest in the 2nd tertile of school-level ethnic density, and lowest in the 3rd tertile (overall p-value for the two parameters associated with the variable equals 0.023). Compared to the 1st tertile the odds are 1.29 (95% CI: 0.71-2.35) times higher in the 2nd tertile and 1.72 (=1/0.58; (95% CI: 1.01-2.94)) times lower in the 3rd tertile.

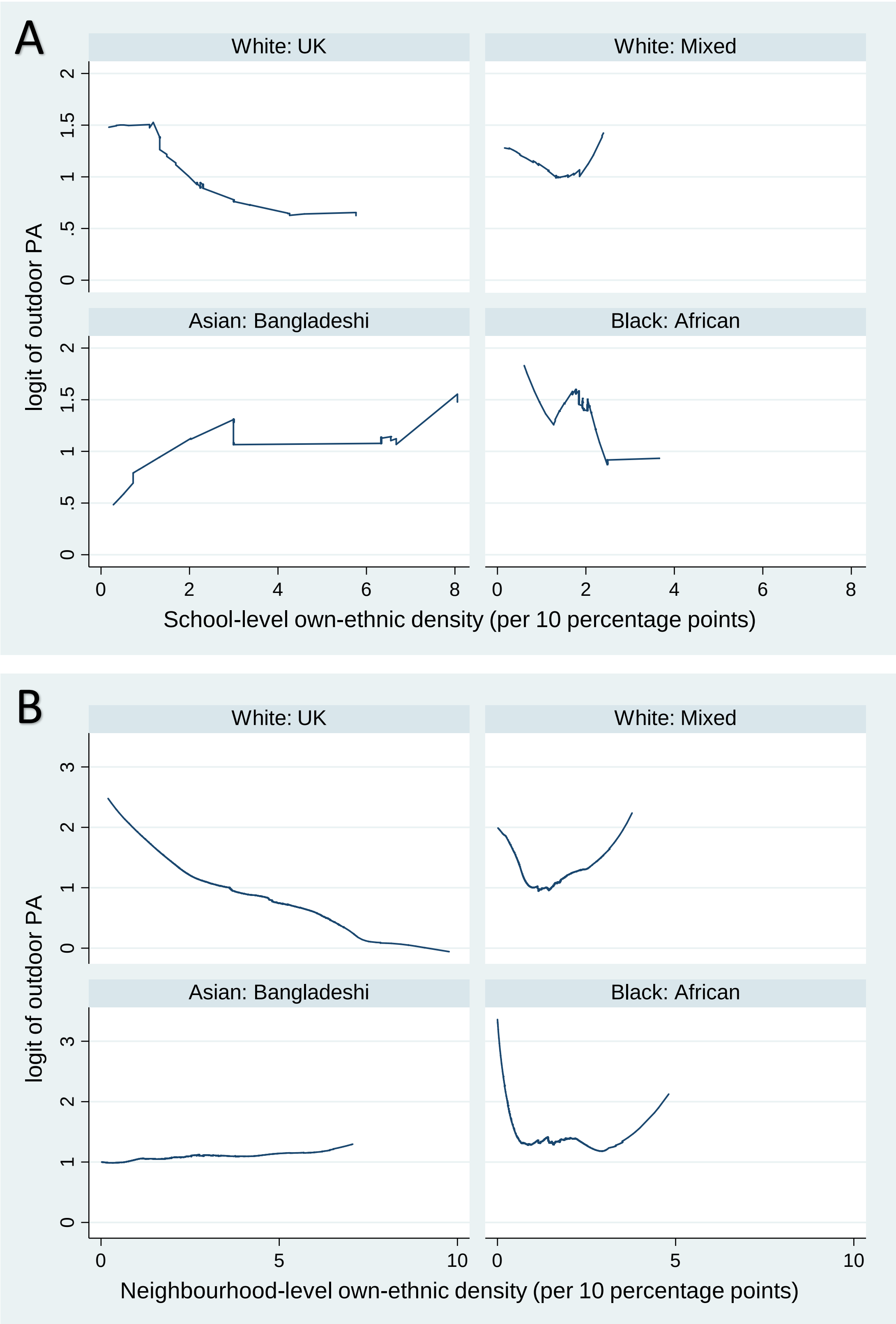


Figure 7.7 Exploration of the functional form of the association between the logit of outdoor physical activity and ethnic density measures using lowess smoother. School-level ethnic density is represented in A and neighbourhood-level ethnic density in B. All waves of the data are used and imputed density measures lower than 1.9 percent are excluded. Bandwidth of 0.8 is used.

Table 7.6 Ethnic group specific odds ratios (OR) of outdoor physical activity vs. not by own-group ethnic density (3 waves of the ORiEL Study, n=1,160)*

Exposure	**Unadjusted OR**	**Partially Adjusted OR[1]**	**95% CI**	**P-value**	**Fully Adjusted OR[2]**	**95% CI**	**P-value**
School-level ethnic density				0.065			0.507
White: UK	0.86	0.86	[0.77 , 0.97]	0.016	0.94	[0.82 , 1.08]	0.390
White: Mixed	0.97	1.05	[0.68 , 1.62]	0.813	1.04	[0.65 , 1.67]	0.874
Asian: Bangladeshi	1.05	1.02	[0.95 , 1.10]	0.546	1.04	[0.94 , 1.14]	0.479
Black: African	0.78	0.77	[0.58 , 1.04]	0.087	0.78	[0.56 , 1.09]	0.142
Neighbourhood-level ethnic density				0.034			0.279
White: UK	0.84	0.85	[0.76 , 0.94]	0.001	0.87	[0.77 , 0.98]	0.021
White: Mixed	1.07	1.05	[0.70 , 1.57]	0.817	1.03	[0.66 , 1.61]	0.890
Asian: Bangladeshi	1.03	1.01	[0.91 , 1.12]	0.871	0.97	[0.84 , 1.12]	0.707
Black: African	0.91	0.89	[0.67 , 1.18]	0.414	0.97	[0.71 , 1.32]	0.849

Results are from logistic regression models estimated with Generalised Estimating Equations to account for the dependency across repeated measurements (unstructured working correlation matrix). Interaction terms between the own-group ethnic density variable and ethnicity were used and ethnic group specific ORs were obtained.
*Own-group density assessed as change per 10 percentage points. [1] Adjusted for time, gender, health condition, family affluence, baseline free school meal status, household composition and time lived in the neighbourhood. [2] Adjusted for time, gender, health condition, family affluence, baseline free school meal status, household composition, time lived in the neighbourhood, the other ethnic density variable and its interaction with ethnicity.

Neighbourhood-level ethnic density

Table 7.6 reports significant associations between outdoor physical activity and neighbourhood-level ethnic density (overall test p-value in the partially adjusted model =0.034). Compared to school-level measures, coefficients take the same signs and are very similar in terms of magnitude. The only significant result is a negative association in the White UK group: an increase in neighbourhood-level ethnic density by 10% decreases the outdoor physical activity by 1.17 (=1/0.85; 95% CI: 1.06-1.32). The estimated association for the Black African group is closer to 1.00 and non-significant (partially adjusted OR=0.89; p-value=0.414) and associations are close to 1.00 for the White Mixed and Bangladeshi groups (partially adjusted OR are 1.05 (95% CI: 0.70-1.57), and 1.01 (95% CI: 0.91-1.12), respectively). Results from the tertiles analysis confirm the linear association with neighbourhood-level ethnic density in the White UK group (Appendix F section F.5).

School vs. neighbourhood

The fully adjusted model (Table 7.6) shows that, in the presence of the two exposures and potential confounders, none of the exposures is significant overall (overall test p-value in the fully adjusted model is 0.507 for school-level ethnic density and 0.279 for neighbourhood-level ethnic density). In the White UK group, point estimates are closer to the null for the exposure variables, remain statistically significant at neighbourhood-level, but not at school-level (fully adjusted OR are 0.87 (95% CI: 0.77-0.98), and 0.94 (95% CI: 0.82-1.08), respectively). The estimate for school-level ethnic density in the Black African group is unchanged but 95% CI increase (OR=0.78 (95% CI: 0.56-1.09)).

That association is however expected to be non-linear, as indicated by model using exposure tertile (Appendix F Table F.14). In the fully adjusted model using tertiles, coefficients remain unchanged, indicating strong evidence of a non-linear association between school-level ethnic density and outdoor physical activity in the Black African group (overall p-value for the 2 parameters associated with the variable equals 0.019). Amongst the Black African adolescents, compared to the 1st tertile, the odds are 1.33 (95% CI: 0.72-2.43) times higher in the 2nd tertile and 1.75 (=1/0.57; (95% CI: 1.02-3.03)) times lower in the 3rd tertile. For the White Mixed and Bangladeshi groups, all odds ratios of the fully adjusted model (Table 7.6) are close to the null (between 0.97 and 1.04) and are not statistically significant (p-values between 0.4 and 0.9).

7.4.2.4. Sensitivity analyses

A series of sensitivity analyses were conducted. Analyses were replicated using different specifications of the working correlation structure in the GEE estimation process (Appendix F section F.3). These indicated no differences in the interpretation of the results. In addition, I fitted the models for each ethnic group separately, as opposed to including interaction terms between ethnic density and ethnicity (Appendix F section F.4), and results also appeared to be very similar. As discussed in the results, I also stratified the analyses using ethnic density tertiles as opposed to continuous scores, which allowed deviation from linearity to be assessed (Appendix F sectionF.5). The use of tertiles allowed to obtain more correct estimates in the presence of non-linear relationships (e.g. between school-level ethnic density and outdoor physical activity in the Black African group), as already reported in the main body of this chapter.

Finally, I compared the results obtained from the imputed datasets with those from a 'naive' complete case analysis (Appendix F sectionF.6). Results indicate that point estimates were slightly over-estimated for walking to school and slightly underestimated for outdoor physical activity in the complete case analysis. The strength of evidence for some of the parameters decreased in the complete case analysis due to larger standard errors. This analysis of the complete cases confirms the results from the analysis of missingness, which suggested that coefficients from the complete case analysis would be slightly biased (Appendix F sectionF.1). Despite the bias and the loss of efficiency, however, the general conclusions about the directions of the main associations are not seriously affected in the complete case analysis.

7.5. Summary

In this chapter, I have investigated the associations between own-group ethnic density at school and neighbourhood-levels and three physical activity outcomes (walking to school, walking for leisure and outdoor physical activity). The analyses were restricted to the four main ethnic groups of the ORiEL study (White UK, White Mixed, Bangladeshi and Black African). I first explored whether each of the two measures of ethnic density was associated with the outcomes using pooled longitudinal models (questions 1.1. and 1.2.). Then, I compared the independent contributions of school-level and neighbourhood-level ethnic densities to explain patterns of physical activity using fully adjusted models (question 1.3.). To do so, I first handled item missingness based on a MAR assumption. I applied the multilevel multiple imputation strategy developed in chapter 6, which accounts for the hierarchical structure of the data.

Using 20 imputed datasets, I have shown that there is evidence that ethnic density at school-level is associated with each of the outcomes for at least one ethnic group (question 1.1.) There is consistent evidence that school-level ethnic density is associated with walking to school. The direction of the associations is such that a higher ethnic density amplifies ethnic-specific propensity to walk to school. A model based on tertiles indicated weak evidence that higher school-level ethnic density in Bangladeshi adolescents might decrease the odds of walking for leisure, a form of physical activity not popular in that ethnic group. There is evidence of a linear association between school-level ethnic density and outdoor physical activity in the White UK group. The association was in the expected direction: a higher ethnic density decreases the odds of outdoor physical activity, which is a form of physical activity less popular in that ethnic group compared to others. Finally, a non-linear association was found for the Black African group at school-level. The shape of the association seems to indicate an increase in the odds of outdoor physical activity with medium levels of school-level ethnic density, followed by an important decrease with highest levels of ethnic density. This type of association had not been anticipated.

Associations between neighbourhood-level ethnic density and the three physical activity outcomes were more mixed and only found for some ethnic groups (question 1.2.). When detected, associations were in the expected direction, so that neighbourhood-level ethnic density amplified ethnic-specific propensity to take part to a particular form of physical activity. There was little evidence that neighbourhood-level ethnic density was associated with walking to school, except for the Bangladeshi adolescents. No associations were found with walking for leisure. There was finally evidence of a negative association between neighbourhood-level ethnic density and outdoor physical activity in the White UK group.

The fully adjusted models, which included both measures of ethnic density, indicated that school-level ethnic density was a stronger predictor of walking to school and walking for leisure, and neighbourhood-level ethnic density a stronger predictor of outdoor physical activity (question 1.3.). With respect to walking to school, associations with school-level ethnic density remained significant in the White Mixed and Black African groups, but not in the Bangladeshi group, which displayed no significant association with neighbourhood-level ethnic density. The fact that the fully adjusted model could not differentiate the independent contributions of school and neighbourhood-levels in the Bangladeshi group is most likely due to a high correlation between the two measures in that specific ethnic group ($r=0.69$). Similarly, the fully adjusted model based on tertiles no longer indicated any evidence of association between school-level ethnic density and walking for leisure in that ethnic group. The associations between neighbourhood-level ethnic density and outdoor physical activity remained significant in the fully adjusted model in the White UK group, as did the non-linear association in the Black African group found in the model based on tertiles for school-level ethnic density.

These results suggest that some aspects of the local socio-cultural environment captured by ethnic density measures play a role in explaining patterns of physical activity. In the next chapter, I will investigate the contribution of other aspects of the social environment, namely social cohesion and social support.

Chapter 8: Associations between neighbourhood trust, social support and physical activity

8.1. Introduction

In this chapter, I present an analysis of the longitudinal associations between perceived neighbourhood trust and social support and four physical activity outcomes. In chapter 6, I have shown that five measures of adolescents' perceptions of their neighbourhood environment (perceived bus stop proximity, traffic-related safety, street connectivity, enjoyment for walking/cycling and personal safety) were mostly unrelated to common forms of physical activity. In chapter 7, I have indicated that neighbourhood ethnic density contributes to explaining differences in walking to school. In this chapter, I investigate other aspects of the social environment – perceived neighbourhood trust and social support – for which a growing body of evidence seems to indicate associations with physical activity.

Amongst the dimensions of the social environment (cf. section 2.4), social capital and social support have received particular scrutiny for their potential contribution to explaining differences in health and in physical activity (Berkman et al. 2014). Social capital designates the resources that are accessed by individuals through their membership to a group or a network, including trust, norms of reciprocity and ability to undertake collective action (Kawachi & Berkman 2014, Putnam 1993). Social contagion, collective efficacy and informal social control are the three main mechanisms by which social capital can affect physical activity (Kawachi & Berkman 2014). Aspects of social capital – including social cohesion and neighbourhood trust – were shown to be associated with a range of health-related behaviours such as alcohol consumption, drug abuse, juvenile delinquency, and physical activity (Lindström 2008, McNeill et al. 2006). Yet, the evidence on associations with physical activity, although consistent, is still scarce in particular in young people and in Europe.

Social support describes resources provided from interpersonal relationships that can influence behaviour such as physical activity (cf. section 2.4.4.). These resources are diverse and include: psychological/emotional support (e.g. encouragement, praise), instrumental support (e.g. equipment, transport to a physical activity facility), co-participation (e.g. performing an activity with an adolescent), informational support (e.g. providing advice or instructions about an activity), and support as a role model (Langford et al. 1997). Parents, family members and friends constitute the main sources of social support for physical activity in adolescents (Mendonça et al. 2014). There is a growing literature on the benefits of social support for health behaviours which has identified social support as one of the most consistent correlates of physical activity in young people (Sallis et al. 2000, 2016). Yet, gaps remain.

The current literature on associations between social capital and social support and physical activity has some limitations. First, most of the literature, especially on social capital, captures total physical activity or leisure-based physical activity and does not explore how a specific aspect of social context could differently affect a range of forms of physical activity, such as outside play, more structured activities or walking to school. Second, there are few investigations on how social capital and social support co-vary over time with physical activity, most of the literature being cross-sectional. Third, there is little evidence as to whether the positive associations observed for the general population are consistent among deprived subpopulations. Fourth, most of the literature has ignored missing data, instead conducting analyses of complete cases, which might lead to bias. Fifth, more longitudinal analyses using large samples are needed in order to confirm cross-sectional and longitudinal associations obtained in smaller studies. Little is known as to whether changes in social capital or social support over a short period of time can lead to immediate change in physical activity.

In this chapter, I use waves 2 and 3 from the ORiEL study to test how neighbourhood trust and social support from family, friends and significant others are longitudinally associated with four common forms of physical activity in adolescents from a deprived population: walking to school, walking for leisure, outdoor physical activity and a composite measure of pay and play physical activity, previously described in the data chapter (chapter 3). These four forms of physical activity were chosen to be consistent with results reported in chapters 6 and 7. Also they are expected to be associated with the measures of neighbourhood trust and social support used in the ORiEL questionnaire. I further investigate the moderating role of gender in the associations, knowing that the types and sources of social support received might differ for boys and girls (Beets et al. 2010). Similar to chapters 6 and 7, I handle item non-response using multilevel multiple imputation and specify a distinct imputation model for the data used and research questions posed in this chapter.

8.2. Research questions

Question 1: Is perception of neighbourhood trust longitudinally associated with physical activity in adolescents in the ORiEL study?

Specifically:

1.1. Is perception of neighbourhood trust associated with different forms of physical activity (walking to school; walking for leisure; outdoor physical activity; pay and play physical activity) across all measurements (i.e. general associations)?

1.2. Does change in perception of neighbourhood trust relate to changes in these four forms of physical activity?

1.3. Do the above associations between perception of neighbourhood trust and physical activity outcomes differ for boys and girls?

Question 2: Are perceptions of social support longitudinally associated with physical activity in adolescents in the ORiEL study?

Specifically:

2.1. Are perceptions of social support from friends, family or significant others associated with different forms of physical activity (walking to school; walking for leisure; outdoor physical activity; pay and play physical activity) across all measurements (i.e. general association)?

2.2. Do changes in perceptions of social support relate to changes in these four forms of physical activity?

2.3. Do the above associations between perceptions of social support and physical activity outcomes differ for boys and girls?

8.3. Methods

To explore the longitudinal associations between perceived neighbourhood trust and social support and physical activity outcomes, I estimated longitudinal and cross-sectional analyses with generalised estimating equation (GEE) using imputed datasets. The data and methods used are outlined below.

8.3.1. Analytical sample

The analytical sample was constructed from ORiEL respondents who participated to wave 2 and wave 3, defined as the waves 2-3 balanced panel in section 3.3. Wave 1 information was not included because the exposure variables were not available at baseline. To increase sample size, analyses were extended to participants present at wave 2 and 3 but absent at baseline. The final sample size includes 2,644 participants and 5,288 observations. For sensitivity and comparability, analyses were also undertaken using the cohort definition of chapter 6, i.e. the 2,260 participants to the 3-wave balanced panel (cf. section 3.3.).

8.3.2. Variables

The variables summarised in Table 8.1 and outlined in the data chapter were used for the analyses presented in this chapter. These include four binary physical activity outcomes, four measures of exposure (one measure of neighbourhood trust and three of social support), a set of potential confounders and a cluster variable. These are described below.

8.3.2.1. Outcomes

Four measures of physical activity hypothesised to be associated with measures of neighbourhood trust and social support in the ORiEL study are examined: walking to school, walking for leisure (dog/exercise), outdoor physical activity and pay and play physical activity. The first three outcomes were examined in chapters 4, 5 and 6 because they were hypothesised to be associated with the measures of the neighbourhood environment measured in the ORiEL study. In addition, I investigate in this chapter a measure of pay and play physical activity, which captures more structured forms of physical activity and which is expected to be influenced by the aspects of the social environment considered in this chapter. As detailed in the data chapter (section 3.5.1.), each binary physical activity outcome captures whether adolescents reported having participated in the activity over the past week. The outdoor physical activity outcome combines participation in any of the following activities: basketball/volleyball, blading, cricket, football, rounders, rugby and roller skating. The pay and play physical activity outcome combines aerobics, climbing, swimming, gymnastics, hockey, martial arts, netball and tennis.

In addition, measures of change in each outcome were created to capture within individual change in the outcomes over time (cf. section 3.5.1.). Change variables are constructed as differences in the binary physical activity status between wave 3 and wave 2. This results in ordinal variables with 3 responses categories (0= stopped reporting the physical activity outcome at wave 3; 1= no change; 2= started reporting the physical activity outcome at wave 3).

Table 8.1 Variable definitions and item missingness at each wave for the waves 2-3 balanced panel (n = 2,644; 5,288 measurements)

Variable	Variable type and use in the analysis	% missing W2	W3
Outcomes			
Walking to school	Ordinal (almost count), 4 categories, non-Normal; binary version used	3.8	3.2
Walking for leisure	Ordinal (almost count), 4 categories, non-Normal; binary version used	6.9	5.3
Outdoor physical activity	Count (0-7), non-Normal; binary version used	12.0	8.8
Pay and play physical activity	Count (0-8), non-Normal; binary version used	11.1	7.5
Exposures			
Neighbourhood trust	Ordinal, 4 categories	16.0	11.8
Social support – Family	Continuous, non-normal; categorised in 3 groups	27.2	13.6
Social support – Friends	Continuous, non-normal; categorised in 3 groups	27.6	13.8
Social support – Significant others	Continuous, non-normal; categorised in 3 groups	27.6	14.3
Potential confounders			
Gender	Binary	Fully observed	
Ethnicity	Nominal variable with 8 categories	0.1	
Health condition	Count score of 9 binary items* (0-9), skewed; binary version used (0/1+)	14.4	14.3
Family affluence	Count score of 3 items (0-9), approximately Normal; categorised in 3 groups	3.8	3.4
Free school meal status	Binary: Yes/No	1.9	1.6
Household composition	Nominal, 4 categories, binary version used (both parents vs. not)	0.9	0.7
Time lived in neighbourhood	Ordinal, 5 categories, binary version used	5.6	4.2
Cluster variable			
School	Assumed to be time invariant (W1 value used if time-varying)	Fully observed	
Auxiliary variables			
Total physical activity	Continuous, approximately log Normal	0.9	0.6
Country of birth	Binary (UK/non-UK)	16.2	
Language spoken at home	Binary (English/Other)	15.1	
Mental health (WEMWBS)	Continuous, approximately square Normal	2.5	2.0
BMI (BMI z score)	Continuous, Normal	8.4	7.3
Self-rated health	Ordinal variable with 3 categories	1.0	1.1
Parental involvement	3 ordinal variables, binary summary variable used	21.3	9.7
Neighbourhood satisfaction	5 ordinal variables, summary score with 3 categories used	19.2	9.4

*requirement that at least five items are completed to get a score because the interest is in whether any condition is reported.

8.3.2.2. Exposures

The four exposure variables capture respondent perceptions; one measure of neighbourhood trust, and measures of social support from three sources: friends, family and significant others. Neighbourhood trust was obtained from a broader set of questions on trust in different groups of people. The question asks whether the respondents 'trust people in [their] neighbourhood'.

The variable response is on a four category Likert scale, such that 1='not at all', 2='a little', 3='some', 4='a lot' (cf. section 3.5.2.3.). The social support measures are derived from the 12-item Multidimensional Scale of Perceived Social Support (MSPSS) (Zimet et al. 1990). It is a composite measure of social support which is non-specific to physical activity and captures more emotional than instrumental forms of support (cf. section 2.4.4.). Summed scores for each source of support were split into tertiles (1='low', 2='medium', 3='high'), owing to a skewed positive distribution of the summed scores (cf. section 3.5.2.4.). Ordinal exposure variables used in this chapter are treated as either discrete or continuous when there is indication of a dose-response relationship.

In addition, change scores in each exposure variable were calculated as the difference between wave 3 and wave 2 in the numeric values to which time-varying exposure variable is coded. Positive scores indicate improvement in the exposure variables over time. These variables assume equivalence of change between response categories (cf. sections 3.5.2.3. and 3.5.2.4.).

8.3.2.3. Potential confounders

The following potential confounders were included in adjusted models: gender, ethnicity (8 categories), family affluence (3 categories derived from the family affluence scale), health condition (no condition vs. 1+ condition(s)), free school meal status, household composition (living with both parents vs. not), and time resident in the neighbourhood (less than 5 years vs. more). Gender and ethnicity were considered to be time-invariant. The other variables were treated as time-varying. Unlike previous analyses, free school meal status was used as time-varying because no measurement is available for adolescents who did not take part to wave 1 (n=384).

8.3.2.4. School

School was considered to be time-invariant for ease of modelling (see below). Between wave 2 and wave 3, n=3 adolescents moved within the surveyed school sample. School attained at wave 2 was used for these adolescents in the imputation model. This simplification is highly unlikely to have any impact on the interpretation of the results.

8.3.3. Analytical strategy used in this chapter

As detailed in the methods chapter (chapter 4), the analytical strategy for the longitudinal analyses is twofold: it involves the handling of missing data with multilevel multiple imputation and the specification of models used to answer the research questions, known as analysis models (or models of interest). The specific models used in this chapter are presented in this section.

8.3.3.1. Handling missing data with multilevel multiple imputation

I handled missing data using multilevel multiple imputation (MI) models. I first described the extent of missingness in each variable of interest and explored the plausibility of different missing data mechanisms. As in chapters 6 and 7, preliminary analyses of the variables of interest revealed that a complete case analysis was likely to be invalid and could generate bias (Appendix G section G.1). MI was therefore used to handle item non-response under the missing at random assumption (MAR). To increase the plausibility of the MAR assumption, reduce bias and improve efficiency (Carpenter & Kenward 2012), I included the following auxiliary variables in the imputation models: log of total physical activity (centred), country of birth, language spoken at home, squared WEMWBS score for positive mental wellbeing (centred), BMI z-score (centred), self-rated health, parental involvement and neighbourhood satisfaction. The selection process of these auxiliary variables is reported in Appendix G (section G.1).

Building on the results of chapters 6 and 7, I explored multilevel MI solutions within the joint modelling framework in order to account for the correlations implied by the 3-level hierarchical structure of the data (repeated measurements, individuals, schools). The analysis models include continuous variables, discrete variables and interaction terms between the exposure variables and gender. Potential interactions were handled by imputing the data separately by gender. The imputation models were implemented using the R package 'jomo' (Quartagno et al. 2018), which is the latest package available to run complex multilevel MI models with unordered discrete variables. For comparison purposes, results of the complete case analysis are provided in Appendix G (section G.7).

8.3.3.2. Analysis models

To answer the research questions of this chapter, I estimated logistic regression models and proportional odds models using GEE as detailed in the methods chapter (section 4.4.3.). These marginal models estimated with GEE have a convenient population-average interpretation of the parameters (Fitzmaurice et al. 2011), although current software implementations only allow for models with 2-level structures. Two types of models are fitted to allow answering different research questions about the nature of the longitudinal associations between the exposure and outcome variables, as detailed below.

Pooled longitudinal models for binary outcomes

To test the presence of general longitudinal associations between each binary physical activity outcome and the four exposure variables (questions 1.1. and 2.1.), I estimated logistic regression models with GEE in Stata 15 ('xtgee') to account for clustering at individual-level (occasions nested within individuals). Final inference across the imputed datasets is obtained with the 'mi estimate' command. In those models, clustering at school-level was ignored, as it was expected to be limited as indicated previously (section 3.5.1.1.). Following results given in Appendix E (section E.3), an unstructured working correlation structure was specified to initiate the GEE estimation process. The final models were replicated using an alternative working correlation structure to ensure that results were not sensitive to its specification (Appendix G section G.4).

For each binary outcome, separate logistic models were estimated with GEE to test the associations with neighbourhood trust and each of the three sources of social support (friends, family, and significant other). I first fitted unadjusted models including each of the four exposure variables in turn and a physical activity outcome. I then specified adjusted models for each exposure and outcome, by including time and all confounders as covariates. The models did not adjust for all exposure variables together, given multicollinearity between the sources of social support (friends, family, and significant others). In the logistic regression models, ordinal exposure variables were included successively as discrete variables and as continuous variables when there was some indication of a dose-response relationship. Improvement in model fit could not be formally tested in the absence of likelihood-ratio tests available for models estimated with GEE (cf. section 4.4.3.4.). I explored whether gender was a moderator by running a series of adjusted models that further included an interaction term between each exposure variable of interest and gender. Gender-specific results are reported when there was some evidence of differences in the associations by gender (p-value of the interaction term <0.1) and when the gender-specific ORs of exposure were statistically significant ($p<0.05$). The model equations are given in Appendix G section G.2.

Cross-sectional proportional odds models for ordinal outcomes

The hypotheses about within individual changes over time (questions 1.2. and 2.2.) were tested using proportion odds models estimated with GEE in SAS 9.4 ('PROC GENMOD' with 'REPEATED' statement) to account for clustering at school-level, although it was expected to be of small magnitude (section 3.5.1.1.). Final inference across the imputed datasets is obtained using the 'PROC MIANALYZE' procedure.

Each ordinal measure of within individual change in a physical activity outcome was modelled in function of within individual change scores in neighbourhood trust and in sources of social support by fitting separate proportional odds models with GEE. Exposure change scores were modelled as continuous variables. I first fitted unadjusted models including each of the four exposure variables in turn and a physical activity outcome. I then specified adjusted models for each exposure and outcome, by including all confounders measured at wave 2. The models did not adjust for all exposure variables together, given multicollinearity between the three sources of social support. Gender-specific results are reported when there was some evidence of difference in the associations by gender (p-value of the interaction term <0.1) and when the gender-specific ORs of exposure were statistically significant (p<0.05). The model equations are given in Appendix G section G.2.

A current restriction of the 'PROC GENMOD' SAS procedure is that the use of the cumulative multinomial distribution to estimate proportional odds models with GEE only allows for 'independent' working correlation structures. This should have limited implications however because the GEE method is such that the parameter estimates and robust standard errors are valid regardless of the working assumption chosen (cf. section 4.4.2.). The main consequence is that sensitivity of the results to the specification of the working correlation structure could not be tested in this chapter.

Another limitation is that the proportional odds assumption could not be formally tested in models estimated with GEE and/or in combination with multiple imputation because the test is currently unavailable in general statistical software (Donneau et al. 2015). I achieved an informal evaluation of the assumption by fitting proportional odds models without accounting for clustering[27]. Using the 'PROC LOGISTIC' procedure in SAS, I tested the proportional odds assumption for each imputed dataset. The hypothesis was plausible for the exposure variables, but appeared to be violated for a few confounders. I then used partial proportional

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[27] Although it should be noted that accounting for clustering might reduce the risk of violating the proportional odds assumption (Agresti 2002).

odds models to allow for nonproportionality for the problematic confounders. Those models maintained the proportional odds assumptions for covariates that did not indicate a violation of the hypothesis in any of the imputed dataset (p>0.05). Results of proportional and partial proportional odds models estimated with maximum likelihood methods, and therefore not accounting for clustering at school-level, are reproduced in Appendix G section G.5. These alternative estimates of the exposure parameters did not differ substantially.

Additional sensitivity analyses applying to both logistic and proportional odds models were conducted by re-running the main models with the following alternative specifications. First, I included BMI as a covariate in adjusted models where walking for leisure and pay and play physical activity were the outcomes (Appendix G section G.6). Some of the literature has suggested that BMI might confound the association between social support and physical activity (Davison & Jago 2009). The analysis was limited to walking for leisure and pay and play physical activity which were the only two outcomes associated with BMI, a necessary condition for it being a confounder. Second, I reproduced the analyses using the 3-wave ORIEL balanced panel used chapter 6 to ensure that the change in the sample definition did not bring about a selection bias (Appendix G section G.3)[28]. Results did not differ from the main analyses.

8.4. Results

This section presents the results of the analyses conducted to answer the research questions on the relationships between physical activity and neighbourhood trust and social support. The first part presents how item non-response is handled using a multilevel multiple imputation model specific to the analyses presented in this chapter. The second part presents the results of the analysis models fitted to answer the research questions.

[28] Note that because of the imputation procedure, I could no longer identify ORiEL members of the 3-wave balanced panel. I used missingness on language spoken at home and country of birth, two almost fully observed variables for those present at baseline, but missing in the waves 2-3 balanced panel, and included as auxiliary variables in the imputation model. I selected adolescents who had at least answered one of those two variables, allowing me to identify back 2,257 out of the 2,260 adolescents of the 3-wave balanced panel.

8.4.1. Missing data handling

8.4.1.1. Description of item missingness

Patterns of missingness for the sample analysed in this chapter are similar to those of the 3-wave balanced panel, and many of the variables used in this chapter were already described in chapter 6 (section 6.4.1.1.). Missingness is less frequent in the present analyses because I excluded the baseline data for which a higher level of missingness is observed (cf. section 3.4.). Table 8.1 indicates the proportion of missing data by wave for the variables of interest and potential auxiliary variables. All variables, except school and gender are subject to some degree of non-response. Unlike the previous results chapters (chapters 5, 6 and 7), ethnicity is not fully observed (0.11% missing). All variables have higher missingness at wave 2 compared to wave 3. The largest drop in missingness is observed for the social support variables (from 27-28% at wave 2 to 13-14% at wave 3), which are also the variables with the highest proportion of missing values. Missingness is also substantial for other questions related to the social environment, including neighbourhood trust (16% at wave 2, 12% at wave 3), parental involvement (21% at wave 2, 10% at wave 3), and neighbourhood satisfaction (19% at wave 2, 9% at wave 3). Amongst the physical activity outcomes, missingness was highest in outdoor physical activity and pay and play physical activity (respectively 12% and 11% at wave 2, 9% and 8% at wave 3), and lower in walking to school and walking for leisure (respectively 4% and 7% at wave 2, 3% and 5% at wave 3). Outdoor physical activity and pay and play physical activity variables have more missing data because they combine multiple items, with each item having missing values. Missingness is above 10% for health condition (14% on both waves), country of birth (16%), and language spoken at home (15%). The latter two auxiliary variables were measured at baseline and are therefore missing for all adolescents who did not take part at that wave. Non-response is lower than 10% for the auxiliary variables BMI (9% at wave 2, 7% at wave 3) and below 5% for all other variables.

8.4.1.2. Imputation model

My imputation strategy was informed by procedures conducted in chapter 6 (section 6.4.1.2.). I imputed the data separately for boys and girls to allow for interaction terms between gender and exposure variables. I used the data in wide format with a fixed effects approach to account for clustering at individual-level, while including school as a random effect. Unlike chapter 6, the current analysis includes only wave 2 and wave 3, but a few more cases per wave. The present imputation analysis was therefore expected to be less computationally demanding.

Following an analysis of missingness (Appendix G section G.1), the imputation models included the variables of the analysis models and the auxiliary variables of Table 8.1 (with the exception of the stratification variable, gender). All continuous variables were normally distributed, treated as outcomes, and rescaled when necessary. All discrete variables were treated as outcomes using the latent normal distribution approach (cf. section 4.3.2.2.).

The initial 'full model' behaved similarly to the final imputation model of chapter 6: it was slow to run but had relatively quick convergence (Table 8.2). An initial 4,000 iterations were obtained and analysed for boys and girls separately.

Results indicate that most of the β coefficients had good convergence as illustrated by a physical activity outcome (β_{13}) in the model for boys (Figure 8.1).

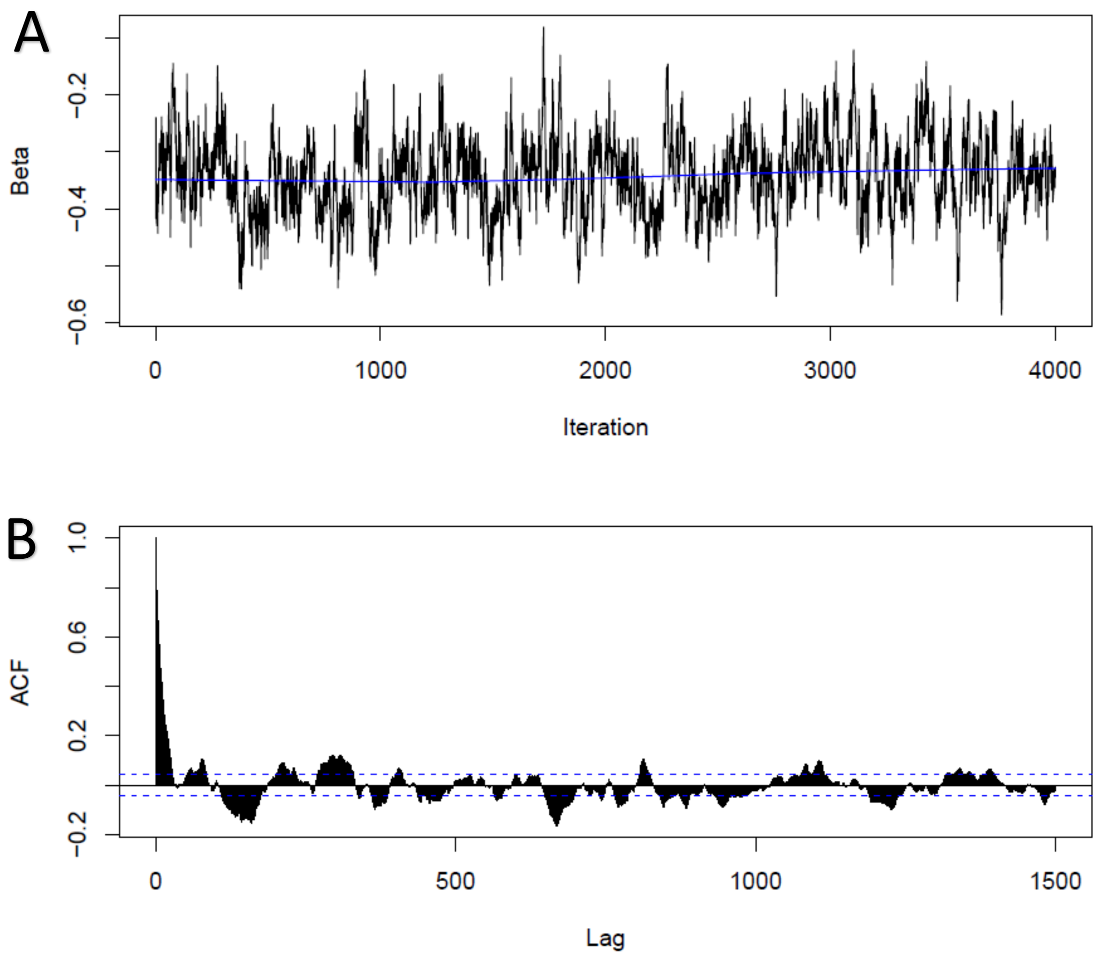

Figure 8.1 Example of time series plot (A) and autocorrelation plot (B) of a β parameter with good convergence. The β parameter of this example corresponds to pay and play physical activity at wave at wave 2 (β_{13}) for boys. Results are from a multilevel imputation model (fixed effects approach with school as a cluster). The autocorrelation plot starts at iteration 2,000. ACF – Autocorrelation Function

Table 8.2 Summary of imputation model of chapter 8

Data format	**Cluster variable**	**Variables**	**Coefficients matrices**	**Computational time for 10 iterations***	**MCMC convergence**
wide	school	normal transformation and centring of continuous variables	Beta [1x 63] Cov u [63x63] Omega [63 x 63]	173 sec	quick convergence and some parameters with remaining auto-correlation recommended burn-in n_{burn} ≥2,000 and n-between $n_{\text{between}} \approx$ 1,000

* Computational time for girls.

Other β parameters (Figure 8.2), indicate some autocorrelation between iterations that are far apart, up to almost 1,500. All autocorrelation plots of the β coefficients crossed at least once the 0.05 benchmark for lags of 1,000.

Parameters of the level 2 covariance matrix (Covariance u) converged quickly to the distribution and stayed well within the [-0.05; 0.05] bounds for autocorrelation. Most of the (co)variances involving the outcomes of the analysis models (walking to school, walking for leisure, outdoor physical activity and pay and play physical activity at each wave) had very good convergence as exemplified by the level 2 variance of walking for leisure at wave 3 for girls (Figure 8.3). Some persistent very low autocorrelations were observed, but disappeared with lags $\geq$ 1,000 (not presented).

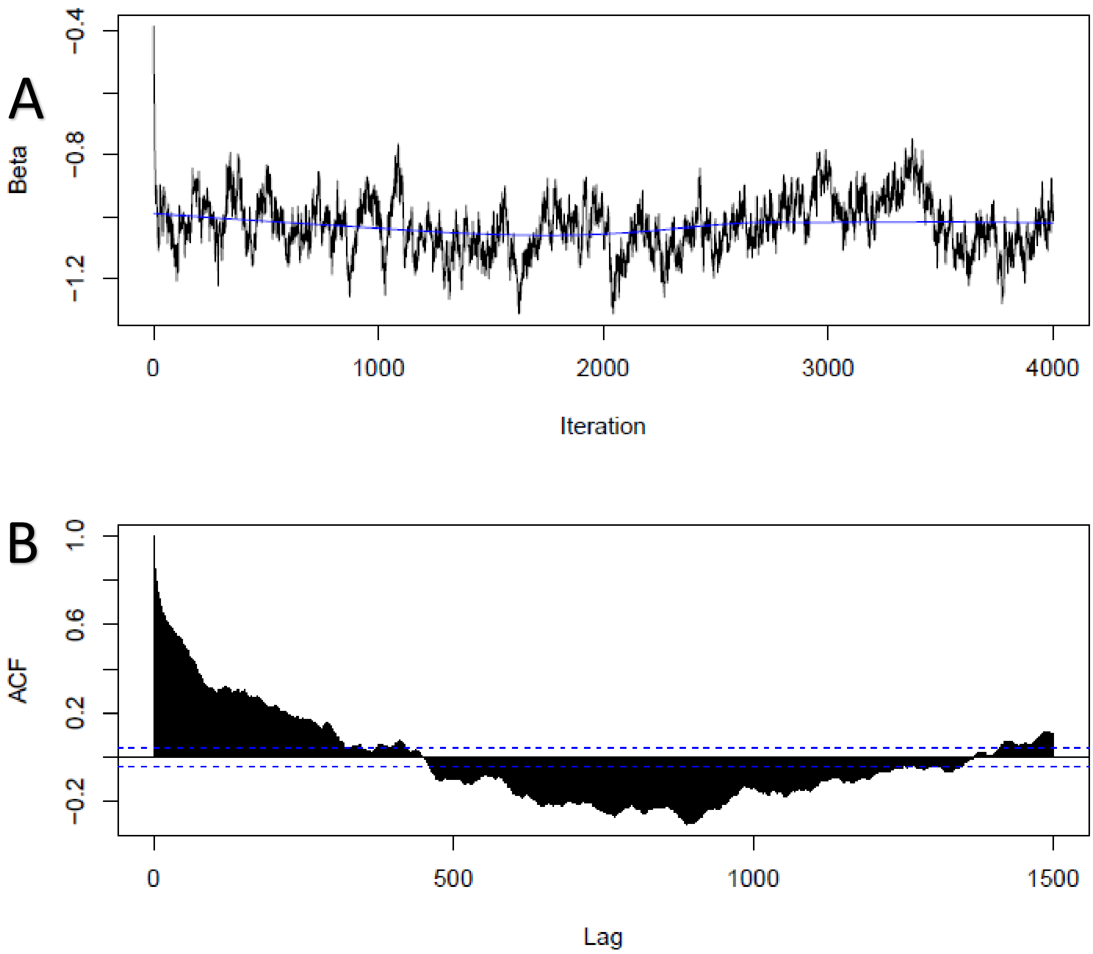

Figure 8.2 Example of time series plot (A) and autocorrelation plot (B) of a β parameter with non-optimal convergence. The β parameter of this example corresponds to Black African at wave 2 (β_{38}) for girls. Results are from a multilevel imputation model (fixed effects approach with school as a cluster). The autocorrelation plot starts at iteration 2,000. ACF – Autocorrelation Function

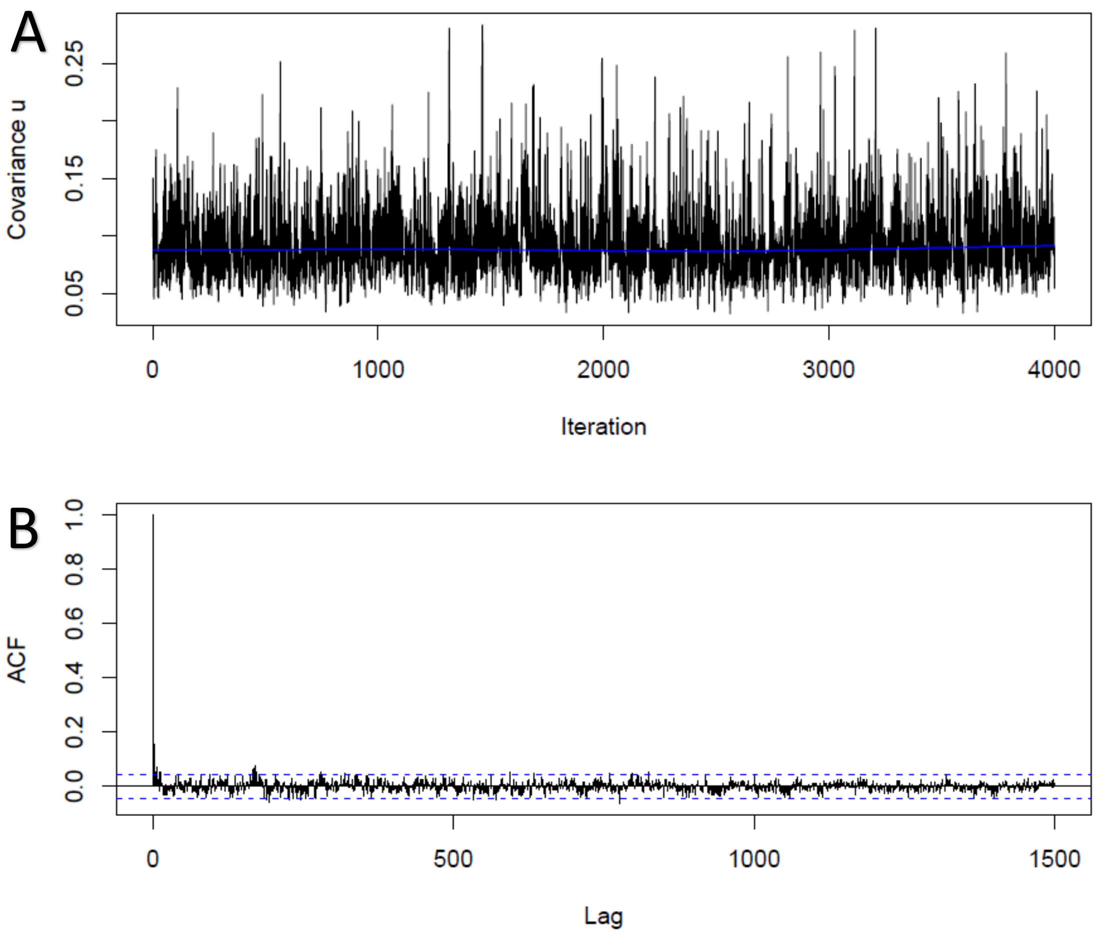

Figure 8.3 Example of time series plot (A) and autocorrelation plot (B) of a level 2 covariance parameter with excellent convergence. The covariance parameter of this example corresponds to the level 2 variance of walking for leisure at wave 3 (Covariance u 10 10) for girls. Results are from a multilevel imputation model (fixed effects approach with school as a cluster). The autocorrelation plot starts at iteration 2,000. ACF – Autocorrelation Function

As in chapter 6 (section 6.4.1.2.), graphs for the level 1 covariances indicate, acceptable to poor mixing when the Metropolis-Hastings algorithm is used (see Figure 8.4 and Figure 8.5 for examples). As discussed in chapters 6 and 7, however, the convergence of level 1 covariances should not affect the results of the imputation given that I will not conduct a full Bayesian analysis to answer the research questions in this thesis.

Overall, results are very similar for boys and girls and indicate quick convergence, but some autocorrelation remains, with lags above 500. I estimated the model to be a suitable imputation model for boys and girls with burn-in of $n_{\text{burn}} \geq$2,000 and an n-between of $n_{\text{between}} \approx$ 1,000. Such a model was projected to require 5 days for producing 20 imputations for each gender.

I fitted the model for both gender with a burn-in of n_{burn} =4,050 and an n-between of n_{between} = 1,000 to produce 20 imputed datasets. The random seed 1,523 was used for replication purposes. The models took c.6 days each to complete the burn-in and impute the data. The gender-specific 20 imputed datasets were merged and transformed back into long format for analysis. The analysis models were run on each imputed dataset and results were combined for final inference using Rubin's rules (Carpenter & Kenward 2012).

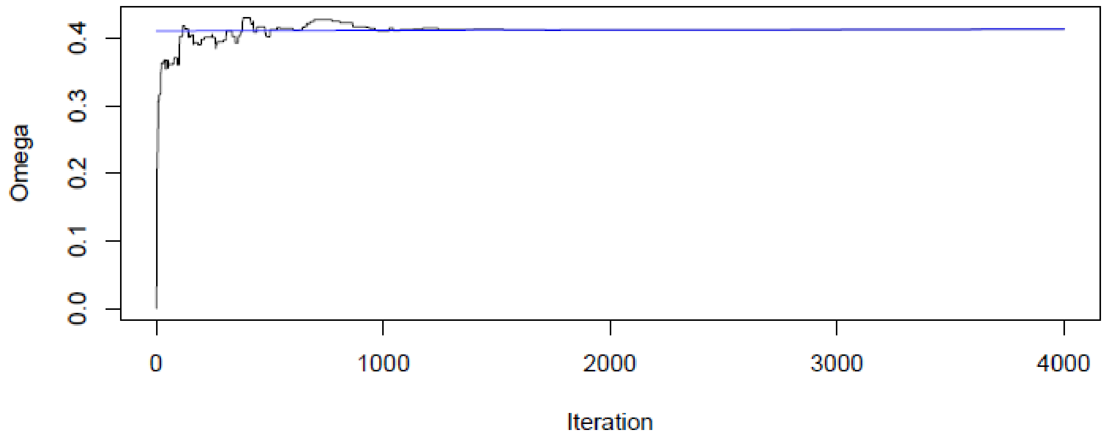

Figure 8.4 Example of time series plot with little variation around the average of a level 1 covariance Omega parameter updated with a Metropolis-Hastings step. Results are from a multilevel imputation model for boys (fixed effects approach with school as a cluster).

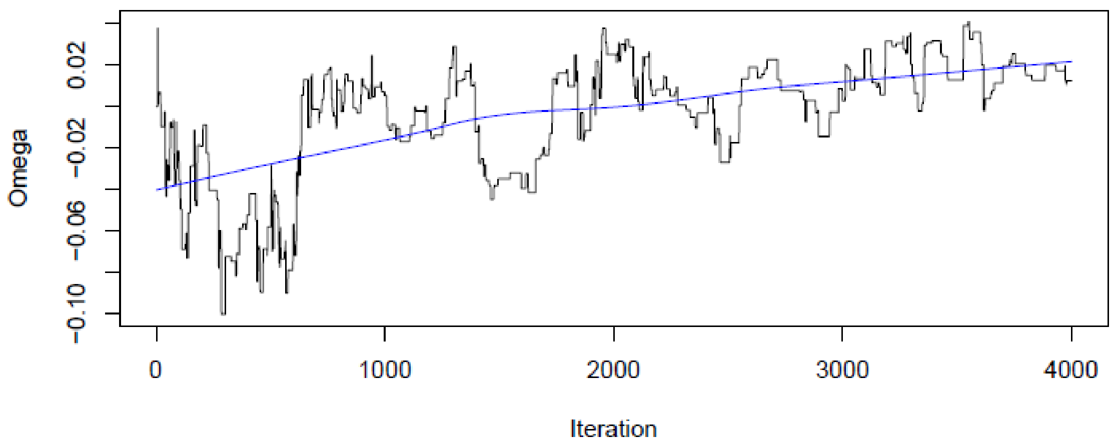

Figure 8.5 Example of time series plot with good mixing of a level 1 covariance Omega parameter updated with a Metropolis-Hastings step. Results are from the multilevel imputation model for boys (fixed effects approach with school as a cluster).

8.4.2. Longitudinal associations between neighbourhood trust and social cohesion and physical activity

In this section, I analyse the 20 imputed datasets to answer the research questions (section 8.2.). These are, first, is neighbourhood trust longitudinally associated with the four forms of physical activity (walking to school, walking for leisure, outdoor physical activity and pay and play physical activity)? Second, are sources of social support (friends, family, and significant other) longitudinally associated with the four forms of physical activity? For each research question, I explore whether the exposures and outcomes are generally associated; whether short-term change in the exposure are associated with change in the outcome; and whether the associations differ for boys and girls.

Analyses were conducted using logistic and proportional odds regression models estimated with GEE to account for clustering at individual-level (pooled longitudinal models) and school-level (cross-sectional models for change scores in exposures and outcomes), respectively. For the pooled longitudinal logistic regression models, parameters are interpreted either as cross-sectional or in terms of change over time (cf. section 4.4.3.1.). For the cross-sectional proportional odds models, results are interpreted as associations between increase in the exposure and change in the outcome status of a same person. In the proportional odds models, the same ORs serve to describe two comparisons of physical activity status: i) no change over time vs. stop reporting physical activity (i.e. no change vs. negative change); and ii) start reporting physical activity vs. no change (i.e. positive change vs. no change). Results are presented for each physical activity outcome in turn, starting with a description of the associations between the confounders and the outcomes for this specific analytical sample[29].

8.4.2.1. Walking to school

Table 8.3 presents unadjusted and adjusted associations between socio-demographic variables and walking to school. After adjustment for all socio-demographic variables, there is some indication that walking to school is more prevalent in girls compared to boys (adjusted OR=1.14 (95% CI: 0.98-1.34); p-value=0.094). Such a difference was not observed using a different analytical sample (cf. section 6.4.2.1.). The previously established ethnic differences in walking to school are however confirmed (unadjusted and adjusted p-value<0.001).

[29] Discrepancies in the covariates-outcomes associations between this analytical sample and the one used in chapter 6 (cf. section 3.3.) are highlighted.

Compared to the White UK adolescents, the odds of walking to school are lower amongst the Black Caribbean and the Black African groups (adjusted ORs are 0.48 (95% CI: 0.33-0.69), 0.65 (95% CI: 0.48-0.87) respectively) and highest amongst the Bangladeshi adolescents (adjusted ORs are 1.32 (95% CI: 0.97-1.79)). Reporting health condition increases the odds of walking to school by 1.21 (adjusted 95% CI: 1.03-1.41; p-value=0.018). Family affluence is not associated with walking to school (unadjusted and adjusted p-values are 0.815 and 0.754 respectively). Living with both parents is associated only in the unadjusted model (unadjusted and adjusted p-values are 0.066 and 0.383 respectively), and taking free school meal increases the odds of walking to school in the adjusted model only (adjusted OR=1.15 (95% CI: 0.98-1.35); p-value=0.097). Having lived more than 6 years in the neighbourhood also increases the odds of walking to school (adjusted p-value = 1/0.65=1.54 (95% CI: 1.33-1.82); p-value<0.001). The modelled time coefficient confirms the absence of support for a decline in walking to school between wave 2 and wave 3 (adjusted OR 0.95 (95% CI: 0.86-1.05); p-value=0.284).

Neighbourhood trust

Results for neighbourhood trust and social support are presented Table 8.4 (pooled longitudinal models) and Table 8.5 (models for change scores). Analyses indicate that there is no evidence for an association between neighbourhood trust and walking to school (adjusted p-value=0.482), or between the change in exposure and change in outcome scores (adjusted p-value=0.591). In unadjusted and adjusted models, ORs are close to 1.00 and confidence intervals are wide. The inclusion of interaction terms between gender and neighbourhood trust (Table 8.4), or change in trust (Table 8.5) indicates no evidence that associations differ by gender (p-values are 0.528 and 0.148 respectively).

Social support

Table 8.4 also indicates an absence of association between the three sources of social support (friends, family or significant other) and walking to school (p-values are all >0.170). Unadjusted and adjusted ORs are all close to 1.00. There is some indication that associations with social support from family may differ by gender (p-value=0.062). However, stratum-specific results (not reported) indicate no significant associations with walking to school (p-value>0.1). Results from the models for change scores (Table 8.5) also display unadjusted and adjusted ORs close to 1.00 (p-values >0.5). However, there was some evidence of a gender interaction with social support from significant others (p-value=0.065). Stratum-specific results reported in Table 8.5 show that, in girls, the odds of improving the walking to school status over time are 1.15 (95% CI: 1.00-1.32) higher for those who have increased social support from significant others. For boys, the association is in the opposite direction and not statistically significant (p-value=0.408).

Table 8.3 Odds ratios (OR) of walking to school vs. not by potential socio-demographic and health confounders (waves 2-3 balanced panel of the ORiEL Study, n=2,644)

Potential confounder		Unadjusted OR	Adjusted OR[1]	95%CI	P-value parameter	P-value unadjusted	P-value adjusted[1]
Gender	Male	1.00	1.00			0.249	0.094
	Female	1.10	1.14	[0.98,1.34]	0.094		
Ethnicity	White: UK	1.00	1.00			<0.001	<0.001
	White: Mixed	0.73	0.77	[0.55,1.08]	0.134		
	Asian: Indian	0.83	0.93	[0.59,1.47]	0.750		
	Asian: Pakistani	0.92	0.97	[0.62,1.52]	0.907		
	Asian: Bangladeshi	1.27	1.32	[0.97,1.79]	0.077		
	Black: Caribbean	0.47	0.48	[0.33,0.69]	<0.001		
	Black: African	0.57	0.65	[0.48,0.87]	0.004		
	Other	0.70	0.77	[0.61,0.98]	0.032		
Health	No condition	1.00	1.00			0.008	0.018
	1+ conditions(s)	1.23	1.21	[1.03,1.41]	0.018		
Family affluence	Low	1.00	1.00			0.815	0.754
	Moderate	0.91	0.89	[0.66,1.21]	0.463		
	High	0.92	0.91	[0.66,1.25]	0.545		
Take free school meal	No	1.00	1.00			0.227	0.097
	Yes	1.10	1.15	[0.98,1.35]	0.097		
Time lived in neighbourhood	>6 years	1.00	1.00			<0.001	<0.001
	<= 5 years	0.63	0.65	[0.55,0.75]	<0.001		
Household composition	Both Parents	1.00	1.00			0.066	0.383
	Other	0.87	0.93	[0.79,1.09]	0.383		
Time		0.95	0.95	[0.86,1.05]	0.284	0.324	0.284

Results are from logistic regression models estimated with Generalised Estimating Equations to account for the dependency across repeated measurements (unstructured working correlation matrix).[1] Adjusted for all other variables of the table.

Table 8.4 Odds ratios (OR) of walking to school vs. not by neighbourhood trust and social support , adjusting for potential confounders (waves 2 and 3* of the ORiEL Study, n=2,644*)

Exposure		**Unadjusted OR**	**Adjusted OR[1]**	**95%CI**	**P-value parameter**	**P-value unadjusted**	**P-value adjusted[1]**	**Gender interaction (p-value) [2]**
Neighbourhood trust	Not at all	1.00	1.00			0.296	0.482	0.528
	A little	1.02	0.99	[0.77,1.26]	0.904			
	Some	1.17	1.10	[0.88,1.39]	0.400			
	A lot	1.06	0.98	[0.75,1.28]	0.898			
Social support – friends	Low	1.00	1.00			0.253	0.170	0.258
	Medium	1.10	1.07	[0.91,1.27]	0.423			
	High	0.95	0.90	[0.76,1.07]	0.247			
Social support – family	Low	1.00	1.00			0.753	0.680	0.062^
	Medium	0.95	0.95	[0.79,1.15]	0.606			
	High	0.94	0.93	[0.78,1.10]	0.386			
Social support – significant others	Low	1.00	1.00			0.916	0.934	0.265
	Medium	0.97	0.97	[0.81,1.16]	0.727			
	High	1.00	0.98	[0.83,1.16]	0.832			

Results are from logistic regression models estimated with Generalised Estimating Equations to account for the dependency across repeated (unstructured working correlation matrix). [1] Adjusted for gender, ethnicity, health condition, free school meal status, family affluence, time lived in the neighbourhood, household composition and time. [2] The adjusted model was replicated for each outcome with an additional interaction term between gender and exposure. ^ None of the gender-specific associations was significant (p-values>0.1).

*Table 8.5 Odds ratios (OR) of change in walking to school predicted by change in neighbourhood trust and social support , adjusting for potential confounders at wave 2 (*n=2,644*)*

Exposure	Unadjusted OR	Adjusted OR[1]	95% CI	P-value unadjusted	P-value adjusted[1]	Gender interaction (p-value) [2]
Neighbourhood trust	1.02	1.03	[0.93 , 1.14]	0.684	0.591	0.148
Social support – friends	0.97	0.97	[0.87 , 1.08]	0.594	0.580	0.140
Social support – family	1.01	1.00	[0.90 , 1.12]	0.819	0.952	0.479
Social support – significant others	1.03	1.02	[0.92 , 1.14]	0.612	0.693	0.065
Social support – sig. others - Boys	0.94	0.93	[0.78 1.10]	0.453	0.408	
Social support – sig. others - Girls	1.15	1.15	[1.00 1.32]	0.050	0.056	

Results are from proportional odds models estimated with Generalised Estimating Equations to account for the clustering of individuals within schools (independent working correlation matrix). Results are displayed as ORs of improvement in walking to school status (constant vs. decrease or increase vs. constant) per unit increase in the original scale of neighbourhood trust or tertile change in social support. ORs > 1 indicate a positive change in the outcome as a response to an improvement in the exposure. [1] Adjusted for gender, ethnicity, health condition, free school meal status, family affluence, time lived in the neighbourhood and household composition at wave 2. [2] The adjusted model was replicated for each outcome with an additional interaction term between gender and exposure.

8.4.2.2. Walking for leisure

Table 8.6 indicates that associations between walking for leisure and socio-demographics are similar to those described in chapter 6 (section 6.4.2.2.). In the present analyses, walking for leisure is estimated to be even more frequent amongst girls than boys (adjusted OR=1.67 (95% CI: 1.46-1.92); p-value <0.001). As with walking to school, there is strong evidence for ethnic differences in walking for leisure: the odds of walking for leisure are lower in all groups compared to the White UK, particularly in the Bangladeshi group (adjusted OR= 0.38; 95% CI: 0.30-0.48; p-value <0.001). There is no evidence that pre-existing health condition, free school meal status and time resident in the neighbourhood are significantly associated with walking for leisure (adjusted p-values=0.208, 0.654 and 0.375 respectively). Both unadjusted and adjusted models indicate associations between family affluence and walking for leisure (adjusted p-value=0.043). There is evidence that those not living with both parents are more likely to walk for leisure (adjusted OR=1.16 (95% CI: 1.01-1.35); p-value=0.04). The modelled time coefficient confirms that the odds of walking for leisure decreased by a factor of 0.79 (adjusted 95% CI: 0.71-0.87; p-value<0.001) between wave 2 and wave 3.

Neighbourhood trust

Table 8.7 indicates no evidence of association between neighbourhood trust and walking for leisure (adjusted p-values=0.314). As expected, estimated ORs are higher for all categories compared to the lowest level of trust. However, there is no evidence of an overall significant difference between the response categories. Modelling the exposure as a dose-response indicates unadjusted and adjusted ORs of 1.03 and 1.04 respectively, but neither reaches statistical significance (p-values=0.414 and 0.250 respectively). In the models specifically investigating within individual change scores (Table 8.8), there is some weak evidence, in unadjusted and adjusted models, that an increase in neighbourhood trust increases the odds of positive change in the walking status by 1.07 (adjusted 95% CI: 0.99-1.15; p-value=0.098). The inclusion of interaction terms between gender and neighbourhood trust (Table 8.7) or its change over time (Table 8.8) provide no evidence that the associations differ by gender (p-values>0.8).

Social support

Unlike neighbourhood trust, there is strong evidence of associations between sources of social support and walking for leisure (Table 8.7). Estimated values for social support from friends indicate an increase in the odds of walking as social support increases, although the gradient in less clear in the adjusted model compared to the unadjusted model. When social support from friends is modelled as a continuous variable (i.e. dose-response relationship), the unadjusted model indicates a strong positive association (OR=1.15; p-value=0.001), however after adjustment for confounders there is some attenuation of the coefficient (adjusted OR= 1.08; 95% CI: 1.00-1.18; p-value=0.050). The family and significant others sources of social support also display consistent associations with walking for leisure. There is evidence of a dose-response relationship: an increase in the tertile in family and significant others sources increases the odds of walking for leisure by 1.15 (adjusted 95% CI: 1.06-1.25; p-value=0.001) and 1.10 (adjusted 95% CI: 1.02-1.20; p-value=0.019) respectively. These associations are also attenuated in the adjusted models.

The models investigating within individual changes scores (Table 8.8) give a slightly different picture. There is strong evidence of positive association between change in social support from friends and change in walking for leisure status (adjusted OR=1.11; 95% CI: 1.01-1.21; p-value=0.022). Results mean that moving up to a higher tertile of social support over time increases the odds of reporting a positive change walking status by 1.11 (interpreted as either to start walking vs. no change, or no change vs. to stop walking).

There is however no evidence of association with change in social support from family and significant others (p-values=0.180 and 0.321 respectively) despite coefficients being in the expected directions (adjusted ORs=1.07 and 1.04 respectively).

The inclusion of interaction terms between gender and each source of social support (Table 8.7) or their change over time (Table 8.8) indicates no evidence that the above associations differ by gender (all p-values >0.150).

Table 8.6 Odds ratios (OR) of walking for leisure vs. not by potential socio-demographic and health (waves 2 and 3 of the ORiEL Study, n=2,644)

Potential confounder		**Unadjusted OR**	**Adjusted OR[1]**	**95%CI**	**P-value parameter**	**P-value unadjusted**	**P-value adjusted[1]**
Gender	Male	1.00	1.00			<0.001	<0.001
	Female	1.67	1.67	[1.46,1.92]	<0.001		
Ethnicity	White: UK	1.00	1.00			<0.001	<0.001
	White: Mixed	0.65	0.63	[0.48,0.84]	0.001		
	Asian: Indian	0.51	0.54	[0.37,0.79]	0.002		
	Asian: Pakistani	0.54	0.59	[0.41,0.85]	0.005		
	Asian: Bangladeshi	0.34	0.38	[0.30,0.48]	<0.001		
	Black: Caribbean	0.40	0.37	[0.25,0.53]	<0.001		
	Black: African	0.39	0.41	[0.31,0.54]	<0.001		
	Other	0.56	0.57	[0.47,0.69]	<0.001		
Health	No condition	1.00	1.00			0.076	0.208
	1+ conditions(s)	1.13	1.09	[0.95,1.25]	0.208		
Family affluence	Low	1.00	1.00			0.034	0.043
	Moderate	1.00	1.04	[0.80,1.35]	0.774		
	High	1.17	1.22	[0.93,1.61]	0.149		
Take free school meal	No	1.00	1.00			0.922	0.654
	Yes	0.99	1.03	[0.89,1.19]	0.654		
Time lived in neighbourhood	>6 years	1.00	1.00			0.119	0.375
	<= 5 years	0.90	0.94	[0.82,1.08]	0.375		
Household composition	Both Parents	1.00	1.00			0.009	0.040
	Other	1.20	1.16	[1.01,1.35]	0.040		
Time		0.80	0.79	[0.71,0.87]	<0.001	<0.001	<0.001

Results are from logistic regression models estimated with Generalised Estimating Equations to account for the dependency across repeated (unstructured working correlation matrix). [1] Adjusted for all other variables of the table.

Table 8.7 Odds ratios (OR) of walking for leisure vs. not by neighbourhood trust and social support , adjusting for potential confounders (waves 2 and 3* of the ORiEL Study, n=2,644*)

Exposure		**Unadjusted OR**	**Adjusted OR[1]**	**95%CI**	**P-value parameter**	**P-value unadjusted**	**P-value adjusted[1]**	**Gender interaction (p-value) [2]**
Neighbourhood trust	Not at all	1.00	1.00			0.193	0.314	0.919
	A little	1.28	1.24	[0.98,1.57]	0.077			
	Some	1.25	1.24	[0.99,1.55]	0.065			
	A lot	1.20	1.22	[0.95,1.57]	0.112			
	Trend*	1.03	1.04	[0.97,1.12]	0.250	0.414	0.250	0.822
Social support – friends	Low	1.00	1.00			0.001	0.079	0.464
	Medium	1.24	1.17	[1.00,1.37]	0.050			
	High	1.31	1.17	[0.99,1.38]	0.058			
	Trend*	1.15	1.08	[1.00,1.18]	0.050	0.001	0.050	0.205
Social support – family	Low	1.00	1.00			<0.001	0.004	0.641
	Medium	1.20	1.19	[1.00,1.42]	0.055			
	High	1.38	1.32	[1.12,1.56]	0.001			
	Trend*	1.17	1.15	[1.06,1.25]	0.001	<0.001	0.001	0.352
Social support – significant others	Low	1.00	1.00			0.001	0.055	0.474
	Medium	1.18	1.11	[0.95,1.30]	0.200			
	High	1.34	1.21	[1.03,1.43]	0.020			
	Trend*	1.16	1.10	[1.02,1.20]	0.019	<0.001	0.019	0.373

Results are from logistic regression models estimated with Generalised Estimating Equations to account for the dependency across repeated (unstructured working correlation matrix). [1] Adjusted for gender, ethnicity, health condition, free school meal status, family affluence, time lived in the neighbourhood, household composition and time. [2] The adjusted model was replicated for each outcome with an additional interaction term between gender and exposure.

Table 8.8 Odds ratios (OR) of change in walking for leisure predicted by change in neighbourhood trust and social support , adjusting for potential confounders at baseline (n=2,644)

Exposure	**Unadjusted OR**	**Adjusted OR[1]**	**95% CI**	**P-value unadjusted**	**P-value adjusted[1]**	**Gender interaction (p-value) [2]**
Neighbourhood trust	1.07	1.07	[0.99 , 1.15]	0.071	0.098	0.862
Social support – friends	1.11	1.11	[1.01 , 1.21]	0.016	0.022	0.392
Social support – family	1.07	1.07	[0.97 , 1.19]	0.172	0.180	0.505
Social support – significant others	1.05	1.04	[0.96 , 1.14]	0.301	0.321	0.162

Results are from proportional odds models estimated with Generalised Estimating Equations to account for the clustering of individuals within schools (independent working correlation matrix). Results are displayed as ORs of improvement in walking for leisure status (constant vs. decrease or increase vs. constant) per unit increase in the original scale of neighbourhood trust or tertile change in social support. ORs > 1 indicate a positive change in the outcome as a response to an improvement in the exposure. [1] Adjusted for gender, ethnicity, health condition, free school meal status, family affluence, time lived in the neighbourhood and household composition at wave 2. [2] The adjusted model was replicated for each outcome with an additional interaction term between gender and exposure.

8.4.2.3. Outdoor physical activity

Outdoor physical activity is associated with many of the considered socio-demographic variables (Table 8.9). Outdoor physical activity is higher in boys (adjusted OR=1/0.21=4.76 (95% CI: 4.00-5.55); p-value<0.001). Ethnic differences are observed (adjusted p-values<0.001): with outdoor physical activity being more prevalent in the Pakistani (adjusted OR=1.84 (95% CI: 1.15-2.94)) and Black African groups (adjusted OR=1.43 (95% CI: 1.05-1.96)) compared to the White UK group. There is also strong evidence that greater family affluence is associated with more outdoor physical activity (adjusted p-value=0.004). Adolescents from the most affluent families have 1.45 (95% CI: 1.07-1.97) times greater odds of reporting outdoor physical activity compared to the least affluent. Free school meal status seems to indicate an opposite relationship, both in the adjusted and unadjusted models, but the level of evidence is weak in the adjusted model (p-value = 0.092). Health status, time lived in the neighbourhood and household composition are not associated with outdoor physical activity (adjusted p-value=0.984, 0.168 and 0.921 respectively). The modelled time coefficient confirms that the odds of outdoor physical activity decreased by a factor of 0.75 (adjusted 95% CI: 0.66-0.84; p-value<0.001) between wave 2 and wave 3.

Neighbourhood trust

Results from Table 8.10 indicate evidence of positive association between neighbourhood trust and outdoor physical activity. ORs take the form of a gradient, and therefore the association is better captured using a trend. Unadjusted model indicates that the increase in one trust response category increases the odds of outdoor physical activity by 1.17 (p-value<0.001). The association is attenuated to 1.10 in the adjusted model (adjusted 95% CI: 1.01-1.19), but remains statistically significant (p-value=0.029). The model without trend, however, only indicates weak evidence of association in the adjusted model (p-value=0.099). Results from the models for within individual change scores (Table 8.12) indicate no evidence of association. Unadjusted and adjusted ORs are very close to 1.00 (adjusted p-values=0.805). The inclusion of interaction terms between gender and neighbourhood trust (Table 8.10) or its change over time (Table 8.12) indicate no evidence that the above associations differ by gender (p-values are 0.680 and 0.567 respectively).

Social support

In contrast to neighbourhood trust, Table 8.10 indicates an absence of association between any source of social support (friend, family or significant other) and outdoor physical activity (adjusted p-values are all >0.7). Unadjusted and adjusted ORs indicate opposite directions of associations. However, there is strong indication that the association with social support from friends might differ by gender (p-value=0.027). There is also some very weak indication that the association might differ for family social support as well (p-value=0.179). Gender-specific results are therefore presented for the three sources of social support in Table 8.11. Stratum-specific results confirm an absence of association between outdoor physical activity and any of the sources of social support in girls (adjusted p-values=0.509, 0.733 and 0.836 respectively). In boys however, there is strong evidence of a positive dose-response relationship with social support from friends (adjusted p-value=0.014) and a weak positive association with social support from family (adjusted p-value=0.060). The associations show that an increase in social support (i.e. change of tertile) increases the odds of outdoor physical activity by 1.21 (adjusted 95% CI: 1.04-1.42) for social support from friends and by 1.15 (adjusted 95% CI: 0.99-1.32) from family. There are also some signs of a positive dose-response relationship with social support from significant others in boys, but the association does not reach statistical significance (adjusted p-value=0.106).

Investigation of the within individual change scores, indicates no evidence of associations between social support and outdoor physical activity (Table 8.12). Estimated ORs are close to 1.00 and adjusted p-values>0.4. The models also give no evidence of a gender interaction (all p-values >0.3).

Table 8.9 Odds ratios (OR) of outdoor physical activity vs. not by potential socio-demographic and health confounders (waves 2 and 3 of the ORiEL Study, n=2,644)*

Potential confounder		**Unadjusted OR**	**Adjusted OR[1]**	**95%CI**	**P-value parameter**	**P-value unadjusted**	**P-value adjusted[1]**
Gender	Male	1.00	1.00			<0.001	<0.001
	Female	0.21	0.21	[0.18,0.25]	<0.001		
Ethnicity	White: UK	1.00	1.00			0.005	0.074
	White: Mixed	1.18	1.26	[0.90,1.76]	0.181		
	Asian: Indian	1.30	1.25	[0.81,1.94]	0.310		
	Asian: Pakistani	2.10	1.84	[1.15,2.94]	0.011		
	Asian: Bangladeshi	1.23	1.14	[0.86,1.49]	0.362		
	Black: Caribbean	0.79	0.87	[0.59,1.30]	0.509		
	Black: African	1.46	1.43	[1.05,1.96]	0.025		
	Other	1.13	1.16	[0.92,1.45]	0.216		
Health	No condition	1.00	1.00			0.483	0.984
	1+ conditions(s)	0.95	1.00	[0.85,1.18]	0.984		
Family affluence	Low	1.00	1.00			<0.001	0.004
	Moderate	1.09	1.17	[0.88,1.56]	0.291		
	High	1.41	1.45	[1.07,1.97]	0.016		
Take free school meal	No	1.00	1.00			0.018	0.092
	Yes	1.20	1.15	[0.98,1.35]	0.092		
Time lived in neighbourhood	>6 years	1.00	1.00			0.188	0.168
	<= 5 years	1.10	1.12	[0.95,1.30]	0.168		
Household composition	Both Parents	1.00	1.00			0.388	0.921
	Other	0.94	1.01	[0.86,1.19]	0.921		
Time		0.77	0.75	[0.66,0.84]	<0.001	<0.001	<0.001

Results are from logistic regression models estimated with Generalised Estimating Equations to account for the dependency across repeated (unstructured working correlation matrix). * Outdoor physical activities include: basketball (or volleyball), blading, cricket, football, rounders, rugby and roller skating. [1] Adjusted for all other variables of the table.

Table 8.10 Odds ratios (OR) of outdoor physical activity vs. not by neighbourhood trust and social support , adjusting for potential confounders (waves 2 and 3 of the ORiEL Study, n=2,644)*

Exposure		**Unadjusted OR**	**Adjusted OR[1]**	**95%CI**	**P-value parameter**	**P-value unadjusted**	**P-value adjusted[1]**	**Gender interaction (p-value) [2]**
Neighbourhood trust	Not at all	1.00	1.00			<0.001	0.099	0.680
	A little	1.03	0.97	[0.76,1.24]	0.832			
	Some	1.16	1.08	[0.86,1.36]	0.510			
	A lot	1.60	1.29	[0.97,1.70]	0.077			
	Trend†	1.17	1.10	[1.01,1.19]	0.029	<0.001	0.029	0.390
Social support – friends	Low	1.00	1.00			0.164	0.748	0.027
	Medium	0.91	1.06	[0.89,1.27]	0.513			
	High	0.86	1.06	[0.89,1.26]	0.517			
Social support – family	Low	1.00	1.00			0.844	0.815	0.179
	Medium	1.01	1.05	[0.88,1.26]	0.577			
	High	1.04	1.05	[0.88,1.25]	0.575			
Social support – significant others	Low	1.00	1.00			0.273	0.881	0.354
	Medium	0.90	1.03	[0.86,1.23]	0.765			
	High	0.89	1.04	[0.89,1.23]	0.604			

Results are from logistic regression models estimated with Generalised Estimating Equations to account for the dependency across repeated (unstructured working correlation matrix). * Outdoor physical activities include: basketball (or volleyball), blading, cricket, football, rounders, rugby and roller skating. [1] Adjusted for gender, ethnicity, health condition, free school meal status, family affluence, time lived in the neighbourhood, household composition and time. [2] The adjusted model was replicated for each outcome with an additional interaction term between gender the exposure. †Exposure modelled as a continuous variable when evidence of improved fit compared to the discrete option.

Table 8.11 Odds ratios (OR) of outdoor physical activity vs. not by social support stratified by gender , adjusting for potential confounders (waves 2 and 3 of the ORiEL Study, n=2,644)*

Exposure		**Unadjusted OR**	**Adjusted OR[1]**	**95%CI**	**P-value unadjusted**	**P-value adjusted[1]**	**Unadjusted OR**	**Adjusted OR[1]**	**95%CI**	**P-value unadjusted**	**P-value adjusted[1]**
			Boys					**Girls**			
Social support – friends	Low	1.00	1.00		0.037	0.039	1.00	1.00		0.607	0.509
	Medium	1.22	1.22	[0.92,1.61]			0.92	0.93	[0.75,1.17]		
	High	1.47	1.47	[1.07,2.02]			0.90	0.88	[0.70,1.10]		
	Trend†	1.21	1.21	[1.04,1.42]	0.014	0.014					
Social support – family	Low	1.00	1.00		0.135	0.166	1.00	1.00		0.951	0.733
	Medium	1.17	1.18	[0.87,1.60]			0.98	0.98	[0.77,1.24]		
	High	1.33	1.31	[0.99,1.74]			0.97	0.92	[0.74,1.15]		
	Trend†	1.15	1.15	[0.99,1.32]	0.045	0.060					
Social support – significant others	Low	1.00	1.00		0.313	0.266	1.00	1.00		0.938	0.836
	Medium	1.14	1.16	[0.87,1.53]			0.96	0.94	[0.74,1.19]		
	High	1.23	1.24	[0.95,1.63]			0.98	0.94	[0.75,1.17]		
	Trend†	1.11	1.12	[0.98,1.28]	0.128	0.106					

Results are from logistic regression models estimated with Generalised Estimating Equations to account for the dependency across repeated (unstructured working correlation matrix). * Outdoor physical activities include: basketball (or volleyball), blading, cricket, football, rounders, rugby and roller skating. [1] Adjusted for gender, ethnicity, health condition, free school meal status, family affluence, time lived in the neighbourhood, household composition and time. [2] The adjusted model was replicated for each outcome with an additional interaction term between gender and exposure. †Exposure modelled as a continuous variable when evidence of improved fit compared to the discrete option.

Table 8.12 Odds ratios (OR) of change in outdoor physical activity predicted by change in neighbourhood trust and social support , adjusting for potential confounders at baseline* (n=2,644)

Exposure	**Unadjusted OR**	**Adjusted OR[1]**	**95% CI**	**P-value unadjusted**	**P-value adjusted[1]**	**Gender interaction (p-value) [2]**
Neighbourhood trust	0.99	0.99	[0.91 , 1.08]	0.822	0.805	0.567
Social support – friends	1.01	1.01	[0.92 , 1.11]	0.879	0.850	0.305
Social support – family	0.97	0.97	[0.88 , 1.06]	0.538	0.493	0.527
Social support – significant others	1.01	1.00	[0.90 , 1.11]	0.874	0.946	0.791

Results are from proportional odds models estimated with Generalised Estimating Equations to account for the clustering of individuals within schools (independent working correlation matrix). Results are displayed as ORs of improvement in outdoor physical activity status (constant vs. decrease or increase vs. constant) per unit increase in the original scale of neighbourhood trust or tertile change in social support. ORs > 1 indicate a positive change in the outcome as a response to an improvement in the exposure.
* Outdoor physical activities include: basketball (or volleyball), blading, cricket, football, rounders, rugby and roller skating. [1] Adjusted for gender, ethnicity, health condition, free school meal status, family affluence, time lived in the neighbourhood and household composition at wave 2. [2] The adjusted model was replicated for each outcome with an additional interaction term between gender and exposure.

8.4.2.4. Pay and play physical activity

Pay and play physical activity appears to be associated with many of the socio-demographic variables considered (Table 8.13). Unlike outdoor physical activity, there is no gender difference in reporting pay and play physical activity (adjusted p-value=0.871). Ethnic disparities are observed (adjusted p-values=0.015): pay and play physical activity is more prevalent in the Indian group (adjusted OR 1.40 (95% CI: 0.96-2.04)) and less prevalent in the Bangladeshi group (adjusted OR=0.80 (95% CI: 0.63-1.00)) compared to the White UK group. Similar to walking to school, reporting a health condition increases the odds of pay and play physical activity (adjusted OR=1.14 (95% CI: 1.00-1.30); p-value=0.046). There is strong evidence that higher family affluence is associated with more outdoor physical activity (adjusted p-value<0.001). Adolescents from the most affluent families are 2.06 (95% CI: 1.59-2.67) times more likely to report pay and play physical activity compared to the least affluent. Free school meal status seems to indicate an opposite relationship, both in the adjusted and unadjusted models, but the level of evidence is weak (adjusted p-value=0.110). There is weak evidence that those not living with both parents or residing in the neighbourhood for more than 6 years report less pay and play physical activity (adjusted p-value=0.091 and 0.088 respectively). The modelled time coefficient indicates that the odds of pay and play physical activity sharply decreased by a factor of 0.58 (adjusted 95% CI: 0.53-0.65; p-value<0.001) between wave 2 and wave 3.

Neighbourhood trust

Results from Table 8.14 indicate that there is evidence of a positive association between neighbourhood trust and pay and play physical activity. ORs take the form of a gradient and therefore associations are better captured using a trend, especially in the unadjusted model. Unadjusted model indicates that the increase in one trust response category increases the odds of pay and play physical activity by 1.12 (p-value=0.001). The association is attenuated to 1.09 in the adjusted model (adjusted 95% CI: 1.02-1.17) and remains statistically significant (p-value=0.013). The model without trend also indicates evidence of association in the adjusted model (p-value=0.025). In particular, reporting a lot of neighbourhood trust compared to not at all, increases the odds of pay and play physical activity by 1.27 (adjusted 95% CI: 0.99-1.63; p-value=0.058). The inclusion of an interaction term between gender and neighbourhood trust indicates no evidence that the above associations differ by gender (p-values=0.695).

Results from the models for within individual change scores (Table 8.15) indicate no evidence of association (adjusted p-value=2.50), despite the fact that the coefficients are in the expected direction (unadjusted and adjusted ORs=1.06). There is some indication that the association with change in neighbourhood trust differs by gender (p-value=0.075). Gender-specific results indeed indicate some evidence of a positive association in boys (adjusted p-value=0.059), and an absence of association in girls (adjusted p-value=0.726). In boys, an increase over time in neighbourhood trust increases the odds of positive change in pay and play physical activity status by 1.13 (adjusted 95% CI: 1.00-1.29).

Social support

Table 8.14 indicates an absence of association between any source of social support (friends, family or significant other) and pay and play physical activity (adjusted p-values are all>0.6). Unadjusted and adjusted ORs are all close to 1.00. Results from the models for change scores (Table 8.15) also display unadjusted and adjusted ORs close to 1.00, and an absence of evidence of association (p-values>0.6). The inclusion of interaction terms between gender and each source of social support (Table 8.14) or their change over time (Table 8.15) indicates no evidence that the associations might differ by gender (all p-values>0.25).

8.4.2.5. Sensitivity analyses

A series of sensitivity analyses were conducted. The main analyses presented in this chapter were first reproduced using only individuals that belong to the 3-wave balanced ORiEL panel to ensure that the panel definition did not alter the results (Appendix G G.3). Second, longitudinal logistic regression models were reproduced using an alternative specification of the working correlation structure in the GEE estimation process, using exchangeable as opposed to unstructured working correlations (Appendix G section G.4). Third, the models for change scores were reproduced without accounting for any form of clustering using proportional odds models and partial proportional odds model with likelihood estimation methods, ensuring that the proportional odds assumption was met in that context (Appendix G section G.5). Fourth, results for walking for leisure and pay and play physical activity were replicated with additional adjustment for BMI, which was associated with both the exposure and these outcomes, and was hypothesised to be a confounder in some of the literature (Appendix G G.6). Results from all these sensitivity analyses were only marginally different from the main results presented in the text and the main interpretations and conclusions were unaffected.

Table 8.13 Odds ratios (OR) of pay and play physical activity vs. not by potential socio-demographic and health confounders (waves 2 and 3 of the ORiEL Study, n=2,644)*

Potential confoundesr		Unadjusted OR	Adjusted OR[1]	95%CI	P-value parameter	P-value unadjusted	P-value adjusted[1]
Gender	Male	1.00	1.00			0.536	0.871
	Female	0.96	0.99	[0.87,1.13]	0.871		
Ethnicity	White: UK	1.00	1.00			0.003	0.015
	White: Mixed	1.07	1.10	[0.84,1.44]	0.484		
	Asian: Indian	1.42	1.40	[0.96,2.04]	0.079		
	Asian: Pakistani	1.09	1.08	[0.76,1.53]	0.683		
	Asian: Bangladeshi	0.77	0.80	[0.63,1.00]	0.054		
	Black: Caribbean	0.81	0.84	[0.60,1.17]	0.306		
	Black: African	0.93	0.96	[0.75,1.23]	0.720		
	Other	1.12	1.12	[0.93,1.36]	0.234		
Health	No condition	1.00	1.00			0.084	0.046
	1+ conditions(s)	1.12	1.14	[1.00,1.30]	0.046		
Family affluence	Low	1.00	1.00			<0.001	<0.001
	Moderate	1.28	1.38	[1.08,1.77]	0.012		
	High	1.93	2.06	[1.59,2.67]	<0.001		
Take free school meal	No	1.00	1.00			0.502	0.110
	Yes	1.04	1.12	[0.98,1.28]	0.110		
Time lived in neighbourhood	>6 years	1.00	1.00			0.105	0.088
	<= 5 years	1.11	1.12	[0.98,1.28]	0.088		
Household composition	Both Parents	1.00	1.00			0.059	0.091
	Other	0.88	0.89	[0.77,1.02]	0.091		
Time		0.59	0.58	[0.53,0.65]	<0.001	<0.001	<0.001

Results are from logistic regression models estimated with Generalised Estimating Equations to account for the dependency across repeated (unstructured working correlation matrix). *Pay and play physical activities include: aerobics, climbing, swimming, gymnastics, hockey, martial arts, netball, and tennis.[1] Adjusted for all other variables of the table.

Table 8.14 Odds ratios (OR) of pay and play physical activity vs. not by neighbourhood trust and social support , adjusting for potential confounders (waves 2 and 3 of the ORiEL Study, n=2,644)*

Exposure		Unadjusted OR	Adjusted OR[1]	95%CI	P-value parameter	P-value unadjusted	P-value adjusted[1]	Gender interaction (p-value) [2]
Neighbourhood trust	Not at all	1.00	1.00			0.005	0.025	0.695
	A little	1.03	0.95	[0.75,1.20]	0.661			
	Some	1.10	1.03	[0.82,1.27]	0.820			
	A lot	1.40	1.27	[0.99,1.63]	0.058			
	Trend†	1.12	1.09	[1.02,1.17]	0.013	0.001	0.013	0.850
Social support – friends	Low	1.00	1.00			0.975	0.891	0.528
	Medium	1.00	1.00	[0.86,1.17]	0.982			
	High	1.01	0.97	[0.83,1.13]	0.678			
Social support – family	Low	1.00	1.00			0.624	0.968	0.470
	Medium	1.00	0.98	[0.84,1.15]	0.843			
	High	1.07	0.98	[0.83,1.16]	0.817			
Social support – significant others	Low	1.00	1.00			0.761	0.867	0.847
	Medium	0.99	0.96	[0.82,1.13]	0.621			
	High	1.05	1.00	[0.85,1.17]	0.965			

Results are from logistic regression models estimated with Generalised Estimating Equations to account for the dependency across repeated (unstructured working correlation matrix). [1] Adjusted for gender, ethnicity, health condition, free school meal status, family affluence, time lived in the neighbourhood, household composition and time. [2] The adjusted model was replicated for each outcome with an additional interaction term between gender and exposure. †Exposure modelled as a continuous variable (dose-response relationship) when evidence of improved fit compared to the discrete option (using Generalised Linear Mixed Models). ^ None of the gender-specific associations was significant. *Pay and play physical activities include: aerobics, climbing, swimming, gymnastics, hockey, martial arts, netball, and tennis.

Table 8.15 Odds ratios (OR) of pay and play physical activity predicted by change in neighbourhood trust and social support , adjusting for potential confounders at baseline (n=2,644)*

Exposure	Unadjusted OR	Adjusted OR[1]	95% CI	P-value unadjusted	P-value adjusted[1]	Gender interaction (p-value) [2]
Neighbourhood trust	1.06	1.06	[0.96 , 1.17]	0.223	0.250	0.075
Neighbourhood trust - Boys	1.14	1.13	[1.00 1.29]	0.045	0.059	
Neighbourhood trust - Girls	0.97	0.98	[0.85 1.12]	0.680	0.726	
Social support – friends	0.99	0.99	[0.92 , 1.07]	0.870	0.815	0.702
Social support – family	0.98	0.98	[0.89 , 1.08]	0.723	0.673	0.287
Social support – significant others	0.98	0.98	[0.89 , 1.08]	0.665	0.669	0.264

Results are from proportional odds models estimated with Generalised Estimating Equations to account for the clustering of individuals within schools (independent working correlation matrix). Results are displayed as ORs of improvement in pay and play physical activity status (constant vs. decrease or increase vs. constant) per unit increase in the original scale of neighbourhood trust or tertile change in social support. ORs > 1 indicate a positive change in the outcome as a response to an improvement in the exposure.
[1] Adjusted for gender, ethnicity, health condition, free school meal status, family affluence, time lived in the neighbourhood and household composition at wave 2. [2] The adjusted model was replicated for each outcome with an additional interaction term between gender and exposure. *Pay and play physical activities include: aerobics, climbing, swimming, gymnastics, hockey, martial arts, netball, and tennis.

Finally, I also produced results from a complete case analysis (Appendix G section G.7). Combined results from the imputed datasets attenuate the estimates of the parameters for which significant associations are observed. In some of the models (e.g. walking to school and outdoor physical activity), conclusions about differences in the associations by gender differ substantially. This confirms the results from the analysis of missingness, which suggested that coefficients from the complete case analysis would be slightly biased (Appendix G section G.1). Despite the bias, however, the general conclusions about the directions of the main associations are not seriously affected in the complete case analysis.

8.5. Summary

In this chapter, I have explored associations between two aspects of the social environment, namely neighbourhood trust and social support and four physical activity outcomes. I explored whether each of the exposure variables was associated with the outcomes using pooled longitudinal models and models for within individual change scores in the exposure and in the outcome. I also tested whether the observed associations differed for boys and girls.

To do so, I first handled item missingness based on a MAR assumption. I applied the multilevel multiple imputation strategy developed in chapter 6, which accounts for the hierarchical structure of the data and imputed the data separately by gender.

Using 20 imputed datasets, I have shown that neighbourhood trust is positively associated with outdoor physical activity and with pay and play physical activity (question 1). I have found very limited evidence that it is associated with walking for leisure and I have found no evidence of association with walking to school. Most of the evidence regarding the association between neighbourhood trust and physical activity outcomes comes from the pooled longitudinal model (question 1.1.). In the models for within individual change scores, I found only limited evidence of association with any of the physical activity outcomes (question 1.2.). I have finally found evidence of gender interaction for the within individual change model for pay and play physical activity. Results show that there is some evidence of positive association between change in trust and change in pay and play physical activity status in boys, but not in girls. Overall, however, the associations between neighbourhood trust and physical activity outcomes do not seem to differ by gender (question 1.3.).

Different associations were found between the three sources of social support (friends, family, significant others) and the physical activity outcomes (question 2). I have found consistent associations between walking for leisure and social support. The pooled longitudinal analysis indicates the presence of a positive dose-response association with all three sources, although social support from family seems to have the strongest association (question 2.1.). The models for within individual change scores confirmed that social support, in particular from friends, could have a rather immediate effect on walking for leisure (question 2.2.). No consistent association was found between social support and walking to school, outdoor physical activity, or pay and play physical activity. I have nevertheless found some evidence of gender interactions for walking to school and for outdoor physical activity (question 2.3.). There is weak evidence that, in girls, within individual increase in social support from significant others is associated with higher chances of positive change in walking to school. In boys, there is strong evidence that higher social support, especially from friends, and potentially from family, increases the odds of outdoor physical activity, which is a form of physical activity prevalent amongst boys. The latter results were not confirmed however by the within individual change models.

Taken together, these results confirm the relevance of neighbourhood trust and social support in explaining differences in some forms of physical activity. The two types of exposure indicate associations with some form of physical activity in the expected directions, however, results were not as consistent as initially hypothesised.

Chapter 9: Discussion and conclusion

9.1. Introduction

This chapter concludes the thesis by discussing how and to what extent the research aims outlined at the end of the literature review have been addressed by the methods, data analysis and interpretation of findings presented here. As stated in section 2.5., this thesis is an investigation of the associations between features of the neighbourhood and home environments and physical activity in adolescents. The aims of this thesis were to:

1. Investigate longitudinal associations between perceptions of the neighbourhood environment and three physical activity outcomes;
2. Explore the associations between ethnic density and three physical activity outcomes;
3. Investigate longitudinal associations between neighbourhood trust and four physical activity outcomes;
4. Investigate longitudinal associations between social support and four physical activity outcomes.

These aims were investigated using the three waves of data collection from the ORiEL study, a representative dataset of adolescents living in East London before and after the London 2012 Olympic and Paralympic Games. Across the analyses, I have applied generalised estimating equations (GEE) methods to account for clustering of the data and handled item non-response using multilevel multiple imputation.

This thesis has advanced the field methodologically and empirically by applying novel analytical approaches to important research questions in the field. In this chapter, I first discuss the analytical innovations applied to this area of study, focusing on how they advance understanding in this field. I then discuss the findings generated from the application of these analytical approaches to a series of original research questions. Bringing these findings together, I discuss the general contributions of this thesis to the research area. I finally discuss the strengths and limitations of this study, possible avenues for future research, policy implications, and provide a general conclusion.

9.2. Analytical innovations applied to the area of research

In this thesis, I have contributed to the literature on the determinants of physical activity by applying innovative quantitative methods. In particular, I have carefully selected and applied an appropriate analytical strategy to model longitudinal data when the exposures and outcomes change over time and I have implemented a sophisticated method to account for item non-response in clustered data.

9.2.1. Prudence when modelling longitudinal and clustered data

Longitudinal data on the relationships between micro-environments (e.g. neighbourhood, home, school) and physical activity are becoming more common, even if the majority of the literature remains cross-sectional (Sallis et al. 2016). Longitudinal study designs are welcome improvements as they can provide better evidence for the existence of hypothesised causal relationships (Fitzmaurice et al. 2011). Various modelling options for discrete data, including marginal models, random effects models and fixed effects models have been applied in the field in recent years (Datar et al. 2013, Kerr et al. 2015, Knuiman et al. 2014, Ranchod et al. 2014). Although marginal models have been praised in the field for the interpretability of their coefficients (Hubbard et al. 2010, Lovasi & Goldsmith 2014), they are far from being the most popular methods in practice. A current limitation in the growing body of longitudinal studies is that the strengths and limitations of each modelling approach are not always well acknowledged (Lovasi & Goldsmith 2014).

In this thesis, I provide a clear rationale for the analytical approach used to model longitudinal data for discrete responses, and explain why marginal models estimated with GEE are the preferred option. I argue that fixed effects models are likely to be ill suited when the follow-up period is short, when there are few waves of study and when the exposure does not change quickly over time. Fixed effects models have been supported in the literature for being able to handle unmeasured confounding associated with self-selection of individuals within neighbourhoods (Knuiman et al. 2014). A major drawback however is that the method is very inefficient, which means that it leads to wide standard errors, which is why the statistical literature recommends against using them without assessing their relevance to the specific context of the current research (Fitzmaurice et al. 2011, Wooldridge 2010). Using fixed effects models in inappropriate circumstances might, in some contexts, lead to misleading conclusions with respect to the association between physical activity and their correlates, as I suspect to be the case in some empirical studies (Kerr et al. 2015).

In addition to providing a strong rationale and promoting more caution about the method used, I also explored an analytical strategy rarely used in the field, namely estimating proportional odds models with GEE. This approach is appealing because it handles ordinal outcomes while providing a marginal interpretation of the parameters. These models might be more relevant to the field because ordinal outcomes are likely to be increasingly common when measuring physical activity or change in physical activity (Lovasi & Goldsmith 2014). An illustration of how to fit marginal models for ordinal outcomes is therefore another contribution of this thesis[30].

9.2.2. Implementation of multilevel multiple imputation with longitudinal data on neighbourhood effects

I have also contributed to the field by applying a recently developed analytical strategy to handle item non-response for clustered data with multilevel multiple imputation. This is important because item missingness is widespread in clustered data commonly used in neighbourhood effects studies. The growing availability of longitudinal data in the field adds a third level of hierarchy in the data that needs to be accounted for in the analytical strategy used to handle missing data. Using the recently developed 'jomo' R package (Quartagno et al. 2018), I have shown that it is possible to effectively use multilevel imputation models for answering typical epidemiological questions involving many discrete variables, a 3-level hierarchical structure (repeated measurements, individuals, areas/schools) and interaction terms.

The empirical literature on neighbourhood effects reviewed in this thesis largely ignored potential bias and loss of information due to missing data. Most studies tend to drop cases with missing data (Crawford et al. 2010, Kerr et al. 2015, Remmers et al. 2014, Stafford et al. 2009), while some used single imputation strategies (Hirsch et al. 2014, Powell-Wiley et al. 2017). In contrast, very few studies handled missing data using multiple imputation; and those

[30] The use of this analytical strategy in the thesis also shows some of the limitations of the current statistical literature. Indeed, to my knowledge, no general statistical software allows the user to test the proportional odds assumptions when models are estimated with GEE and/or combined with multiple imputation (Donneau et al. 2015).

that did so, did not account for the hierarchical structure of the data in the imputation model (Astell-Burt et al. 2012).

In this thesis, I proposed a general strategy for handling missing data in neighbourhood effect studies with a 3-level hierarchical structure. I showed that it is important to describe the extent of missing data and to assess the potential impact of missingness on bias in order to verify the validity of a complete case analysis. Having shown that a complete case analysis was likely to be biased, I proposed an imputation strategy based on the missing at random (MAR) assumption that can account for datasets with a 3-level structure, as long as there are not too many repeated measurements on the same individuals. The imputation strategy was a development of the approach used by the ORiEL research team (Clark et al. 2017, Cummins et al. 2017, Fahy et al. 2016, Smith et al. 2015a) with two major improvements. First, I proposed imputing the data in the wide format to allow for a full account of the 3-level data structure (i.e. by implementing clustering at school-level as opposed to accounting for repeated measurements and including school as fixed effect, as done by the ORiEL team). Second, I used the computationally efficient 'jomo' R package (Quartagno et al. 2018) which allowed for the inclusion of more discrete variables in the imputation model and imputed the data much faster than the REALCOM Impute software (Carpenter et al. 2011). Results from the imputed data were mostly similar to the complete case analysis in terms of the direction of the associations but the strength of the associations was mostly reduced once the data was imputed and results combined into a final inference. This means that interpretation of a complete case analysis would have led to the wrongful conclusion that the associations between the neighbourhood and home environments and physical activity were of greater magnitude than they appear to be.

In sum, the methodological contribution of this thesis was to illustrate how multilevel multiple imputation can be used to account for 3-levels structures of a dataset that includes many discrete variables with missing values. The same analytical strategy could easily be applied to studies with similar data structures (e.g. a few repeated measurements themselves clustered at school, home or neighbourhood levels), which are expected to become more common in the field.

9.3. Discussion of the main results

In this thesis, I have applied these innovative analytical approaches to answer important research questions on the role of the neighbourhood and home environments in explaining physical activity behaviours in adolescents. I have shown in chapter 2 that the evidence base for most of the questions tackled in this thesis is sparse in adolescents, specifically in deprived and ethnically diverse populations. I have contributed to the field by providing robust cross-sectional and longitudinal evidence on the significance of perceptions of the neighbourhood environment (chapters 5 and 6), ethnic density (chapter 7), neighbourhood trust (chapter 8) and social support (chapter 8) to explain common forms of physical activity in adolescents. The following sections summarise these results and interpret them in light of the literature and current UK context.

9.3.1. Perceptions of the neighbourhood and physical activity

In this section, I discuss the results reported in chapters 5 and 6 on whether perceptions of the neighbourhood were associated with physical activity. Following a preliminary analysis of the complete cases at baseline (chapter 5), I examined whether five measures of perceptions of the neighbourhood – bus stop proximity, traffic safety, street connectivity, enjoyment of the neighbourhood for walking/cycling, and personal safety – were associated with three common forms of physical activity, after controlling for individual socio-demographic characteristics. The physical activity outcomes analysed were walking to school, walking for leisure and outdoor physical activity.

Longitudinal analyses indicate little evidence that perceptions of the neighbourhood and their change over time are important predictors of adolescents' physical activity and their change over time in the ORiEL study. Specifically, walking to school and its change were not associated with any of the five measures of perceptions, or changes in these perceptions over time. There was some evidence that greater perceived proximity to bus stops is associated with a small decrease in the probability of walking for leisure. The degree of evidence was somewhat stronger when the exposure was operationalised as a trajectory of change within the same adolescents. This means that a within individual increase in bus stop proximity is associated with a higher probability of ceasing walking for leisure over time. Results also indicate that poorer perception of personal safety increases the probability of walking for leisure. There was some indication that better perception of street connectivity is associated with more outdoor physical activity. Finally, despite evidence that physical activity outcomes and some perceptions differ by gender (cf. section 3.5.1.), I found very little evidence that the associations between perceptions of the neighbourhood and physical activity differed by gender.

Despite the limited number of investigations on associations between perceptions of the neighbourhood and physical activity in adolescents, these results provide more evidence to support the argument that perceptions of the neighbourhood are not an important factor in explaining physical activity in adolescents and its change over time (Davison & Lawson 2006, Ding et al. 2011, Sterdt et al. 2014). Although few studies have been previously conducted in deprived adolescent populations (Bauman & Bull 2007), these results might be surprising in light of some literature that suggests that deprived populations are expected to be more affected by some aspects of their neighbourhood such as disorder and crime neighbourhood (Lovasi et al. 2009).

An important element of this thesis has been the exploration of different ways of conceptualising the exposure-outcome association – as a general association with the outcome, an association with exposure accumulation, and an overall association between trajectories. Measuring the general prediction of exposure had the greatest power to detect associations as they use both longitudinal and cross-sectional sources of information (Agresti 2002, Fitzmaurice et al. 2011), whereas the latter two approaches restricted the analyses to within individual change. The findings reported here suggest that there is no evidence to support the hypothesis that the accumulation of past perceptions of the environment has an impact on current physical activity, and very limited evidence to support the hypothesis that the overall trend in perception of the environment is associated with the trend in physical activity. This might reflect the fact that the perceptions of the neighbourhood environment measured were not consistent and fluctuated over time (cf. section 3.5.2.1.). These modelling strategies could nevertheless be relevant for future analyses in different contexts.

A few of the associations explored deserve a detailed discussion. In the literature, recent convincing cross-sectional and longitudinal evidence has been documented on the association between access to recreational facilities and various forms of physical activities (Davison & Lawson 2006, Ding et al. 2011, Wong et al. 2014). These associations could not be appropriately explored with the data at hand, given that the question on perceived proximity to destinations in the ALPHA questionnaire refers to the nearest facility in general (Spittaels et al. 2010). Unfortunately, this measure seems to poorly capture accessibility to the broader range of sport and recreational facilities available in the neighbourhood (Scott et al. 2007). Not surprisingly, none of the baseline associations related to recreational facilities indicated any evidence of association with the physical activity outcome, and the association was therefore omitted in the longitudinal analyses.

Amongst the items measuring proximity to destinations in the ALPHA questionnaire, bus stop proximity appeared to be relevant for some forms of physical activity. It was expected that perception of closer proximity to a bus stop would decrease the odds of walking to school, given that adolescents younger than 16 year old can travel by bus free in London (Transport for London 2018). A negative association was observed, but it did not reach significance. However, a significant negative association was found between within individual change in perception of bus stop proximity and change in walking for leisure. This association could indicate shift in behaviour during adolescence toward greater independent mobility and associated increased awareness of the local environment. Previous studies in London have indeed indicated that the introduction of free buses in London has been associated with a reduction in the number of trips by walking, but has at the same time allowed adolescents to reach other destinations (Green et al. 2014). It might therefore be that an increase in bus use as adolescents get older and become more independent might be associated with the replacement of walking for leisure by other forms of activities.

Findings on the associations between crime-related safety and physical activity found in this thesis deserve to be discussed in light of the literature (An et al. 2017, Carver et al. 2008, Davison & Lawson 2006, Panter et al. 2008). Compared to general neighbourhood safety, it is hypothesised that fear of crime, stranger danger and personal safety – all three involving emotions and anxiety – are expected to be stronger predictors of physical activity by bringing about self or parental constraint on outdoor physical activities, including walking (Foster & Giles-Corti 2008). These associations have been confirmed in qualitative studies (Lorenc et al. 2013) and are expected to be particularly relevant in deprived populations, which are more at risk of crime-related safety problems (Lovasi et al. 2009). Despite these theoretical expectations, I only found some evidence of association between the MESA item on personal safety ('I feel safe walking in my neighbourhood, day or night') and walking for leisure. This corroborates the inconsistent results observed in previous, mostly cross-sectional, quantitative investigations (Alton et al. 2007, Davison et al. 2008, De Meester et al. 2013, Esteban-Cornejo et al. 2016, Gómez et al. 2004, Molnar et al. 2004, Panter et al. 2008, Prins et al. 2009). Differences in the outcome measurement, exposure measurement (parents' perceptions vs. adolescents'), study design (longitudinal vs. cross-sectional) or study setting do not appear to explain inconsistencies found in the current quantitative literature.

Two general factors might explain why few associations were observed between perceptions of the neighbourhood and physical activity in this thesis. First, the measures of physical activity used are not specific to a context location (e.g. park, neighbourhood), which can lead to an underestimation of the associations with perceptions of the neighbourhood (Ding et al. 2011, Sallis et al. 2006). Although the study of different forms of physical activity (i.e. walking to school, walking for leisure and outdoor physical activity) is already a conceptual improvement compared to most studies in the field (Ding et al. 2011), the use of location-specific measures of physical activities is likely to increase the consistency of the results, as illustrated by some recent cross-sectional studies (D'Haese et al. 2015, Esteban-Cornejo et al. 2016). Second, adolescents' perceptions of the neighbourhood might simply not matter for physical activity. In this study, within adolescent perceptions of the neighbourhood substantially varied over time (cf. section 3.5.2.1.). This could indicate that adolescents aged 12-14 years old do not have well-formed perceptions of their environment, and that their behaviours might still depend more on their parents and their parents' perceptions of the neighbourhood. Esteban-Cornejo et al. (2016) showed that US adolescents of a similar age tended to have different traffic-related and crime-related safety perceptions than their parents. The authors indicated that most parents' perceptions were associated with some forms of physical activity, whereas adolescents' perceptions were unrelated.

9.3.2. Own-group ethnic density and physical activity

Associations between own-group ethnic density and physical activity were examined in chapter 7. In that chapter, I explored whether own-group ethnic densities were associated with physical activity in a deprived adolescent population, after controlling for individual socio-demographic characteristics. Sub-group analyses for each ethnic group for walking to school, walking for leisure and outdoor physical activity for both school-level and neighbourhood-level own-group ethnic densities were conducted.

Ethnic densities at school- and neighbourhood-levels are associated with some physical activity outcomes. There was consistent evidence that school-level ethnic density is associated with walking to school. The direction of the association indicates that a higher ethnic density amplifies ethnic-specific propensity to walk to school. Indeed, a higher ethnic density seems to additionally increase the propensity to walk to school in the Bangladeshi adolescents; conversely, it seems to decrease it in the White Mixed and Black African groups, which are groups with lower prevalence of walking to school. No prior study has examined the association between ethnic density and physical activity in the UK (Bécares et al. 2012b), but some studies on smoking have reported comparable results. In particular, a large study conducted using electronic health records of adults from the boroughs of Hackney, Lambeth, Newham and Tower Hamlets showed that the negative association between smoking and ethnic density was greater in ethnic minority groups where smoking was the least socially accepted (Mathur et al. 2017). Another study conducted in a deprived population (Uphoff et al. 2016) also indicated that a higher South Asian density was associated with a lower probability of smoking during pregnancy in the Pakistani women, a group in which smoking is uncommon, whereas no protective effect was found amongst the White British women.

As discussed in section 2.4.2.1., there are three main theoretical pathways by which ethnic density might influence health and health-related behaviours (Bécares & Nazroo 2013, Bécares et al. 2009, Das-Munshi et al. 2010, Halpern & Nazroo 2000, Karlsen et al. 2012, Pickett & Wilkinson 2008). Own-group ethnic density might: i) increase civic engagement; ii) increase social capital and social support; and iii) reduce exposure to racism and discrimination. With respect to walking to school, the latter two processes are likely to be more salient. An increase in neighbourhood social capital and social support might in addition provide resources to cope better with experiences of racism and discrimination. As a result, experience of racism might not translate into a change in health behaviours. The three hypothesised pathways imply that higher ethnic density might provide greater opportunities to conduct ethnic-specific preferred health behaviours, which can lead to an amplification of ethnic differences if these cultural norms differ by ethnic group.

Explaining observed associations in terms of amplification of ethnic-specific cultural norms seems plausible in this context. Previous studies have shown differences of knowledge, norms and expectations about health behaviours across ethnic minority groups (Koshoedo et al. 2015, Rawlins et al. 2013). In addition, studies have shown that 'homophily' or the tendency for friendships to form between those who are alike, is more frequent amongst ethnic minority groups, and that adolescents tend to adopt health behaviours that are similar to their friends' behaviours (Lorant et al. 2016). These behaviours have been recognised as being both potentially positive and negative for health. Alternative explanations have been offered in the literature to explain ethnic differences (Nazroo 2014), but these seem less consistent with the amplification phenomenon observed. One of those alternative explanations is that observed associations might reflect the degree of acculturation, or the fact that ethnic minorities shift their behaviour over time and become more westernised so that health-related cultural differences between minority groups and the majority diminish (Bécares et al. 2011, Pickett et al. 2009). Acculturation might indeed confound the amplification phenomenon. In the ORiEL study, however, I have found no evidence of association between the physical activity outcomes and either country of birth or language spoken at home in the ethnic group studied. Although acculturation might not be fully captured by the two variables (Bécares et al. 2011), these should at least have displayed some indication of an association if acculturation was playing a major role. Another alternative explanation for the results observed might come from differences in racism and discrimination across ethnic groups. Racism is considered as having a central role in the development of ethnic inequalities in health, and might affect perceived safety, fear of crime and health behaviours (Foster et al. 2014a,b; Karlsen et al. 2012, Lorenc et al. 2013, Rawlins et al. 2013). However, the experience of racism alone would not be enough to explain why the association with ethnic density is positive for some ethnic groups and negative for others. Therefore, it is plausible to explain these results in terms of amplification of ethnic-specific cultural norms, which might themselves, but not necessarily, have been the result of broader contextual and structural socio-economic inequalities (Karlsen & Nazroo 2002, Nazroo 1998).

The associations observed for walking to school should be interpreted cautiously for the following reasons. First, despite being in the expected direction, associations are modest and not statistically significant in all ethnic groups. The strength of the association indicates that a 10 percent increase in ethnic density is estimated to increase the odds of walking to school by 0.44 to 1.10. Second, no clear associations were found with the other physical activity outcomes. The only other consistent evidence of an association was for the White UK group, for whom a higher ethnic density decreases the odds of outdoor physical activity, which is less popular in that ethnic group compared to others. The reasons for inconsistent results relating to walking to school and outdoor physical activity are not clear. A possible explanation for outdoor physical activity might be the composite nature of the measure, which pools a series of activities with different levels of popularity across ethnic groups, and therefore dampens differences.

In chapter 6, I also compared the relative importance of school-level and neighbourhood-level ethnic density in explaining differences in physical activity. As expected, school-level density appears to matter more for walking to school, and neighbourhood-level ethnic density for outdoor physical activity. Where associations were observed, they were usually for both measures in partially adjusted models. However, in models adjusted for both ethnic density measures, only one of the measures would usually remain significant. A notable exception are Bangladeshi adolescents, for whom stronger associations between neighbourhood-level ethnic density and walking to school were observed, but no significant associations were found in the fully adjusted model. These results can be explained by the overlap between school-level and neighbourhood-level density measures in that group (r=0.69), and the fact that the ethnic density of Bangladeshi adolescents was very high in some schools (up to 80%), reaching a potential threshold above which an increase in ethnic density might not have any further effect. Astell-Burt et al. (2012) have also investigated the relative influences of neighbourhood and school-level densities in adolescents in London and reported negative associations with perception of racism, but the authors did not compare the relative influence of the two measures.

9.3.3. Neighbourhood trust and physical activity

In chapter 8, I explored associations between neighbourhood trust and four physical activity outcomes. I hypothesised that a positive perception of neighbourhood trust was likely to favour time spent outdoor in the neighbourhood and related physical activities, as well as participation in structured forms of physical activity by adolescents, after controlling for individual socio-demographic characteristics.

This investigation is based on the premise that increased trust in others is an indication of increased cognitive social capital, which is likely to translate into an increase in social contagion, collective efficacy, and informal social control mechanisms (Kawachi & Berkman 2014, Kawachi et al. 1999, Sampson 2012). These three processes have been hypothesised to have potential benefits for health in general but also for health-related behaviours such as physical activity (Kawachi & Berkman 2014).

Perceived neighbourhood trust was positively associated with outdoor physical activity and with pay and play physical activity. However, there was very limited evidence for an association with walking for leisure and no evidence of an association with walking to school. Few studies have investigated the associations between trust (or social capital more broadly) and physical activity in adolescents. Although based on different measures, those studies found positive associations with physical activity. Carroll-Scott et al. (2013) showed that adolescents of a similar age to ORiEL participants were likely to report more days of exercise if they also reported greater presence of social ties with friends and neighbours. In Chicago, Cradock et al. (2009) also indicated that adolescents from diverse neighbourhoods were more likely to participate in sports activity and to report physical activity at follow-up if they were living in a neighbourhood that had higher baseline level of social cohesion. In cities in the US, Franzini et al. (2009) found that parent-reported collective efficacy, collective socialisation of children, exchange and social ties among neighbours were positively correlated with self-reported physical activity. Kimbro et. (2011) also reported a small but positive association between collective efficacy and physical activity in young children, as reported by their mothers. Finally, a recent cross-national study indicated that in high-income nations collective efficacy was associated with objectively-measured total physical activity in 9-11 year old children (Sullivan et al. 2017).

Another result of these analyses is that I found very little evidence that gender moderates the associations between neighbourhood trust and physical activity. The few studies that investigate such associations did not report significant gender differences either (Lindström 2011).

The findings reported here are the first to investigate associations between trust and different forms of physical activity in the UK. Despite the fact that associations with walking for leisure were not very consistent, trust is positively associated with all investigated forms of *leisure-time* physical activity, i.e. walking for leisure, outdoor physical activity, and pay and play physical activity. This suggests that the same underlying mechanisms might be at play, which is consistent with the fact that studies using total (recreational) physical activity as an outcome found similar positive associations. In contrast, I found no evidence of an association with *utilitarian* walking, measured as walking to school. This is also consistent with a recently reported study conducted in adults living in European cities that reported a negative association between neighbourhood-level social cohesion and transport-related physical activity (Mackenbach et al. 2016).

In the analyses conducted in this thesis, most of the evidence for an association between neighbourhood trust and physical activity comes from pooled longitudinal models, in which the association comes either from cross-sectional information or from within individual changes over time. I also conducted some analyses to relate within individual changes in the exposure to within individual changes in each of the outcomes. These models showed very limited evidence of associations. Interestingly, however, a model for boys indicated that an increase in neighbourhood trust over time was associated with an improvement in pay and play physical activity. This result suggests that, despite the very short period of time in which change is observed, improvement in neighbourhood trust or social capital more broadly, might have positive consequences for physical activity. These analyses should be replicated in different contexts using longer follow-ups in order to identify whether observed within individual associations apply to all forms of recreational physical activity. Unfortunately, there are currently very few longitudinal investigations of the relationship between any aspect of social capital and physical activity in the literature.

Overall, the results described in this thesis are consistent with the literature and indicate an association between recreational physical activity and neighbourhood trust. The magnitude of the association is small however, which suggests that neighbourhood trust only marginally contributes to explaining differences in physical activity.

9.3.4. Social support and physical activity

In chapter 8, I investigated the association between three sources of social support and four physical activity outcomes. I tested whether support provided by family, friends and significant others was associated with physical activity, after controlling for individual socio-demographic characteristics. Exploration of the associations with social support were conducted with walking to school, walking for leisure, outdoor physical activity, and pay and play physical activity.

I found consistent associations between social support and walking for leisure. Pooled longitudinal analysis indicates the presence of a positive dose-response relationship with all three sources of support, although social support from family has the strongest association. No consistent associations were found between social support and walking to school, outdoor physical activity, or pay and play physical activity. Some significant interactions with gender were reported.

These results contrast somewhat with the literature on social support and physical activity in young people in which consistent positive associations have been reported (Beets et al. 2010, Laird et al. 2016, Mendonça et al. 2014, Yao & Rhodes 2015). There are several possible reasons for this. First, the present study did not include a measure of total physical activity, for which positive association might be observed. In this thesis, I found positive associations for walking for leisure and suggestions of associations for outdoor physical activity (the other two measures displaying ORs close to 1.00). There might, therefore, be positive overall associations between the sources of social support studied and total physical activity. Second, the absence of reference to physical activity in the social support instrument used in this thesis, namely the Multidimensional Scale of Perceived Social Support (MSPSS), might also be a factor. In contrast to the MSPSS, social support tools used in the physical activity literature, such as the Activity Support Scale (Davison & Jago 2009), make explicit reference to physical activity. It has even been suggested that social support measurements should be specific to the activities under investigation because each domain of physical activity might require different forms of support (Beets et al. 2010). As a result, having an overall measure of social support might under-estimate associations between social support and the forms of physical activity studied in this thesis. Third, the MSPSS is general and does not make any reference to the type of support received (Zimet et al. 1990). The MSPSS is particularly relevant to predicting mental health outcomes (Dahlem et al. 1991) and seems to better capture emotional aspects of social support. Questionnaire items include, for example, ‘my family is willing to help me make decisions’, ‘I can talk about my problems with my friends’, or ‘there is a special person in my life who cares about my feelings’. Instrumental support, co-participation and modelling, which were all shown to be relevant aspects of social support for physical activity (Beets et al. 2010, Laird et al. 2016, Mendonça et al. 2014), are not explicitly mentioned in the MSPSS instrument. Therefore, if adolescents were receiving non-emotional forms of support, they might not have reported it in the MSPSS. In particular, more structured activities captured by pay and play physical activity typically require instrumental support from the parents, such as paying participation fees, buying equipment, and providing transportation (Edwardson & Gorely 2010). The absence of association reported in this thesis might then reflect the fact that such aspects of social support are poorly captured by MSPSS.

In this thesis, consistent positive associations were found between social support and walking for leisure. Few studies have investigated these associations, however, some associations were documented for leisure-time physical activity in general (Beets et al. 2010). Using adult samples from Portugal and Belgium, De Bourdeaudhuij et al. (2005) indicated that social support from friends and from family were associated with various forms of physical activity, including walking for leisure. Using a larger sample of Australian women, Ball et al. (2007) also indicated positive associations between social support from family and recreational walking in adults. Despite the presence of these associations in adults, associations between types of social support might be quite different in children and adolescents. The reasons for only finding significant positive association with walking for leisure in the ORiEL study are not clear. A possible explanation is that walking for leisure is the outcome measure that is most affected by overall positive emotional support.

Results related to walking for leisure also indicate that within individual change in social support was associated with change in walking for leisure. Significant associations were found for social support from family and friends, with stronger evidence for the role of friends. These results are consistent with the few studies that investigated changes in social support and changes in physical activity (Davison & Jago 2009, Dowda et al. 2007, Lau et al. 2016, Zook et al. 2014). These generally showed that increasing or maintaining general social support and encouragement from parents and friends during adolescence matters for physical activity. In this thesis, I was able to show that changes in social support over a very short period were associated with changes in walking for leisure. This indicates that interventions targeting social support might have benefits for that form of physical activity.

When exploring whether results might differ for boys and girls, I found some evidence that gender moderated the associations for walking to school and for outdoor physical activity. In boys, I found strong evidence that higher social support from friends, and possibly from family, increases the odds of outdoor physical activity. The presence of an association is consistent with the literature. Previous studies on social support from friends have indicated that emotional support, such as encouragement and co-participation were consistently associated with leisure-time physical activity (Mendonça et al. 2014). Emotional support from parents has also been shown to be related to leisure-time physical activity (Mendonça et al. 2014). However, the fact that the association was only observed for boys was not expected. An explanation might be that boys were sometimes shown to receive more social support for physical activity than girls (Beets et al. 2010). Whereas boys and girls receive similar amount of social support in the ORiEL study according to the MSPSS, the type of support received might differ for boys and girls and be more relevant to physical activity for boys (e.g. transportation, co-participation, encouragement). Another caveat of these results is that they were not observed in the within individual change models. This means that there is not enough evidence that within individual change in social support between the wave 2 and the wave 3 of the study lead to an increase outdoor physical activity in boys, unlike the evidence reported for walking for leisure.

Finally, there is weak evidence that within individual increase in social support from significant others in girls is associated with change in walking to school. This finding is hard to interpret because no similar association is observed in the pooled longitudinal analysis.

9.3.5. Interpretation of the results in the context of urban regeneration and social changes in East London at the time of the Olympic Games

The wider applicability of findings presented in this thesis should be considered in light of urban regeneration and social changes affecting the study area around the time of the London 2012 Olympic and Paralympic Games. The bid to host The London 2012 Games was centred on creating the first ‘Legacy Games’ and was grounded on leaving a lasting legacy for the residents of East London, with a particular focus on young people. This was to be achieved through improvements to infrastructure and housing, stimulating economic development and aiming to ‘inspire a generation’ to be more physically active. The majority of urban and social changes linked to the Olympics and Paralympics Games occurred in the London Borough of Newham, site of the main Games venues, visitor spaces and athletes village.

Adolescent participants in the ORiEL cohort would have been exposed to varying degrees of change in their local environments as a result of construction and regeneration activities brought about by the London 2012 Olympic and Paralympic Games. Regeneration relevant to the ORiEL cohort primarily consisted of the construction of services, infrastructure and facilities supporting the Olympic Park and Stratford City developments. Regeneration components comprise transport networks (walking/cycling paths and public transport); new and refurbished civic space, parks and green areas; improvements in accessibility to services and facilities of communities on the periphery of the regeneration sites and development of retail, business and community facilities (Cummins et al. 2017). Access to most new facilities and services, and improved public realm was not possible until after the Games, with the Olympic Park itself first opening in July, 2013. Olympic regeneration projects have acted to accelerate the ongoing urban regeneration that has been taking place in East London for the last two decades. Although the Olympic regeneration generally contributed to improving the urban infrastructures in East London, by the same token, it has also been suggested to have negatively affected pre-existing local communities by accelerating the gentrification and displacement of lower-income households (Watt 2013).

In addition to urban regeneration, a series of Olympic-related activities might have affected the local communities, before, during and after the Games. These short-term events mainly aimed to engage the local residents with the Games, and were coordinated around a series of arts, sporting and social programmes such as the 2012 Cultural Olympiads, the London Prepares Series, the London 2012 Inspire programme, as well as other activities (e.g. the opportunity to volunteer during the Games; the availability of local authorities budgets for the improvement of neighbourhood aesthetics). The local areas that hosted the Games were finally particularly affected during the 'Games-time', which resulted in a massive influx of visitors, an increased presence of police in and around the Olympic Park (which was associated with a temporary increase in perception of safety), and an improvement of transport access (Thompson et al. 2015).

These physical, economic and social transformations of East London occurring around the time of the 2012 Games contributed to accelerate change processes that were already in operation in East London since the Docklands redevelopment in 1980s. It is likely that aspects of the neighbourhood and home environments examined in this thesis have been affected by these accelerated transformations of East London. In particular, I identified substantial within-individual changes in perceptions of the neighbourhood environment (perceived proximity to nearest bus stop, traffic safety, street connectivity, enjoyment of the neighbourhood for walking/cycling and personal safety), neighbourhood trust and social support. It is therefore possible that the extent of change in these exposure variables is specific to the context of this study and that fewer changes in the neighbourhood and home environments would naturally occur in other 3-year follow-up studies conducted in less dynamic urban settings.

9.4. Contributions to the literature

This study is one of the first large-scale UK investigations of multiple socio-environmental predictors of physical activity in adolescents using a longitudinal design. It therefore fills several gaps in the science. First, most of the evidence regarding the associations between adolescent physical activity and perceptions of the neighbourhood (An et al. 2017, Ding et al. 2011), social support (Laird et al. 2016, Mendonça et al. 2014, Yao & Rhodes 2015), and social capital/cohesion (Lindström 2008) comes from North America and Australia. Although these are high-income countries, the structure of the cities in these countries substantially differs from the European and British contexts. Such differences are likely to affect the neighbourhood environments and context in which physical activity is conducted. Consequently, the underlying mechanisms by which various aspects of the neighbourhood and home environments affect physical activity might differ (Van Dyck et al. 2010). Despite this, the results of this thesis on the associations between social support and neighbourhood trust and physical activity are consistent with the evidence gathered in both high and low-income countries (Sallis et al. 2016). This suggests a form of universality in the results.

Second, deprived and ethnic minority adolescent populations have been understudied in the field (Bauman & Bull 2007). Deprived populations are expected to be more affected by some aspects of the neighbourhood, such as crime and disorder than affluent populations (Lovasi et al. 2009). The ORiEL population is also known to be at higher risk of physical inactivity (Sport London 2017, Stansfeld 2003). Results from the analyses presented in this thesis indicate modest associations, which are in line with the strength of evidence found in less deprived adolescent populations. I have therefore found no evidence that associations between aspects of the neighbourhood and home environments and physical activity might be stronger in a deprived context, compared to the general population.

Third, this study followed adolescents over-time and provides evidence that changes in some features of the neighbourhood and home environments were associated with changes in reported physical activity. Such a large-scale investigation has rarely been conducted to date. This study therefore provides evidence that could be used to design interventions (Bauman et al. 2012). In particular, I have shown that changes in social support and neighbourhood trust within a short time-frame have the potential to affect different physical activity outcomes in adolescents.

Fourth, this study confirms the hypothesis that the determinants of physical activity depend on the domain or type of physical activity (Bauman et al. 2012, Giles-Corti et al. 2005, Sallis et al. 2006). Few empirical studies have systematically investigated the associations between potential determinants and measures of different types of physical activity (see D'Haese et al. (2015) and Esteban-Cornejo et al. (2016) for examples of recent small-scale studies). This thesis confirms that the predictors of physical activity differ by form of activity. I have shown that walking to school was best predicted by ethnic density; walking for leisure by perceived social support; and outdoor and pay and play physical activities by neighbourhood trust. As a result, interventions to increase physical activity are likely to require targeting different determinants, each having a different impact on different types of activity.

Fifth, this thesis has explored several levels of influence on physical activity behaviours depicted in socio-ecological models (Kremers et al. 2006, Sallis et al. 2006). Amongst the environmental, inter-individual, and intra-individual factors studied, the results of this thesis generally indicate that parents might have an important role in shaping adolescents' physical activity. Adolescence has been described as a critical period in the life course marked by rapid growth and development, and is typically characterised by an increasing need for autonomy and a desire to make lifestyle choices that conform to peers (Papas et al. 2007). As children grow up, they spend progressively less time with parents and family and more time with their friends (Larson et al. 1996) and gradually gain more independent mobility from their parents (Mackett et al. 2007). As adolescents begin to explore the environment around them independent of parental influences, the way the neighbourhood is designed – in terms of proximity to destination, street connectivity, traffic safety – was expected to influence adolescents' physical activity (Giles-Corti et al. 2009, Papas et al. 2007). However, in this study, I found little evidence that adolescents' perceptions of the neighbourhood were related to physical activity. This might therefore suggest that despite their greater mobility, adolescents still rely on their parents' perceptions to guide their activity patterns, or that the built environment influences them without being aware of it. The suggestion that parents still strongly influence adolescents' physical activity is reinforced by two other findings of this thesis. First, neighbourhood trust was positively associated with leisure-time physical activity; and second, ethnic density amplifies differences in walking to school. These associations suggest that informal social control and social cohesion within the local and ethnic community influence adolescents' physical activity. Informal social control (i.e. 'eye-on-the-street') has been presented in the literature as one of the factors allowing adolescents to benefit from independent mobility (Giles-Corti et al. 2009). That is, when informal social control is present in the neighbourhood or in the ethnic group, parents are more likely to allow adolescents more independent mobility, which might translate into walking to school, or leisure type of physical activity. The role of parents has finally also been indicated in the results on social support. Whereas emotional support from friends seems to matter to some extent, perceived social support from parents was prominent for walking for leisure. Taken together, these results appear to indicate that parents have a key role in the processes by which the neighbourhood and home environments influence physical activity behaviours.

Overall, the results found in this study indicate that the studied aspects of the neighbourhood and home environments only have a marginal role in explaining differences in physical activity. Most of the associations explored did not reach statistical significance and the magnitude of the associations indicates that only a fraction of the variation in physical activity could be explained by perceptions of the neighbourhood environment, ethnic density, social cohesion/capital and social support in adolescents living in East London. The small magnitude of associations could be partially explained by the use of binary outcomes (Lovasi et al. 2012), imperfect measurements of exposure and outcome variables, and the correction of a bias caused by missing data using multiple imputation. However, previous evidence on the neighbourhood and home environments and physical activity tend to indicate associations of similar size (Mendonça et al. 2014, Yao & Rhodes 2015). It therefore appears that other factors might matter more in explaining why some adolescents are active, and remain active over time, while others are not.

9.5. Strengths and limitations

9.5.1. Strengths

The strengths of this thesis have been emphasised throughout this chapter. A major strength has been the rigorous application of analytical innovations to the area of research (cf. section 9.2.). In particular, I have proposed a clear rationale for using generalised estimating equations (GEE) methods for binary and ordinal outcomes, tested various hypotheses on the nature of longitudinal associations and used multilevel multiple imputation to take into account item non-response.

Additional strengths are inherent to the ORiEL study. ORiEL is a large-scale cohort study that contains state of the art and validated survey instruments on physical activity (Y-PAQ), perceptions of the neighbourhood environment (from ALPHA and MESA questionnaires) and general social support (MSPSS). As a result, this thesis is one of the first large-scale studies to examine the longitudinal associations between features of the neighbourhood and home environments and physical activity in an adolescent population. The Y-PAQ questionnaire, further allowed for the study of four common types of physical activity, and thus explored how different aspects of physical activity were associated with different exposures. The ORiEL study is a representative sample of the ethnic diversity of East London, providing evidence from populations less studied in the physical activity research. The ORiEL study had a high response rate (87% at baseline) and retention rate (73.2% for the 3-wave balanced panel), which is consistent with best practice in other school-based cohorts (Booker et al. 2011).

9.5.2. Limitations

This research also has limitations. It is bound by the measurements available in the ORiEL study (Appendix A), which had been designed to answer different research questions (Cummins et al. 2017). First, the available social support and neighbourhood trust measures are general and do not specifically target physical activity, which could have affected the strength of associations found. Second, physical activity measured by the Y-PAQ is self-reported and might therefore be subject to recall and social desirability biases (Prince et al. 2008). However, the use of objective physical activity measure was not practically possible given the size of the study. Third, the Y-PAQ questionnaire does not have situational reference (Giles-Corti et al. 2005) and did not capture *where* the reported activity was taking place (e.g. garden, neighbourhood, parks). It is expected that a situational reference would have increased the consistency of the associations found with neighbourhood exposure variables (D'Haese et al. 2015, Esteban-Cornejo et al. 2016). Fourth, the physical activity outcomes used had to be dichotomised, which decreases the power to detect associations (Lovasi et al. 2012). Despite these limitations, a strength of the work presented in this thesis has been to improve the understanding of how specific activities relate to different exposures by exploring four forms of physical activity – walking to school, walking for leisure, outdoor physical activity and pay and play physical activity.

Large-scale studies of ethnic minorities are rare in the field, especially in the UK. The ethnic diversity of the ORiEL study is therefore a major strength. From a statistical standpoint, however, the super-diversity of the ORiEL sample was a limiting factor in this thesis. Over 200 ethnic categories were self-reported for minor groups, which resulted in a large and highly heterogeneous 'Other' ethnic group category for which results are difficult to interpret (Smith et al. 2015b). The super-diversity of the sample restricted my ability to explore whether the associations between the neighbourhood and home environments and physical activity differed by ethnic group. Nonetheless, I explored ethnic differences in the ethnic density analyses for the main ethnic groups (chapter 7) and some promising results were found, despite low statistical power.

The ORiEL study is one of the few large longitudinal studies to investigate the association between the neighbourhood and home environments and physical activity. Unfortunately, its short period of follow-up (3 waves; 2 years) restricted the ability to test some of the hypotheses in this thesis. In chapter 6, the hypothesis of the existence of an enduring cumulative and long-term influence of perceptions of the neighbourhood on physical activity only had three data points available. In chapter 7, the influence of time-change in ethnic-density on physical activity could not be tested, given the slow pace at which school-level ethnic density changed over time. In chapter 8, only two data points were available for the exposure variables, which also hampered the possibility of observing associations in terms of within individual changes.

Despite the methodological innovation and rigour of the analyses of this thesis, some caveats to the statistical methods employed should be mentioned. First, I did not test the sensitivity of the missing at random assumption. The use of multilevel multiple imputation under missing at random is already an improvement compared to analyses of the complete cases under missing completely at random, which are unfortunately still the norm in the field. In the presented analyses, there remains a risk that the results might be biased because the data might be missing not at random. Conducting sensitivity analysis to the missing at random assumption is still an area of development in the statistical literature (Carpenter & Kenward 2012) and was therefore beyond the scope of this thesis. Using the ORiEL data, Clark et al. (2017) explored departure from missing at random through tipping-point sensitivity analysis in which data were imputed under missing not at random with increasing departure from the assumption. They concluded that the missing at random assumption was plausible. As many of the variables used in this thesis are common to Clark et al.'s study, bias in the analyses of this thesis – if any – is expected to be small.

A second methodological limitation relates to the use of GEE methods to estimate logistic regression models. GEE methods do not allow to account for the three-level structure of the data (repeated measurements, individuals, schools). Alternative estimation methods such as alternating logistic regression would allow a 3-level structure (Molenberghs & Verbeke 2005).

Nonetheless, the potential benefit of those alternative methods is likely to be marginal because clustering at school-level is expected to be very small. Another limitation has been the use of GEE to account for clustering in cross-sectional models, whereas the data were unbalanced and there were few clusters(n=25). In this context, using the 'sandwich' estimator of the standard errors following the GEE estimation is likely to slightly underestimate the standard errors (Fitzmaurice et al. 2011), which could explain why slightly smaller standard errors were found for the models that accounted for clustering as opposed to the single-level logistic regression models reported in appendices. The extent of bias appears however to be negligible in the analyses of this thesis.

A final methodological limitation is that I was unable to assess causal relationships. The methods used have indicated that changes in the neighbourhood and home environments were associated with changes in physical activity. Although the theory generally suggests that the local environment and its perceptions influence physical activity, the temporal sequencing of the associations could not be assessed. In addition, the methods used did not allow me to take into account the time-varying associations between different states of the covariates and the outcomes over time, which might bias the associations reported (Fitzmaurice et al. 2011, Robins & Hernán 2009).

9.6. Recommendations for future research

Throughout the discussion of study findings, several recommendations for future research have arisen to improve our understanding of the determinants of physical activity. These include:

1. Developing situation-specific measures of neighbourhood and home environments and physical activity to better capture the hypothesised processes, which are expected to depend on the type of physical activity under study.

2. Replicating the analysis on ethnic density using a larger and/or less ethnically diverse dataset. These analyses would serve to test whether the amplification of ethnic differences is also observed in different populations and/or applies to other health behaviours that are expected to be associated with ethnicity.

3. Examining the appropriate geographical scale for capturing ethnic density, beyond administrative geographical areas. This includes exploring measures of ethnic density specific to the activity space of adolescents/adults, and testing whether the most appropriate scale might vary depending on contextual elements, such as the degree of urbanisation and the ethnic composition of the area.

4. Further exploring the relative roles of the built environment, parental and adolescents' perceptions in explaining differences in types of physical activity.

5. Replicating the analyses conducted in this thesis using longer time-series to better assess the associations between time-varying exposure and physical activity outcomes. Alternatively, a well-designed evaluation of an intervention targeting aspects of the environment might also contribute to understanding of the causal nature of the associations investigated.

6. Applying multilevel imputation methods in longitudinal studies that investigate the determinants of physical activity. As the number of longitudinal investigations is expected to increase in the near future, studies with a data structure similar to the one described in this thesis (i.e. few repeated measurements on individuals clustered in schools or neighbourhoods) will become more common. The analytical strategy proposed in this thesis to handle item non-response could be easily implemented in those studies as well.

9.7. Policy implications

This thesis presents evidence that different types of physical activity have differing patterns of prevalence in an adolescent population, and in turn, different types of physical activity are associated with different features of the neighbourhood and home environments. Adolescents' perceptions of their neighbourhood environment (including proximity, aesthetics, street connectivity, traffic safety and personal safety) and changes in those perceptions over time did not consistently predict physical activity. School-level ethnic density increased the chance of walking to school for members of some ethnic groups and decreased it for others. Adolescents with greater trust in their neighbours had higher chances of reporting outdoor physical activity, and pay and play physical activity. Finally, social support from family, friends and significant others was shown to predict walking for leisure and its change over time.

This evidence suggests that there may be no 'one-size fits all' strategy to increase adolescent physical activity and rather that specific policy initiatives should be developed to target specific types of physical activity. Policy initiatives should therefore tailor interventions to modify key neighbourhood and home environment predictors of specific physical activity types. Three specific examples for the design of potential future interventions are outlined below.

First, the results of this thesis show that improving social cohesion (as measured by neighbourhood trust) could increase participation in leisure-time physical activity in adolescents. This aspect of the social environment is potentially modifiable and could therefore be the target of community interventions. Previous research has shown that social cohesion and social capital have benefits beyond physical activity, including mental health and personal safety, and could benefit the broader local community (Kawachi & Berkman 2014). Interventions targeting social capital and social cohesion have focused on the engagement of residents in the construction of more attractive urban places (Semenza et al. 2007), or have involved multiple-component community engagement programmes (e.g. 'Well London' programme (Frostick et al. 2017)). Whereas some interventions have successfully increased social cohesion and social capital, it remains unclear whether such interventions might bring about changes in the outcome of interest, which is leisure-time physical activity in this context.

Second, I have identified that social support is longitudinally associated with walking for leisure. Social support is another modifiable aspect of the social environment and could therefore be the target of policy interventions at family or community levels. Although the evidence found in this thesis is limited, the evidence that social support positively influences physical activity is well established (Sallis et al. 2016). The current evidence suggests that interventions should prioritise parental encouragement and instrumental support for physical activity (e.g. equipment, transport to a physical activity facility). The role of peers should also be considered, in particular co-participation and encouragement. To date, there is limited evidence on the effectiveness of either family-based or peer-based interventions targeting social support for physical activity (Van Lippevelde et al. 2012). Suggested forms of interventions include parental training, family counselling and preventive messages on the benefits of physical activity for children, or the use of social media to promote physical activity participation within networks of friends (Lau et al. 2016). Future interventions targeting social support are likely to benefit some aspects of physical activity, given that social support is the most consistent predictor of physical activity.

Third, the results of this thesis indicate that interventions targeting the determinants of physical activity should be tailored to the population of interest. For example, this thesis has shown that own-group ethnic density increased walking to school in some ethnic groups and decreased it in others. This suggests that there may be underlying ethnic- or cultural- specific norms towards physical activity that may moderate the impact of interventions in ethnically diverse populations. This means, for example, that intervention programmes trying to improve walking to school might be more or less effective depending on the ethnic composition of the community at stake and ethnic- or cultural- specific norms regarding walking to school within that community. In the context of East London, results suggest that such interventions might be more successful amongst Bangladeshi adolescents who attend predominantly Bangladeshi schools and less successful amongst Black African adolescents who attend schools with a high proportion of co-ethnics. Evidence produced from this thesis therefore suggests that policy interventions are more likely to be successful if they are tailored to the specificities of the social and cultural norms of the population of interest.

9.8. Conclusion

Whereas the health benefits of regular physical activity are well established (Strong et al. 2005), 26% of adults and 87% of adolescents do not achieve the recommended level of physical activity in England (Health and Social Care Information Centre 2017, Scholes 2016). It also appears that ethnic minorities and deprived populations are particularly at risk of physical inactivity (Griffiths et al. 2013, Owen et al. 2009, Sport London 2017). Adolescence, being a transition period during which life-long health behaviours form, appears to be a crucial period during which physical activity can be addressed (Papas et al. 2007). In this thesis, I tried to answer why some young people in deprived and ethnically diverse populations are and remain physically active during adolescence, while others remain or become inactive. Specifically, I investigated whether four features of the neighbourhood and home environments – namely perceptions of the neighbourhood environment, ethnic density, neighbourhood trust and social support – predicted common forms of physical activity.

The analyses reported here showed that adolescents' perceptions of their neighbourhood environment (including proximity, aesthetics, street connectivity, traffic safety and personal safety) and their changes over time did not consistently predict the forms of physical activity investigated, i.e. walking to school, walking for leisure and outdoor physical activity. School-level ethnic density increased the chance of walking to school in some ethnic groups and decreased it in others; whereas walking for leisure and outdoor physical activity were not consistently associated with ethnic density. Adolescents with higher perceived trust in their neighbours had higher chances to report leisure-time physical activity (i.e. outdoor physical activity, and pay and play physical activity). Finally, general social support from family, friends and significant others were shown to predict walking for leisure and its change over time. In boys only, social support from friends was shown to predict outdoor physical activity.

Results from this thesis contribute to our understanding of the individual, family, peer, community and neighbourhood influences on physical activity in adolescents. The predictors of physical activity identified in this thesis are mostly amenable to change and therefore could be the target of promotion programmes and interventions aiming to improve physical activity.

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Appendices

Appendix A Relevant questions from the ORiEL questionnaire

* * * * * * Strictly Confidential * * * * * * Strictly Confidential * * * * * * Strictly Confidential * * * * * *

Olympic Regeneration in East London (ORiEL Study)

ORiEL

Olympic Regeneration in East London

Your answers are CONFIDENTIAL

Nobody other than the research team will know what your answers are.

They will NOT be seen by your parents or teachers.

Please read each question carefully before ticking the boxes.

There are no right or wrong answers.

Your views are important to us.

Enjoy!

ORiEL study
Queen Mary University of London
Tel: 020 7882 2039

Some Questions About You

1. Are you **male** or **female**?

Male	☐1
Female	☐2

2. What is your **date of birth**?

______/_______/________
date month year

3. What **language** is spoken in your home **most of the time?**

✓ **ONE language only**

English	☐1	Hindi	☐2	Gujerati	☐3	Punjabi	☐4
Bengali	☐5	Sylheti	☐6	Tamil	☐7	Mandarin	☐8
Urdu	☐9	Patois/Creole	☐10	Hakka	☐11	African Language	☐12
Yiddish	☐13	Hebrew	☐14	Cantonese	☐15	Polish	☐16

Other (s) (please write)____

4. What **religious group** or church do you belong to?

✓ **ONE box only**

None	☐1	Methodist	☐2	Jewish	☐3	Sikh	☐4
Catholic	☐5	Baptist	☐6	Muslim/Islam	☐7	Hindu	☐8
Church of England	☐9	Other Christian	☐10	Don't know	☐11		

Other (s) (please write)____

5. Which **category** best describes **you?** - This is your race or ethnic group

✓ **ONE box only**

White	White: UK	☐ 1
	White: Irish	☐ 2
	White: Greek	☐ 3
	White: Turkish	☐ 4
	White: Jewish	☐ 5
	White: Kurdish	☐ 6
	White: Polish	☐ 7
	White: Other (please write) ___________________	
Mixed	Mixed: White and Black Caribbean	☐ 8
	Mixed: White and Black African	☐ 9
	Mixed: White and Asian	☐ 10
	Mixed: Other (please write) __________________	
Asian	Asian: Indian	☐ 11
	Asian: Pakistani	☐ 12
	Asian: Bangladeshi	☐ 13
Black	Black: Caribbean	☐ 14
	Black: African	☐ 15
	Black: Somali	☐ 16
	Black: British	☐ 17
	Black: Other (please write) ___________________	
Other	Arab	☐ 18
	Chinese	☐ 19
	Vietnamese	☐ 20
	Other (please write) _________________________	

Your Home and Family

These questions are about your home. If you live in different homes, **answer for the home where you live most of the time.**

6. How many other people do you live with at home?

write the number on the line below

I live with ________ other adults and children

7. Who do you **live with most of the time?**

✓ **ALL boxes that apply**

Mum	☐1	Brother or Sister	☐8
Dad	☐2	Step-brother or sister	☐9
Step-dad	☐3	Half-brother or sister	☐10
Step-mum	☐4	Grandmother	☐11
Mum's boyfriend / partner	☐5	Grandfather	☐12
Dad's girlfriend / partner	☐6	Other relative (e.g. Aunt)	☐13
Foster parent	☐7	Other non relative	☐14

8. Does your **Mum** or **Step-Mum** that **you live with** have a job?

✓ **ONE box only**

Mum or Step-Mum has a job	☐1
Mum or Step-Mum does not have a job	☐2
Mum or Step-Mum is a student	☐3
Don't live with Mum or Step-Mum	☐4

9. Does your **Dad** or **Step-Dad** that **you live with** have a job?

✓ **ONE box only**

Dad or Step-Dad has a job	☐ 1
Dad or Step-Dad does not have a job	☐ 2
Dad or Step-Dad is a student	☐ 3
Don't live with Dad or Step-Dad	☐ 4

10. Do you have **free school meals**? No ☐ 1 Yes ☐ 2

11. Does your family **own a car, van or truck**? No ☐ 1 Yes ☐ 2

12. Do you have **your own bedroom** for yourself? No ☐ 1 Yes ☐ 2

13. During the past 12 months, how many times did you **travel away on holiday** with your family?

Not at all ☐ 1 Once ☐ 2 Twice ☐ 3 More than twice ☐ 4

14. How many **computers** does your family own? eg. Laptop, PC. (Do **NOT** include games consoles. eg. PS3)

None ☐ 1 One ☐ 2 Two ☐ 3 More than two ☐ 4

15. How **many rooms**, other than the kitchen, hall and bathroom **does your home have?**

write the number on the line below

My home has ________ rooms **not including** the kitchen, hall and bathroom

16. Thinking about the last year, **when you are at home**, how much **does noise from *road traffic* bother, disturb or annoy you?**

✓ **ONE box only**

not at all ☐1 a little ☐2 quite a bit ☐3 very much ☐4 extremely ☐5

17. **How long** have you **lived in this country?**

✓ **ONE box only**

All my life	Over 10 years	6-10 years	1-5 years	Less than 1 year
☐1	☐2	☐3	☐4	☐5

18. **Which country** were **you born in?**

UK ☐1 Other (write in)__________________________

19. Did **you or your family** come to this country as **refugees**? (A refugee is someone who leaves their own country suddenly because of problems living there)

✓ **ONE box only**

No ☐1 Yes ☐2 Don't know ☐3

20. What is your **address** and **postcode**? *We'd like to know this so we can see how close you live to the Olympics. Your address will be kept **private** and only the researchers will see it.*

My house or flat number is… ____

My street or estate is called… ____

My postcode is…
e.g. *E8 6GU* ____

About You

21. Below are some statements **about feelings and thoughts**. Please tick the box that best **describes your experience** of each **over the last 2 weeks**

✓ **ONE box on EVERY line**

	None of the time	Rarely	Some of the time	Often	All of the time
I've been feeling hopeful about the future	☐1	☐2	☐3	☐4	☐5
I've been feeling useful	☐1	☐2	☐3	☐4	☐5
I've been feeling relaxed	☐1	☐2	☐3	☐4	☐5
I've been feeling interested in other people	☐1	☐2	☐3	☐4	☐5
I've had energy to spare	☐1	☐2	☐3	☐4	☐5
I've been dealing with problems well	☐1	☐2	☐3	☐4	☐5
I've been thinking clearly	☐1	☐2	☐3	☐4	☐5
I've been feeling good about myself	☐1	☐2	☐3	☐4	☐5
I've been feeling close to other people	☐1	☐2	☐3	☐4	☐5
I've been feeling confident	☐1	☐2	☐3	☐4	☐5
I've been able to make up my own mind about things	☐1	☐2	☐3	☐4	☐5
I've been feeling loved	☐1	☐2	☐3	☐4	☐5
I've been interested in new things	☐1	☐2	☐3	☐4	☐5
I've been feeling cheerful	☐1	☐2	☐3	☐4	☐5

PLEASE CHECK: Have you ticked ONE box on EVERY LINE???

Your Health

22. In general, would you say your health is

✓ **ONE box only**

very good ☐1 good ☐2 fair ☐3 bad ☐4 very bad ☐5

23. Do you have any **long-standing illness or disability?** By this we mean a health **problem that has troubled you over a period of time**, or is likely to affect you over a period of time?

✓ **ONE box only**

No I don't have a long standing illness ☐1

Yes I do have a long standing illness ☐2

24. Do you have any of these health problems?

✓ **ALL that you have**

Asthma ☐1

Anaemia ☐2

Eczema ☐3

Epilepsy ☐4

Diabetes ☐5

Hearing problems ☐6

Eyesight problems ☐7

Hay fever ☐8

Chronic Fatigue Syndrome / M.E. ☐9

Other health problem(s) *please write in* ___________________

25. Thinking back over **the last 3 months**, how often **have you had the following?**

✓ **ONE box for each problem you have**

	Rarely or never	About once a month	About once a week	More than once a week	Daily
Headache	☐1	☐2	☐3	☐4	☐5
Stomach ache	☐1	☐2	☐3	☐4	☐5
Back Pain	☐1	☐2	☐3	☐4	☐5
Other aches and pains	☐1	☐2	☐3	☐4	☐5

26. Do you have any difficulties moving about, walking, climbing stairs, or use special equipment to help you to be mobile?

No ☐1

Yes ☐2

Physical Activities

These questions are to see **how much exercise you do**. Please read the example below and then read the following questions carefully.

Example Question: How many times did you do the following **physical** activities in the **past 7 days?**

EXAMPLE

If you took part in PE lessons **two times** in the past 7 days then you must tick this box

If your PE lessons are usually 45 minutes long, please write in **0 hrs** and **45 mins**

	Never	Once	2-3 times	4 or more times	Each time that did this, how long did you normally do it for?
PE class	☐1	☐2	✓3	☐4	__0_hrs _45_mins

28. How many times did you do the following **physical** activities <u>**at school**</u> in the **past 7 days?**

✓ **ONE box on EVERY line**

	Never	Once	2-3 times	4 or more times	Each time that you did this, how long did you normally do it for?
PE class	☐1	☐2	☐3	☐4	____hrs ____mins
Walk to school	☐1	☐2	☐3	☐4	____hrs ____mins
Cycle to school	☐1	☐2	☐3	☐4	____hrs ____mins
Travel to school by car/bus	☐1	☐2	☐3	☐4	____hrs ____mins

29. How many times did you do the following activities **outside school** in **the past 7 days?**

✓ **ONE box on EVERY line**

Activities (**NOT** at school)	Never	Once	2-3 times	4 or more times	Each time that you did this, how long did you normally do it for?	
Aerobics	☐1	☐2	☐3	☐4	____hrs	____mins
Softball/rounders	☐1	☐2	☐3	☐4	____hrs	____mins
Basketball/Volleyball	☐1	☐2	☐3	☐4	____hrs	____mins
Cricket	☐1	☐2	☐3	☐4	____hrs	____mins
Dancing	☐1	☐2	☐3	☐4	____hrs	____mins
Football	☐1	☐2	☐3	☐4	____hrs	____mins
Gymnastics	☐1	☐2	☐3	☐4	____hrs	____mins
Hockey (field/ice/street)	☐1	☐2	☐3	☐4	____hrs	____mins
Martial arts	☐1	☐2	☐3	☐4	____hrs	____mins
Netball	☐1	☐2	☐3	☐4	____hrs	____mins
Rugby	☐1	☐2	☐3	☐4	____hrs	____mins
Running or jogging	☐1	☐2	☐3	☐4	____hrs	____mins
Swimming	☐1	☐2	☐3	☐4	____hrs	____mins
Tennis/badminton/ squash/other racquet sport	☐1	☐2	☐3	☐4	____hrs	____mins
Ten Pin Bowling	☐1	☐2	☐3	☐4	____hrs	____mins
Household chores	☐1	☐2	☐3	☐4	____hrs	____mins
Climbing wall	☐1	☐2	☐3	☐4	____hrs	____mins
Horse riding	☐1	☐2	☐3	☐4	____hrs	____mins
Rollerblading/skating	☐1	☐2	☐3	☐4	____hrs	____mins
Gardening	☐1	☐2	☐3	☐4	____hrs	____mins
Skateboarding	☐1	☐2	☐3	☐4	____hrs	____mins
Skipping	☐1	☐2	☐3	☐4	____hrs	____mins
Walking for exercise/the dog	☐1	☐2	☐3	☐4	____hrs	____mins
Other (write in) ____________	☐1	☐2	☐3	☐4	____hrs	____mins

Your Neighbourhood

We'd like to ask you about the neighbourhood **where you live.**

By your neighbourhood we mean **ALL the area** that you could **walk to in 10-15 minutes**.

Please give the answer that best applies to you and your view of your neighbourhood.

39. **How long** have you lived in the neighbourhood **where you live now**

✓ **ONE box only**

All my life	Over 10 years	6-10 years	1-5 years	Less than 1 year
☐1	☐2	☐3	☐4	☐5

40. About how long would it take to get from your home to the **nearest** businesses or services listed below if you **walked** to them?

✓ **ONE box on EVERY line**

	1-5 mins	6-10 mins	11-20 mins	21-30 mins	More than 30 mins
Local shop	☐1	☐2	☐3	☐4	☐5
Supermarket	☐1	☐2	☐3	☐4	☐5
Local services such as bank, post office or library	☐1	☐2	☐3	☐4	☐5
Fast food restaurant or takeaway	☐1	☐2	☐3	☐4	☐5
Bus stop	☐1	☐2	☐3	☐4	☐5
Tram, tube or train station	☐1	☐2	☐3	☐4	☐5
Sport and leisure facility. e.g. swimming pool, fitness centre, gym	☐1	☐2	☐3	☐4	☐5
Open recreation area. e.g. park, sports field or other open space	☐1	☐2	☐3	☐4	☐5

41. How **safe** is your neighbourhood?

✓ **ONE box on EVERY line**

	Strongly disagree	Slightly disagree	Slightly agree	Strongly agree
It is not safe to leave a bicycle <u>locked</u> in my neighbourhood	☐1	☐2	☐3	☐4
There are not enough safe places <u>to cross</u> busy streets in my neighbourhood	☐1	☐2	☐3	☐4
Walking is unsafe because of the <u>traffic</u> in my neighbourhood	☐1	☐2	☐3	☐4
Cycling is unsafe because of the <u>traffic</u> in my neighbourhood	☐1	☐2	☐3	☐4
It is unsafe in my neighbourhood <u>during the day</u> because of the level of crime/ anti-social behaviour	☐1	☐2	☐3	☐4
It is unsafe in my neighbourhood <u>during the night</u> because of the level of crime / anti-social behaviour	☐1	☐2	☐3	☐4

42. How **nice** is your neighbourhood?

✓ **ONE box on EVERY line**

	Strongly disagree	Slightly disagree	Slightly agree	Strongly agree
My local neighbourhood is a nice environment for walking or cycling	☐1	☐2	☐3	☐4
My neighbourhood is generally free from litter or graffiti	☐1	☐2	☐3	☐4
There are trees along streets in my neighbourhood	☐1	☐2	☐3	☐4
In my neighbourhood there are a lot of badly maintained, unoccupied or ugly buildings	☐1	☐2	☐3	☐4

43. **How easy is it to walk or cycle** in your neighbourhood?

✓ **ONE box on EVERY line**

	Strongly disagree	Slightly disagree	Slightly agree	Strongly agree
There are many shortcuts for walking in my neighbourhood	☐1	☐2	☐3	☐4
Cycling is quicker than driving in my neighbourhood during the day	☐1	☐2	☐3	☐4
There are many road junctions in my neighbourhood	☐1	☐2	☐3	☐4
There are so many different routes that I don't have to go the same way every time	☐1	☐2	☐3	☐4
The streets in my neighbourhood are hilly, making my neighbourhood difficult to walk or cycle in	☐1	☐2	☐3	☐4

44. **Do you agree or disagree** with the following statements?

✓ **ONE box on EVERY line**

	Strongly disagree	Slightly disagree	Neither agree nor disagree	Slightly agree	Strongly agree
I feel safe walking in my neighbourhood, day or night	☐1	☐2	☐3	☐4	☐5
Violence is not a problem in my neighbourhood	☐1	☐2	☐3	☐4	☐5
My neighbourhood is safe from crime	☐1	☐2	☐3	☐4	☐5

33. We'd like to know how much you **trust** different groups of people. Generally speaking, would you say that you…?

✓ ONE box on EVERY line	A lot	Some	A little	Not at all	Not applicable
Trust people in your neighbourhood	☐1	☐2	☐3	☐4	☐5
Trust people at your school	☐1	☐2	☐3	☐4	☐5
Trust people at your church or place of worship	☐1	☐2	☐3	☐4	☐5
Trust people who work in the stores you shop at	☐1	☐2	☐3	☐4	☐5
Trust the police in your local community	☐1	☐2	☐3	☐4	☐5

15

35. Please show how much you agree or disagree with each statement about the area where you live.

✓ **ONE box on EVERY line**

	Strongly agree	Slightly agree	Neither agree nor disagree	Slightly disagree	Strongly disagree
I like this area	☐1	☐2	☐3	☐4	☐5
I want to leave this area	☐1	☐2	☐3	☐4	☐5
Other people think this is a good area	☐1	☐2	☐3	☐4	☐5
I feel part of this area	☐1	☐2	☐3	☐4	☐5
I have friends that live in this area	☐1	☐2	☐3	☐4	☐5

People Around You

55. We are interested in **how you feel about the following statements.** Read each statement carefully and indicate how you feel about each statement. (**Neutral** means you **do not agree or disagree**)

✓ **ONE box on EVERY line**

	Disagree very strongly	Disagree strongly	Disagree mildly	Neutral	Agree mildly	Agree strongly	Agree very strongly
There is a special person who is around when I am in need	☐1	☐2	☐3	☐4	☐5	☐6	☐7
There is a special person with whom I can share my joys and sorrows	☐1	☐2	☐3	☐4	☐5	☐6	☐7
My family really tries to help me	☐1	☐2	☐3	☐4	☐5	☐6	☐7
I get the emotional help and support I need from my family	☐1	☐2	☐3	☐4	☐5	☐6	☐7
I have a special person who is a real source of comfort to me	☐1	☐2	☐3	☐4	☐5	☐6	☐7
My friends really try to help me	☐1	☐2	☐3	☐4	☐5	☐6	☐7
I can count on my friends when things go wrong	☐1	☐2	☐3	☐4	☐5	☐6	☐7
I can talk about my problems with my family	☐1	☐2	☐3	☐4	☐5	☐6	☐7
I have friends with whom I can share my joys and sorrows	☐1	☐2	☐3	☐4	☐5	☐6	☐7
There is a special person in my life who cares about my feelings	☐1	☐2	☐3	☐4	☐5	☐6	☐7
My family is willing to help me make decisions	☐1	☐2	☐3	☐4	☐5	☐6	☐7
I can talk about my problems with my friends	☐1	☐2	☐3	☐4	☐5	☐6	☐7

PLEASE CHECK: Have you ticked ONE box on EVERY LINE???

Appendix B Supplementary material for chapter 3

Table B.1 Summary of confirmatory factor analyses on perceptions of the neighbourhood environment

		Pearson correlation			Polychoric correlation		
	Model summary from pooled 3-wave panel data (n=4,443)	**Satorra-Bentler GOF**			**INDICATIVE GOF**		
		RMSEA	**CFI**	**TLI**	**RMSEA**	**CFI**	**TLI**
Model 1	all items; 5 Latent Variables: proximity, safety (traffic + crime from ALPHA), aesthetics, connectivity, crime safety (MESA)	0.053	0.861	0.843	0.074	0.834	0.813
Model 2	drop 'hilly roads'; 5 Latent Variables: proximity, safety (traffic + crime from ALPHA), aesthetics, connectivity, crime safety (MESA)	0.052	0.873	0.856	0.073	0.850	0.831
Model 3	drop 'hilly road', 'badly maintained buildings'; 5 Latent Variables: proximity, safety (traffic + crime from ALPHA), Aesthetics, connectivity, crime safety (MESA)	0.051	0.887	0.871	0.072	0.863	0.844
Model 4	drop 'hilly road', 'badly maintained buildings'; 5 Latent Variables: proximity, traffic safety, aesthetics, connectivity, crime safety (ALPHA + MESA)	0.057	0.856	0.836	0.078	0.839	0.817
Model 4 b	drop 'hilly road', 'badly maintained buildings', 'lock bike'; 5 Latent Variables: proximity, traffic safety, aesthetics, connectivity, crime safety (ALPHA + MESA)	0.055	0.872	0.853	0.077	0.852	0.830
Model 5	drop 'hilly road', 'badly maintained buildings'; 5 Latent Variables: proximity, traffic safety, aesthetics, connectivity, crime safety (ALPHA + MESA); Measurement error correlation	0.047	0.908	0.890	0.067	0.886	0.864
Model 5 b	drop 'hilly road', 'badly maintained buildings', 'lock bike'; 5 Latent Variables: proximity, traffic safety, aesthetics, connectivity, crime safety (ALPHA + MESA); Measurement error correlation	0.048	0.905	0.887	0.070	0.883	0.860
Model 6	drop 'hilly road', 'badly maintained buildings'; 5 Latent Variables: proximity, traffic safety, aesthetics, connectivity, crime safety (ALPHA + MESA); Measurement error correlation; cross-loading allowed	0.043	0.918	0.905	0.063	0.896	0.880
Model 7	drop 'hilly road', 'badly maintained buildings'; 5 Latent Variables: proximity, traffic safety, aesthetics, connectivity, crime safety (ALPHA + MESA+ 'graffiti'); cross-loading allowed	0.043	0.921	0.908	0.063	0.899	0.883
Model 8	drop 'hilly road', 'badly maintained buildings'; 6 Latent Variables: proximity, traffic safety, aesthetics, connectivity, crime safety (ALPHA), crime-related safety(MESA)	0.038	0.939	0.929	0.055	0.923	0.911

Table B.2 Longitudinal descriptive analysis of proximity (n=2,214)

proximity	Overall		Between		Within
	Freq.	Percent	Freq.	Percent	Percent
Low	332	5.99	274	12.38	50.79
Medium	2248	40.58	1408	63.60	64.17
High	2960	53.43	1600	72.27	73.21
Total	5540	100.00	3282	148.24	67.46

Table B.3 Longitudinal descriptive analysis of aesthetics (n=2,233)

aesthetics	Overall		Between		Within
	Freq.	Percent	Freq.	Percent	Percent
Low	941	16.15	713	31.93	51.75
Medium	2712	46.56	1655	74.12	62.77
High	2172	37.29	1328	59.47	62.14
Total	5825	100.00	3696	165.52	60.42

Table B.4 Longitudinal descriptive analysis of crime-related safety (n=2,226)

crime-related safety	Overall		Between		Within
	Freq.	Percent	Freq.	Percent	Percent
Low	1720	30.27	1121	50.36	59.84
Medium	2193	38.60	1458	65.50	58.84
High	1769	31.13	1114	50.04	62.60
Total	5682	100.00	3693	165.90	60.28

Table B.5 Longitudinal descriptive analysis of social support from significant others (n=2,124)

Social support: significant others	Overall		Between		Within
	Freq.	Percent	Freq.	Percent	Percent
Low	1418	39.26	1078	50.75	78.71
Medium	985	27.27	844	39.74	68.84
High	1209	33.47	931	43.83	74.6.0
Total	3612	100.00	2853	134.32	74.45

Appendix C Supplementary material for chapter 4

C.1. Definition of the missing data mechanisms

The data which one intends to collect on a certain number of variables (let say p) is usually denoted by a vector **Y** = $(\mathrm{Y}_1, \mathrm{Y}_2, \mathrm{Y}_3, \dots, \mathrm{Y}_\mathrm{p})^\mathrm{T}$. **Y** includes outcomes and covariates. For each individual from whom one intends to obtain data, one can partition **Y** into the data that were observed $\mathbf{Y}_\mathrm{o}$ and the data that are missing $\mathbf{Y}_\mathrm{m}$, such that $\mathbf{Y} = \{\mathbf{Y}_\mathrm{o}, \mathbf{Y}_\mathrm{m}\}$.

For each variable of **Y** and each individual one intends to collect information from, one defines a missing value indicator R such that:

$$\mathrm{R} = \begin{cases} 1 \text{ if Y is observed} \\ 0 \text{ if Y is missing} \end{cases}$$

All the value measured by R can be combined in a vector **R** as done for **Y**.

Having define **R** and **Y**, I can now define the missing data mechanism in a broad sense: it is the probably that some values are missing given the values taken by the observed, and unobserved observations. Formally: $\mathrm{P}(\mathbf{R}|\mathbf{Y}_\mathrm{o}, \mathbf{Y}_\mathrm{m})$.

Depending on the extent to which that probably depends on the unobserved missing values, the observed values or none, a different type of missing data mechanism is defined and implies different consequences for statistical analysis.

Missing Completely At Random (MCAR)

Data are Missing Completely at Random (MCAR) when the probability of missingness does depend neither on the observed nor on the unobserved values. Algebraically,

$$\mathrm{P}(\mathbf{R}|\mathbf{Y}_\mathrm{o}, \mathbf{Y}_\mathrm{m}) = \mathrm{P}(\mathbf{R}).$$

Under an MCAR mechanism, the chance of the data being missing is unrelated to their values; therefore, the observed data are representative of the population for which one intended to collect data. An example of MCAR is to randomly assign two different versions of a questionnaires to a large number of participants. The process generating missing values is known and is due to the randomisation. Knowledge of the observed and unobserved values would not help to predict whether a value is missing or not. In such an instance, the characteristics of participants receiving different versions of the questionnaire would be similar, given large enough sample sizes.

Missing At Random (MAR)

Data are Missing At Random (MAR) if, given the observed data, the missingness mechanism does not depend on the unseen data. That is:

$$\mathrm{P}(\mathbf{R}|\mathbf{Y}_{\mathrm{o}}, \mathbf{Y}_{\mathrm{m}}) = \mathrm{P}(\mathbf{R}|\mathbf{Y}_{\mathbf{o}}).$$

Therefore, the probability of missingness is allowed to depend on the value of the data. Yet, once this is taken into account, it will not depend on anything else. Under that condition, any systematic differences between the missing values and the observed values can be explained by differences in the observed data. For example, males might be more likely to answer sensitive questions about depression than females, such that once gender is taken into account, there are no more differences in the probability in answering the questions.

Missing Not At Random (MNAR)

If neither MAR nor MCAR hold, one is left with a Missing Not at Random (MNAR) mechanism. Under MNAR, even if one accounts for the available observed information, the probability of missingness depends on the missing values themselves or unobserved variables, such that systematic difference remain between the missing and the unobserved values. Formally the mechanism is defined as:

$$\mathrm{P}(\mathbf{R}|\mathbf{Y}_{\mathrm{o}}, \mathbf{Y}_{\mathrm{m}}) \neq \mathrm{P}(\mathbf{R}|\mathbf{Y}_{\mathbf{o}}).$$

MNAR can happen when the missing value itself determines the probability of missingness or if some unmeasured quantity influences both the value of the missing variable and the probability of missingness. For example, individual with very high income or very low income may refuse to provide income-related information, after controlling for other socio-economic variables.

C.2. The imputation procedure

Despite its popularity for handling missing data in frequentist inference, it should be stressed that MI is fundamentally a Bayesian methodology (Enders 2010) and was initially developed by Rubin (1987) within a Bayesian framework. This section describes in more detail how the imputation procedure works. It serves as important background knowledge for assessing the convergence of imputation models and for selecting appropriate parameters in the imputation phase.

The imputation procedure is iterative, each iteration is generally referred to as a ‘cycle’. There are essentially two steps in each cycle: the imputation step (I-step), which imputes the missing data, and the posterior step (P-step) which updates the parameters of the imputation model (Enders 2010).

The I-step is straightforward and similar to the use of regression to predict missing values using the observed data of each specific individual with partially missing information. In order not to have imputed values that exactly equal the predicted values, a random element is added.

A P-step follows. The vector of means and covariance matrix that form the building blocks of imputation models are recalculated using the fully imputed data set from the preceding I-step. A posterior distribution of the means vector and the covariance matrix are calculated. In Bayesian methodology, a parameter is a random variable with a distribution of values, as distinct from a frequentist approach where a parameter is a single value that is estimated. To obtain a posterior distribution, one needs a prior distribution and a likelihood function. Most MI procedures use non-informative prior distributions so that the shape of the posterior distribution depends solely on the likelihood function (Enders 2010). The imputed data of the preceding I-step is therefore used to calculate the posterior distribution, from which specific values of the parameters are randomly drawn.

In practice, these estimates are simulated using Markov Chain Monte Carlo (MCMC) techniques (Gelman et al. 2003). The Gibbs sampler (Gelman et al. 2003) is commonly used in the joint modelling approach (Carpenter & Kenward 2012), which is the approach used in this thesis. The imputed values obtained from the I-step can then be used for the next P-step and the whole procedure is repeated many times. The procedure eventually allows for the generation of multiple instances of the data containing unique estimates of the missing values.

A series of initial iterations of the process, known as the ‘burn-in’, should be ignored until the MCMC sampler has converged to its stationary distribution (Carpenter & Kenward 2012). Once the sampler has converged, a first imputed dataset can be retained. There should be a sufficient number of cycles between successive retained datasets to ensure that they are approximately independently drawn. Indeed, the MCMC process is such that imputed values from successive cycles are likely to be correlated. The imputed values in each of the *M* datasets should be carefully selected such that each set of imputed values is stochastically independent of the previously retained imputation.

Despite being a Bayesian methodology (Enders 2010), MI is often used within a frequentist inferential framework. The handling of missing data with multiple imputation often precedes the use of frequentist models of statistical analysis, meaning that MI does not require a fully Bayesian approach to analysis. This idea is well expressed by Zaslavsky (1994):

> 'Because it may be so difficult to specify fully a Bayesian analysis, in many problems the best strategy can be to use a model-based Bayesian inference for the part that requires it, in particular the imputation of missing data, and to use frequentist methods, relying on estimates of means and variances and on approximate normality, for the rest of the inference. Multiple imputation is a device for such a combined approach'

C.3. Example of multilevel multiple imputation model fitted

This appendix provides the full equation and the R codes used to fit one of the imputation models of this thesis. This model corresponds to the final imputation model of chapter 6. The model was fitted separately for boys and for girls. The joint model is as follows:

$$
\begin{cases}
Y_{w1,1,i,j} = \beta_{0,w1,1} + u_{w1,1,j} + \epsilon_{w1,1,i,j} \\
\dots \\
Y_{w1,3,i,j} = \beta_{0,w1,3} + u_{w1,3,j} + \epsilon_{w1,3,i,j} \\
\dots \\
Y_{wp,1,i,j} = \beta_{0,wp,1} + u_{wp,1,j} + \epsilon_{wp,1,i,j} \\
\dots \\
Y_{wp,3,i,j} = \beta_{0,wp,3} + u_{wp,3,j} + \epsilon_{wp,3,i,j} \\
Z_{x1,1,1,i,j} = \beta_{0,x1,1,1} + u_{x1,1,1,j} + \epsilon_{x1,1,1,i,j} \\
\dots \\
Z_{x1,1,k-1,i,j} = \beta_{0,x1,1,k-1} + u_{x1,1,k-1,j} + \epsilon_{x1,1,k-1,i,j} \\
\dots \\
Z_{x1,3,1,i,j} = \beta_{0,x1,3,1} + u_{x1,3,1,j} + \epsilon_{x1,3,1,i,j} \\
\dots \\
Z_{x1,3,k-1,i,j} = \beta_{0,x1,3,k-1} + u_{x1,3,k-1,j} + \epsilon_{x1,3,k-1,i,j} \\
\dots \\
Z_{xm,1,1,i,j} = \beta_{0,xm,1,1} + u_{xm,1,1,j} + \epsilon_{xm,1,1,i,j} \\
\dots \\
Z_{xm,1,k-1,i,j} = \beta_{0,xm,1,k-1} + u_{xm,1,k-1,j} + \epsilon_{xm,1,k-1,i,j} \\
\dots \\
Z_{xm,3,1,i,j} = \beta_{0,xm,3,1} + u_{xm,3,1,j} + \epsilon_{xm,3,1,i,j} \\
\dots \\
Z_{xm,3,k-1,i,j} = \beta_{0,xm,3,k-1} + u_{xm,3,k-1,j} + \epsilon_{xm,3,k-1,i,j} \\
Z_{FSM,i,j} = \beta_{0,FSM} + u_{FSM,j} + \epsilon_{FSM,i,j} \\
Z_{BIRTH,i,j} = \beta_{0,BIRTH} + u_{BIRTH,j} + \epsilon_{BIRTH,i,j} \\
Z_{ETH,1,i,j} = \beta_{0,ETH,1} + u_{ETH,1,j} + \epsilon_{ETH,1,i,j} \\
\dots \\
Z_{ETH,7,i,j} = \beta_{0,ETH,7} + u_{ETH,7,j} + \epsilon_{ETH,7,i,j}
\end{cases}
$$

$$
\boldsymbol{\epsilon_{i,j}} = \begin{pmatrix} \epsilon_{w1,1,i,j} \\ \dots \\ \epsilon_{w1,3,i,j} \\ \dots \\ \epsilon_{wp,1,i,j} \\ \dots \\ \epsilon_{wp,3,i,j} \\ \epsilon_{x1,1,1,i,j} \\ \dots \\ \epsilon_{x1,1,k-1,i,j} \\ \dots \\ \epsilon_{x1,3,1,i,j} \\ \dots \\ \epsilon_{x1,3,k-1,i,j} \\ \dots \\ \epsilon_{xm,1,1,i,j} \\ \dots \\ \epsilon_{xm,1,k-1,i,j} \\ \dots \\ \epsilon_{xm,3,1,i,j} \\ \dots \\ \epsilon_{xm,3,k-1,i,j} \\ \epsilon_{FSM,i,j} \\ \epsilon_{BIRTH,i,j} \\ \epsilon_{ETH,1,i,j} \\ \dots \\ \epsilon_{ETH,7,i,j} \end{pmatrix} \sim N(\mathbf{0}, \boldsymbol{\Omega_e}) \quad \boldsymbol{u_j} = \begin{pmatrix} u_{w1,1,j} \\ \dots \\ u_{w1,3,j} \\ \dots \\ u_{wp,1,j} \\ \dots \\ u_{wp,3,j} \\ u_{x1,1,1,j} \\ \dots \\ u_{x1,1,k-1,j} \\ \dots \\ u_{x1,3,1,j} \\ \dots \\ u_{x1,3,k-1,j} \\ \dots \\ u_{xm,1,1,j} \\ \dots \\ u_{xm,1,k-1,j} \\ \dots \\ u_{xm,3,1,j} \\ \dots \\ u_{xm,3,k-1,j} \\ u_{FSM,j} \\ u_{BIRTH,j} \\ u_{ETH,1,j} \\ \dots \\ u_{ETH,7,j} \end{pmatrix} \sim N(\mathbf{0}, \boldsymbol{\Omega_u})
$$

Adolescents i nest within schools j. This joint model treats all variables as outcomes Y including, ethnicity which is fully observed. The p continuous variables are indexed as $w1, \dots, wp$. Each measurement occasion (wave) is represented by a different variable, indexed as 1,..,3. For example, $Y_{w2,3}$ represents the second continuous variable (i.e. Mental Health Score; squared centred and scaled WEMWBS score) measured at wave 3. I used an underlying multivariate normal approach to model categorical variables using latent normal variables Z. The k categories of each categorical variable are represented by $k-1$ latent variables. The indexes $x1, \dots, xm$ represent the m categorical variables of the model. For example, for the first categorical variable Y_{x1} I used the latent variables $Z_{x1,1}, Z_{x1,2}, \dots, Z_{x1,k-1}$. These variables are further indexed 1,..,3 to indicate the wave at which they were measured. $Z_{x1,3,2}$ represents the 2nd latent variable of the variable Y_{x1}, measured at wave 3. Free school meal status (FSM), country of birth (BIRTH) and ethnicity (ETH) are time-invariant and therefore not indexed with 1,…3. FSM and BIRTH are binary variables and only represented by one latent variable each, i.e. Z_{FSM} and Z_{BIRTH}). Individual-specific residuals and school-specific random effects are gathered in the vectors $\boldsymbol{\epsilon_{i,j}}$ and $\boldsymbol{u_j}$ respectively. Both are assumed to follow multivariate normal distributions with common covariance matrices $\boldsymbol{\Omega_e}$ and $\boldsymbol{\Omega_u}$.

The model was fitted in R using the 'jomo' package with the following codes (example for girls):

```
#define the Y variables in the imputation model
Y<-data.frame(lntotpa01, lntotpa02, lntotpa03,wemtot20_01,
              wemtot20_02, wemtot20_03, bmi01, bmi02, bmi03,
              walk1, walk2, walk3, dogwalk1, dogwalk2,
              dogwalk3, paout71, paout72, paout73, ibus_rr1,
              ibus_rr2, ibus_rr3, traffic1, traffic2, traffic3,
              infra1, infra2, infra3, nice31, nice32, nice33,
              n_safe2a1, n_safe2a2, n_safe2a3, daysafe31,
              daysafe32, daysafe33, srh1, srh2, srh3, health21,
              health22, health23, fas_cat1, fas_cat2, fas_cat3,
              fsm_ref_r1, birth_ref1, d_eth_8cat1)

clus<-data.frame(school_ref1) #define the cluster variable
#define the burn-in, n-between and number of imputations
nburn<-50
nbetween<-500
nimp<-20
#load the dataset containing the parameters saved after 4000
burn-in
load("FE_with_school_Balanced_female4.RData")
#save the last values of the paramters
betafin<-matrix(imp$collectbeta[,,nburn],1,81)
omegafin<-as.matrix(imp$collectomega[,,nburn])
ufin<-as.matrix(imp$collectu[,,nburn])
covufin<-as.matrix(imp$collectcovu[,,nburn])
imp<-NULL #clear the memory
#Run the imputation model
imp<-jomo(Y, beta.start = betafin,
          l1cov.start = omegafin, u.start = ufin,
          l2cov.start = covufin, clus=clus,
          nburn=nburn, nbetween=nbetween, nimp=nimp)
```

C.4. Choosing an analytical approach for modelling hierarchical discrete data

This appendix reviews modelling approaches to handle hierarchical data with binary outcomes and assesses their relevance in the context of this thesis. I argue that marginal models are preferred over the use of cluster-robust standard errors in combination with generalised linear models (GLM), fixed effects models, and random effects models in the context of this thesis.

Generalised linear models with cluster-robust standard errors

A first choice to make when dealing with clustered data is to decide between an approach that specifically accounts for the hierarchical nature of the data in the estimation process, or an approach that solely corrects the standard errors at the end of the estimation process to account for clustering.

The second approach typically uses a standard GLM together with a cluster-robust estimator of the standard errors. Cluster-robust estimators of standard errors consist of re-calculating standard errors to account for usually one level of clustering in the data (e.g. repeated measurements on individuals, or clustering of adolescents in schools). Cluster-adjustment assumes that observations within groups are correlated but that observations across clusters are independent. The cluster-robust approach is a variant the Huber-White heteroskedasticity-consistent estimator of the standard errors (Wooldridge 2015) that additionally accounts for any intra-cluster correlation[31] (Primo et al. 2007). In settings where the number of clusters is large[32], the approach provides consistent estimates of the coefficients and of the standard errors (Rabe-Hesketh & Skrondal 2012).

In contrast, a hierarchical approach to accounting for clustering explicitly models the covariance components and adds some additional parameters to the model specification. The estimation of the fixed parameters therefore differs when compared to those obtained using GLM (Rabe-Hesketh & Skrondal 2012). This approach is generally preferred in applied longitudinal analysis, as the field has developed a wide range of models specifically designed to account for clustering due to repeated measurements (Fitzmaurice et al. 2011, Molenberghs & Verbeke 2005, Verbeke & Molenberghs 2009). Although robust-cluster standard errors might be valid in various settings, models for hierarchical data are preferred in this thesis owing to the flexibility and their applicability in a broader range of circumstances. Longitudinal models for instance allow for the use of a lagged response, and for specific investigation of the covariance structure if it is of interest (Rabe-Hesketh & Skrondal 2012).

Whereas models for hierarchical data are used in the main analyses of this thesis, cluster-robust estimations of the standard errors are nevertheless employed in the analysis of the baseline data as an 'easy fix' to inaccurate standard errors that might arise due clustering at school-level. Results still need to be interpreted with caution due to the small number of clusters which can cause downwards biased of the standard errors (Fitzmaurice et al. 2011) and due to bias caused by the violation of the MCAR assumption.

---

[31] From a technical point of view, cluster-adjustment takes the Huber-White sandwich estimator of the standard errors one-step further by allowing off-diagonal elements from the same cluster to be nonzero. By doing this, one allows for any arbitrary correlation of the observations within clusters, any arbitrary heteroskedasticity in the error term, but no correlation across clusters (Primo et al. 2007).

[32] There is no clear-cut definition of large however. Depending on the extent of clustering and whether the data are balanced or not, many more clusters might be needed to avoid downward biased of the standard errors.

Fixed effects models

A second decision in terms of analytical strategy is to consider using a fixed effects approach to modelling. Amongst the many models for longitudinal data, a class of models known as fixed effects models, which has its origins in the econometrics literature, is increasingly used in the social sciences (Fitzmaurice et al. 2011). Fixed effects models attempt to account for the 'unit heterogeneity problem', which means that clusters (i.e. individuals with repeated measurements or schools composed of pupils) might differ from one another due to some unmeasured confounding variable(s). The approach is mainly used in the longitudinal context, although it can also be applied to cross-sectional data (Schempf & Kaufman 2012). With longitudinal data, the intent of fixed effects models is to control for all potential time-invariant confounding factors by restricting the analysis to within individual changes over time. This contrasts with random effects models and marginal models that use both sources of variation to estimate the regression parameters, and cannot guarantee the absence of residual confounding (Verbeke & Molenberghs 2009).

For Gaussian outcomes, the benefits of fixed effects versus random effects models have been widely discussed (Fitzmaurice et al. 2011, Wooldridge 2015). The Hausman test[33] has often been used as a criterion to decide whether a fixed effects model should be preferred (Wooldridge 2015). Recent methodological development however seem to have resolved the dilemma by offering models that capitalise on most of the appealing features of both the random and the fixed effects approaches (Allison 2009, Bell & Jones 2015, Fitzmaurice et al. 2011). Unfortunately, such 'hybrid' models do not have an equivalent with equally appealing properties when the outcomes are binary or ordinal (Bell et al.), meaning that one still needs to make a choice.

In this thesis, the fixed effects approach to longitudinal analysis is not followed for three main reasons. First, fixed effects models are consistent as the number of repeated measurements tends to infinity. Thus, having many clusters with few observations in each of them (i.e. 3 in the ORiEL context; one for each wave) is likely to lead to poor estimations of the parameters (Wooldridge 2010). In addition, fixed effects estimates are likely to be very inefficient with few measurement points (Wooldridge 2010). Efficiency depends on the extent of within-individual

[33] A Hausman test informs on whether the exogeneity assumption (or orthogonality of the error terms and covariates) holds. Essentially it investigates whether the within-individual effects and the between-individual effects are different by comparing the fit of a fixed effects and a random effects model (Wooldridge 2010, 2015).

change. With only three measurement points, using fixed effects models would mean that changes in exposure and outcome have to be very frequent in order to be able to capture an effect. Fixed effects estimates are also particularly subject to bias if measurement errors are large compared to real change over-time (Rabe-Hesketh & Skrondal 2012). It should further be noted that fixed effects models for binary outcomes are based on conditional logits and therefore only make use of the information on individuals who changed response category over time, which makes the estimates even less efficient and reliable than in the Gaussian context (Allison 2009).

Second, the fixed effects approach prevents the investigation of exposure variables that do not change over time (Wooldridge 2015). Consequently, that analytical approach would not allow studying the association between neighbourhood ethnic density and physical activity, as the available ethnic composition data for small areas in the UK is limited to the most recent Census.

Third, compared to non-random sampling settings in which fixed effects models have proved very useful (e.g. pooled time-series of cross-sectional data of non-randomly selected hospitals or countries), unobserved residual confounding is expected to be much more restricted in the context of ORiEL. Indeed, in the ORiEL study, individuals are randomly selected (by the intermediate of school) from an underlying population (i.e. adolescents from East London schools), so that the personal characteristics of individuals should also be randomly distributed (Wooldridge 2010). Using a random effects or marginal approach would then allow for inference to that population.

Although the main arguments for not using the fixed effects approach are specific to the longitudinal models, there are also arguments for not treating schools as fixed effects to account for clustering in cross-sectional analysis. Including school as a fixed effects would indeed restrict inference to a specific set of schools sampled, whereas the target of inference is the *population* of adolescents from all schools in East London (Rabe-Hesketh & Skrondal 2012). In addition, this would imply adding 24 additional dummy variables in the model and prevent a proper examination of ethnicity interactions due to the segregation of ethnic groups by school (Schempf & Kaufman 2012).

Marginal versus conditional models

Having decided to use neither GLM with cluster-robust standard errors, nor fixed effects models, a third major choice in the analytical strategy is that between marginal and conditional models, which are also known as subject-specific models (e.g. random effects, multilevel or mixed models). With Gaussian outcomes, there is a convenient one-to-one correspondence between mixed models that specify a fixed component and a random component, and marginal models that define a mean structure, a variance function and a correlation/covariance structure accounting for association across clustered observations[34] (Fitzmaurice et al. 2011). The fixed components of the model, or mean structure, has an easy interpretation in terms of population-average change in the outcome.

With non-Gaussian outcomes, and binary outcomes in particular, there is no such direct correspondence between the marginal and the mixed models[35] (Fitzmaurice et al. 2011, Molenberghs & Verbeke 2005). In other words, there is no general framework under which marginal and mixed models have a similar interpretation. Marginal models are usually estimated with generalised estimating equations (GEE), and the most common forms of mixed models in the GLM context are generalised linear mixed models (GLMM).

The choice between mixed models and marginal models has to be made on subject-matter grounds. Marginal models describe population-average effects whereas mixed models describe conditional subject-specific effects. Because marginal models separately specify a model for the mean response component and a model for the within-subject association, the regression coefficients have an interpretation that does not depend on the assumptions made about the within-subject association (Fitzmaurice et al. 2011). Thus, the regression coefficients in marginal models describe the effects of covariates on the population mean response. Conversely, mixed models assume that some of the parameters are heterogeneous across individuals, according to some underlying distribution. Conditional on these random effects, it is assumed that measurements on the same cluster are independent. GLMM can be seen as a natural extension of linear mixed models with the use of random effects to capture the correlation within clusters. However, because non-linear link functions are usually used in GLM as opposed to the linear function used in linear models, regression parameters from a GLMM have a subject-specific interpretation, and not a population average interpretation (Agresti 2002, Fitzmaurice et al. 2011, Molenberghs & Verbeke 2005). Parameters indicate, for

[34] Note that a mixed model implies a marginal model, but different mixed models might have the same marginal model (Molenberghs & Verbeke 2005). In practice, one fits a marginal model and interprets it in terms of a meaningful multilevel model.

[35] A key problem is the absence of a unique multivariate Bernoulli (or Poisson) distribution as is the case with the Multivariate Normal distribution (Molenberghs & Verbeke 2005).

each separate cluster, to what extent difference in mean response is related to difference in the covariates.

In public health and epidemiological research, the population-averaged effect of a treatment or an intervention is often of interest, as opposed to the specific effect observed on individuals (Agresti 2002, Fitzmaurice et al. 2011). In this thesis, the interest lies in how changes in the neighbourhood and home environments affect, *on average*, physical activity in the study population. For this reason, marginal models are preferred over generalised linear mixed models. More specifically, I am using GEE to estimate marginal models for both longitudinal and cross-sectional data.

Appendix D Supplementary material for chapter 5

D.1 Model equations of chapter 5

Two types of generalised linear models are used in chapter 5: linear regression models (for log of total physical activity) and logistic regression models (for daily recommended physical activity, walking to school, walking for leisure, outdoor physical activity and pay and play physical activity). In all models, cluster-robust standard errors are used to adjust the standard errors for clustering at school level.

Linear regression models

The equation of the adjusted linear model fitted in Table 5.2 is as follows:

$$Log(Y_i) = \beta_0 + \beta_1 Prox1_i + \beta_2 Prox2_i + \beta_3 Traf\_safe1_i + \beta_4 Traf\_safe2_i + \beta_5 Connect1_i + \beta_6 Connect2_i + \beta_7 Aest1_i + \beta_8 Aest2_i + \beta_9 Safe1_i + \beta_{10} Safe2_i + \beta_{11} Season_i + \beta_{12} Girl_i + \beta_{13} EtH1_i + \beta_{14} EtH2_i + \beta_{15} EtH3_i + \beta_{16} EtH4_i + \beta_{17} EtH5_i + \beta_{18} EtH6_i + \beta_{19} EtH7_i + \beta_{20} FSM_i + \beta_{21} HealtH1_i + \beta_{22} HealtH2_i + \beta_{23} FAS1_i + \beta_{24} FAS2_i + \beta_{25} Bor1_i + \beta_{26} Bor2_i + \beta_{27} Bor3_i + \beta_{28} BirtH_i + \beta_{29} Par\_empl1_i + \beta_{30} Par\_empl2_i + \beta_{31} Par\_empl3_i + \beta_{32} Par\_empl4_i + \beta_{33} Par\_empl5_i$$

Where:

i= individual

Y_i = total physical activity outcome

$Prox1_i, Prox2_i$ = Perceived proximity to destination dummy variables (reference category: low)

$Traf\_safe1_i, Traf\_safe2_i$ = Perceived traffic safety dummy variables (reference category: low)

$Connect1_i, Connect2_i$ = Perceived street connectivity dummy variables (reference category: low)

$Aest1_i$, $Aest2_i$ = Perceived aesthetics dummy variables (reference category: low)

$Safe1_i Safe2_i$ = Perceived crime-related safety dummy variables (reference category: low)

$Season_i$ = Season of interview dummy variable (reference category: winter)

$Girl_i$= dummy variable for girls

$EtH1_i$,..., $EtH7_i$= Ethnicity dummy variables (reference category: White UK)

FSM_i= Baseline free school meal status (reference category: no free school meal)

$HealtH1_i, HealtH2_i$ = Health conditions dummy variables (reference category: no condition)

$FAS1_i, FAS2_i$= Family affluence dummy variables (reference category: low)

$Bor1_i, \dots, Bor3_i$ = Borough dummy variables (reference category: Newham)

$BirtH_i$ = Country of birth dummy variable (ref category: UK)

$Par\_empl1_i, \dots, Par\_empl5_i$ = Parental employment dummy variables (reference category: both unemployed)

Logistic regression models

The generic form of the logistic regression models used in Table 5.3-Table 5.9 is expressed as follows:

$$logit\{\Pr(Y_i = 1|\boldsymbol{x_i})\} = \boldsymbol{x}_i'\boldsymbol{\beta}$$

Where:

i= individual

Y_i = physical activity outcome: daily recommended physical activity, walking to school, walking for leisure, outdoor physical activity or pay and play physical activity

$\boldsymbol{x_i}$ = a matrix representing the variables included in the model

$\boldsymbol{\beta}$ = a vector representing the coefficients of the model, including a constant

In the adjusted models, $\boldsymbol{x}_i'\boldsymbol{\beta}$ takes the following form:

$\boldsymbol{x}_i'\boldsymbol{\beta} = \beta_0 + \beta_1 Exposure\_cat2_i + \cdots + \beta_4 Exposure\_catm_i + \beta_5 Covariate\_1_i + \cdots + \beta_{4+p} Covariate\_p_i$

Where:

$Exposure\_cat2_i, \dots, Exposure\_catm_i$= dummy variables representing m-1 categories of the exposure variable of interest

$Covariate\_1_i, \dots, Covariate\_p_i$= dummy variables for all other variables included in the adjusted model

Appendix E Supplementary material for chapter 6

E.1 Analysis of missingness for chapter 6

This appendix presents results from analyses of the missing data of the variables used in chapter 6. The analyses were conducted in order to inform: i) the validity of the complete case analysis; ii) the plausibility of the MAR assumption; and iii) the selection of the auxiliary variables of the imputation model. Note that these analyses are only informative and should be interpreted with caution as some assumptions might be violated in some of the models (e.g. clustering at individual level, normality in the error terms).

Validity of the complete case analysis

In many instances, analyses of cohort studies are conducted on the complete cases, ignoring missing data and implicitly assuming the data to be MCAR. For the complete case analysis to be valid, the probability of being a complete case has to be independent of the outcome, conditional on the covariates in the models of interest (Carpenter & Kenward 2012). This is assessed in Table E.1 using logistic regression models (and therefore assuming that observations are independent, i.e. ignoring clustering).

Results indicate that walking to school has significant bivariate associations with missingness of personal safety, and some evidence with missingness on the two socio-economic variables (family affluence and free school meals). The strength of evidence of associations weakens in the adjusted models. Adjusted models indicate that missingness on perceived connectivity might be related to walking to school.

Walking for leisure is most likely not associated with missingness of the exposure variables (i.e. measures of neighbourhood perceptions), as indicated both in adjusted and unadjusted models. There is weak evidence of an association between missingness on FSM and walking for leisure.

The odds of outdoor physical activity are associated with missingness on most of the exposure variables but not with missingness on potential confounders. Associations weaken and even sometimes change direction in fully adjusted models. There remains evidence that the probability of having missing personal safety is more likely amongst those who reported outdoor physical activity (adjusted OR = 0.42, p-value=0.049).

Overall, these results indicate that a complete case analysis might lead to some bias. Due to widespread item missingness, this analysis cannot be fully conclusive however. It is unclear whether weaker associations in the fully adjusted models are themselves biased (because of the change in the sample) or if they indicate that the complete case analysis is still valid once controlling for all relevant variables (i.e. once adjusted for covariates, missingness does not depend that much on the outcomes). Given that some significant associations remain in the adjusted models, the results overall indicate that a complete case analysis is very likely to be biased, which by the same token, rules out the MCAR assumption.

Table E.1 Assessment of complete case analysis validity: unadjusted and adjusted ORs of item response for each covariate with missing values by outcome variable (adjusted and unadjusted results; n = 2,260; 6,780 measurements)

Covariate	N missing	% missing	Outcome	N	OR	P-value	N*	OR*	P-value*
Bus stop proximity	702	10.4	Walk to school	6446	1.05	0.652	4341	0.51	0.027
			Walk for leisure	6102	0.87	0.179	4216	0.95	0.812
Perceived traffic safety	911	13.4	Outdoor PA	5798	0.71	0.010	4055	1.13	0.654
			Walk to school	6446	1.14	0.140	4341	0.87	0.588
			Walk for leisure	6102	1.08	0.382	4217	1.19	0.457
Perceived street connectivity	1275	18.8	Outdoor PA	5798	0.67	<0.001	4057	1.21	0.467
			Walk to school	6446	1.05	0.554	4456	0.72	0.077
			Walk for leisure	6102	0.93	0.341	4328	0.88	0.405
Nice neighbourhood			Outdoor PA	5798	0.86	0.097	4156	1.14	0.436
for walking/cycling	855	12.6	Walk to school	6446	1.12	0.213	4105	0.60	0.221
			Walk for leisure	6102	0.93	0.449	3992	0.54	0.062
Feeling safe	1022	15.1	Outdoor PA	5798	0.69	0.001	3841	0.89	0.778
			Walk to school	6446	1.19	0.038	4303	1.12	0.713
			Walk for leisure	6102	0.96	0.655	4188	0.86	0.595
			Outdoor PA	5798	0.67	<0.001	4032	0.42	0.049
Health condition	741	10.9	Walk to school	6446	1.09	0.363	4707	0.91	0.454
			Walk for leisure	6102	1.09	0.342	4576	0.99	0.898
			Outdoor PA	5798	0.99	0.911	4390	1.31	0.032
FAS Categories	264	3.9	Walk to school	6446	1.29	0.092	4347	1.22	0.386
			Walk for leisure	6102	1.15	0.367	4221	1.17	0.500
			Outdoor PA	5798	0.97	0.850	4064	0.99	0.968
Take FSM at wave 1	138	2.0	Walk to school	6446	1.45	0.061	4120	1.00	0.988
			Walk for leisure	6102	1.65	0.025	4009	1.74	0.089
			Outdoor PA	5798	1.16	0.503	3860	1.12	0.732

*Adjusted for all other covariates in the table, plus gender and ethnicity. Results from logistic regression models. . Response is coded 1 and missingness 0. PA – physical activity

Plausibility of the MAR mechanism

As explained in the methods chapter (chapter 4), MAR is plausible if the probability of each variable being missing depends on the fully (or mostly fully) observed variables. To investigate this, I conducted missingness analyses on the variables with the highest proportions of missing values, i.e. the three outcomes (walking to school, walking for leisure and outdoor physical activity) and the five exposure variables (bus stop proximity, traffic safety, connectivity, nice neighbourhood and personal safety). I ran a series of logistic regressions to identify variables predictive of missing values (Table E.2). Variables used were (almost) fully observed variables from the model of interest (gender, ethnicity, family affluence, free school meals) and auxiliary variables *a priori* hypothesised to be associated with the probability of missingness and/or of the variables with missing values (Table E.1). Auxiliary variables retained are school, length of interview, country of birth, self-rated health, mental health (WEMWBS total score), total physical activity (log-transformed) and BMI (z-score). The latter BMI score has a slightly higher proportion of missing values and is therefore investigated separately to be able to identify whether adjusting for BMI (and therefore changing the analytical sample) might distort the other associations.

Amongst the (almost) fully observed variables of the model of interest, gender, ethnicity, school and, to a lower extent, FSM are good predictors of missingness (Table E.2). There is less evidence that FAS categories predict missingness. The predictive ability of the auxiliary variables varies. There is good evidence that mental health predicts missingness on all perception variables but also on walking to school. Total PA is a good predictor of missingness on the physical activity variables, but less on the perception variables. There is some evidence that BMI predicts physical activity outcomes but also some perception variables. Results are more mixed for self-rated health and country of birth; in particular, country of birth does not seem to be associated with missingness of the variables considered. As for session progress, as expected, it is strongly associated with missingness on all variables. In general, the shorter the session, the higher the chance of having missing values on the variables.

This analysis shows that at least some variables are predictive of missingness, which supports the plausibility of the MAR assumption. Variables with more missing values are also likely to predict missingness on the variables of the models of interest so that an imputation model with the wide range of variables considered will further strengthen the plausibility of the assumption. However, it is not possible to rule out MNAR, and it might be that even accounting for all these variables, the missingness mechanism depends on unmeasured variables. There is however no theoretical or practical reason to believe that this could be the case.

Table E.2 Assessment of the MAR assumption: (almost) fully observed predictors of item missingness for the variables with high levels of missing values.

Missingness variable	Predictor	Adjusted p-value	BMI Adjusted p-value
Walking to school	Gender	0.102	0.192
	Ethnicity	0.008	0.006
	School	0.084	0.061
	FAS Categories	0.742	0.875
	Take FSM at W1	0.608	0.762
	Country of Birth	0.624	0.640
	Self-rated health	0.247	0.268
	Session progress	0.078	0.093
	total PA(log)	0.008	0.001
	WEMWBS score	0.003	0.003
	BMI(z-score)	.	0.117
Walking for leisure	Gender	<0.001	<0.001
	Ethnicity	<0.001	<0.001
	School	0.002	0.002
	FAS Categories	0.069	0.032
	Take FSM at W1	0.284	0.377
	Country of Birth	0.817	0.751
	Self-rated health	0.454	0.425
	Session progress	<0.001	<0.001
	total PA(log)	<0.001	<0.001
	WEMWBS score	0.708	0.964
	BMI(z-score)	.	0.086
Outdoor physical activity	Gender	0.005	0.011
	Ethnicity	<0.001	<0.001
	School	<0.001	<0.001
	FAS Categories	0.054	0.018
	Take FSM at W1	0.080	0.077
	Country of Birth	0.362	0.227
	Self-rated health	0.681	0.522
	Session progress	<0.001	<0.001
	total PA(log)	0.036	0.017
	WEMWBS score	0.774	0.783
	BMI(z-score)	.	0.091
Bus stop proximity	Gender	<0.001	<0.001
	Ethnicity	0.004	0.005
	School	<0.001	<0.001
	FAS Categories	0.171	0.142
	Take FSM at W1	0.001	0.001
	Country of Birth	0.132	0.058
	Self-rated health	0.058	0.012
	Session progress	<0.001	<0.001
	total PA(log)	0.699	0.377
	WEMWBS score	0.003	<0.001
	BMI(z-score)	.	0.007
Traffic safety	Gender	<0.001	<0.001
	Ethnicity	<0.001	<0.001

	School	<0.001	<0.001
	FAS Categories	0.554	0.700
	Take FSM at W1	0.001	0.004
	Country of Birth	0.414	0.377
	Self-rated health	0.353	0.122
	Session progress	<0.001	<0.001
	total PA(log)	0.582	0.334
	WEMWBS score	0.002	<0.001
	BMI(z-score)	.	0.042
Perceived street connectivity	Gender	0.051	0.088
	Ethnicity	0.001	0.005
	School	<0.001	<0.001
	FAS Categories	0.270	0.501
	Take FSM at W1	0.006	0.009
	Country of Birth	0.549	0.532
	Self-rated health	0.053	0.095
	Session progress	<0.001	<0.001
	total PA(log)	0.452	0.465
	WEMWBS score	<0.001	<0.001
	BMI(z-score)	.	0.972
Enjoyment of neighbourhood for walking/cycling	Gender	<0.001	<0.001
	Ethnicity	<0.001	<0.001
	School	<0.001	<0.001
	FAS Categories	0.521	0.830
	Take FSM at W1	0.002	0.002
	Country of Birth	0.441	0.365
	Self-rated health	0.286	0.415
	Session progress	<0.001	<0.001
	total PA(log)	0.773	0.548
	WEMWBS score	0.001	<0.001
	BMI(z-score)	.	0.389
Feeling safe	Gender	<0.001	<0.001
	Ethnicity	0.001	0.004
	School	<0.001	<0.001
	FAS Categories	0.260	0.573
	Take FSM at W1	<0.001	<0.001
	Country of Birth	0.608	0.482
	Self-rated health	0.081	0.224
	Session progress	<0.001	<0.001
	total PA(log)	0.606	0.564
	WEMWBS score	0.002	0.002
	BMI(z-score)	.	0.761

Results from logistic regression models.

Selecting variables for the imputation model

The imputation model should include variables of the models of interest and relevant auxiliary variables. The later should be included only if they are likely to reduce bias and/or to increase efficiency (Carpenter & Kenward 2012). Variables predictive of the chance of missing values identified above should be included in the imputation model only if they also predict the underlying missing values, in which case, they are likely to reduce bias and improve efficiency.

Auxiliary variables should however be excluded if they do not predict the underlying values themselves. Variables associated with the underlying values - but not the chance of missing values - should be included because they will improve efficiency, although they are not going to reduce bias.

Table E.3 reports (multinomial) logistic regression results of associations between auxiliary variables and the variables with most missing values (outcomes and exposures of the models of interest). Total physical activity is strongly associated with the physical activity outcomes. The mental health score is associated with almost all variables. Self-rated health and country or birth are strongly associated with some of the perception and the physical activity variables, which indicates that these auxiliary variables might increase efficiency rather than reduce bias (in view of the results from Table E.2). BMI is associated with walking for leisure, traffic safety and personal safety, but not with the other variables of Table E.3. Surprisingly, session progress turned out to be associated with traffic safety and nice neighbourhood, as well as bus distance. These associations are unexpected and might reflect systematic measurement error caused by the survey context. Including session progress in the imputation model might therefore exacerbate that bias, which is why I recommend not including session progress in the imputation model.

Overall, the analysis shows that an imputation model with the auxiliary variables considered – country of birth, self-rated health, total physical activity, mental health and BMI – are very likely to potentially reduce bias and improve efficiency compared to a complete case analysis. In the imputation models, the three continuous auxiliary variables were zero-centred and transformed to make them resemble normal distributions.

Finally, the variable measuring daytime perceived safety in the neighbourhood (from the ALPHA questionnaire) was also included in the imputation model. The variable was excluded from the main missing data analysis produced in this appendix because of its high level of missingness (which affected convergence of some of the multinomial logistic regressions). Additional analyses however (not presented) revealed that it was predictive of most of the perceptions variables and their missingness, which indicated a potential to reduce bias and increase efficiency.

Table E.3 Associations between variables with missing values and auxiliary variables, adjusted for auxiliary variables, gender, ethnicity, school, FSM and FAS. Results from (multinomial) logistic regression with and without BMI adjustment.

Variable with missing value	Predictor	p-value	BMI adjusted p-value
Walking to school	Country of Birth	0.594	0.942
	Self-rated health	0.987	0.981
	Session progress	0.422	0.426
	total PA(log)	<0.001	<0.001
	WEMWBS score	0.308	0.157
	BMI(z-score)	.	0.858
Walking for leisure	Country of Birth	0.019	0.044
	Self-rated health	0.001	0.001
	Session progress	0.343	0.296
	total PA(log)	<0.001	<0.001
	WEMWBS score	0.008	0.039
	BMI(z-score)	.	0.004
Outdoor physical activity	Country of Birth	0.002	0.006
	Self-rated health	0.077	0.075
	Session progress	0.612	0.713
	total PA(log)	<0.001	<0.001
	WEMWBS score	0.020	0.012
	BMI(z-score)	.	0.524
Bus stop proximity	Country of Birth	0.403	0.147
	Self-rated health	0.476	0.435
	Session progress	0.030	0.036
	total PA(log)	0.039	0.051
	WEMWBS score	0.001	0.002
	BMI(z-score)	.	0.842
Traffic safety	Country of Birth	0.640	0.437
	Self-rated health	0.008	0.013
	Session progress	0.101	0.142
	total PA(log)	0.003	0.004
	WEMWBS score	<0.001	<0.001
	BMI(z-score)	.	0.015
Perceived street connectivity	Country of Birth	0.082	0.070
	Self-rated health	<0.001	<0.001
	Session progress	0.612	0.711
	total PA(log)	0.005	0.001
	WEMWBS score	<0.001	<0.001
	BMI(z-score)	.	0.473
Enjoyment of neighbourhood for walking/cycling	Country of Birth	0.011	0.006
	Self-rated health	<0.001	<0.001
	Session progress	0.019	0.042
	total PA(log)	0.008	0.019
	WEMWBS score	<0.001	<0.001
	BMI(z-score)	.	0.327
Feeling safe	Country of Birth	0.004	0.002
	Self-rated health	<0.001	<0.001
	Session progress	0.647	0.858
	total PA(log)	0.191	0.298
	WEMWBS score	<0.001	<0.001
	BMI(z-score)	.	0.017

E.2 Model equations of chapter 6

This appendix provides a general form of the types of models fitted in chapter 6. Three types of models are fitted: pooled longitudinal models, cross-sectional models for cumulative exposure and models for trajectories of exposure and outcome.

Pooled longitudinal models (general association)

The time-varying measures of perceptions are used. The adjusted models account for time-invariant (gender, ethnicity, baseline FSM) and time-varying confounders (health status and family affluence) and include all five time-varying perceptions of the neighbourhood environment. A time trend is included to reflect the general decrease in physical activity during adolescence. The models are fitted with GEE to account for clustering at individual level *i*. The adjusted logistic model is expressed as follows:

$$logit\{\Pr(Y_{ij} = 1|\boldsymbol{x_{ij}})\} = \boldsymbol{x'_{ij}\beta}$$

Where:

i= individual

j= repeated measures

Y_{ij} = physical activity outcome (walking to school, walking for leisure or outdoor physical activity) for individual *i* at occasion *j*

$\boldsymbol{x_{ij}}$ = a matrix representing the variables included in the model for all individuals at each occasion

$\boldsymbol{\beta}$ = a vector representing the coefficients of the model, including a constant

In the adjusted model, $\boldsymbol{x'_{ij}\beta}$ takes the following form:

$$\boldsymbol{x'_{ij}\beta} = \beta_0 + \beta_1 Bus\_prox_{ij} + \beta_2 Traf\_safe1_{ij} + \beta_3 Traf\_safe2_{ij} + \beta_4 Connect1_{ij} + \beta_5 Connect2_{ij} + \beta_6 Nice1_{ij} + \beta_7 Nice2_{ij} + \beta_8 Safe1_{ij} + \beta_9 Safe2_{ij} + \beta_{10} Safe3_{ij} + \beta_{11} Safe4_{ij} + \beta_{12} Girl_i + \beta_{13} EtH1_i + \beta_{14} EtH2_i + \beta_{15} EtH3_i + \beta_{16} EtH4_i + \beta_{17} EtH5_i + \beta_{18} EtH6_i + \beta_{19} EtH7_i + \beta_{20} FSM_{i1} + \beta_{21} HealtH_{ij} + \beta_{22} FAS1_{ij} + \beta_{23} FAS2_{ij} + \beta_{24} time_j$$

Where:

Bus_prox_{ij} = Perceived bus stop proximity dummy variable (reference category: far away)

$Traf\_safe1_{ij}, Traf\_safe2_{ij}$ = Perceived traffic safety dummy variables (reference category: low)

$Connect1_{ij}, Connect2_{ij}$ = Perceived street connectivity dummy variables (reference category: low)

$Nice1_{ij}$, $Nice2_{ij}$ = Enjoyment of neighbourhood dummy variables (reference category: disagree)

$Safe1_{ij}, \ldots, Safe4_{ij}$ = Perceived personal safety dummy variables (reference category: strongly disagree)

$Girl_i$= dummy variable for girls (time invariant)

$EtH1_i$,…, $EtH7_i$= Ethnicity dummy variables (reference category: White UK; time invariant)

FSM_{i1}= Baseline free school meal status (reference category: no free school meal)

$HealtH_{ij}$ = Health conditions dummy variable (reference category: no condition)

$FAS1_{ij}, FAS2_{ij}$= Family affluence dummy variables (reference category: low)

$time_j$= continuous variable indicating the wave (1, 2 or 3)

Five additional models are run with an interaction term each between gender and an aspect of perception of the neighbourhood environment. For instance, the adjusted model with an interaction term between gender and traffic safety is as follows:

$$\boldsymbol{x'_{ij}\beta} = \beta_0 + \beta_1 Bus\_prox_{ij} + \beta_2 Traf\_safe1_{ij} + \beta_3 Traf\_safe2_{ij} + \beta_4 Connect1_{ij} + \beta_5 Connect2_{ij} + \beta_6 Nice1_{ij} + \beta_7 Nice2_{ij} + \beta_8 Safe1_{ij} + \beta_9 Safe2_{ij} + \beta_{10} Safe3_{ij} + \beta_{11} Safe4_{ij} + \beta_{12} Girl_i + \beta_{13} EtH1_i + \beta_{14} EtH2_i + \beta_{15} EtH3_i + \beta_{16} EtH4_i + \beta_{17} EtH5_i + \beta_{18} EtH6_i + \beta_{19} EtH7_i + \beta_{20} FSM_{i1} + \beta_{21} HealtH_{ij} + \beta_{22} FAS1_{ij} + \beta_{23} FAS2_{ij} + \beta_{24} time_j + \beta_{25} Traf\_safe1_{ij} * Girl_i + \beta_{26} Traf\_safe2_{ij} * Girl_i$$

Cross-sectional models for cumulative exposure and binary outcomes

Models are fitted to predict physical activity outcomes at wave 3 based on the cumulative exposure variables. Logistic regression models are estimated with GEE to account for clustering at school level (*j* in this model). The exposure variables are treated as continuous variables and the adjusted model adjusts for gender, ethnicity, baseline FSM, health status and family affluence reported at wave 3. The adjusted model is:

$$logit\{\Pr(Y_{ij} = 1|\boldsymbol{x_{ij}})\} = \boldsymbol{x'_{ij}\beta}$$

Where:

i = individual

j = school

$$\boldsymbol{x'_{ij}\beta} = \beta_0 + \beta_1 Cum\_prox_{ij} + \beta_2 Cum\_traf\_safe_{ij} + \beta_3 Cum\_connect_{ij} + \beta_4 Cum\_nice_{ij} + \beta_5 Cum\_safe_{ij} + \beta_6 Girl_{ij} + \beta_7 EtH1_{ij} + \beta_8 EtH2_{ij} + \beta_9 EtH3_{ij} + \beta_{10} EtH4_{ij} + \beta_{11} EtH5_{ij} + \beta_{12} EtH6_{ij} + \beta_{13} EtH7_{ij} + \beta_{14} FSM_{ij} + \beta_{15} HealtH_{ij} + \beta_{16} FAS1_{ij} + \beta_{17} FAS2_{ij}$$

Cum_prox_{ij} = cumulative proximity score

$Cum\_traf\_safe_{ij}$= cumulative traffic safety score

$Cum\_connect_{ij}$ = cumulative street connectivity

Cum_nice_{ij}= cumulative enjoyment of neighbourhood score

Cum_safe_{ij}= cumulative personal safety score

In addition, five models with interaction terms between cumulative perception score and gender were fitted. For example, the model with gender*cumulative personal safety interaction is:

$$\begin{aligned} \boldsymbol{x}_{ij}'\boldsymbol{\beta} = {} & \beta_0 + \beta_1 Cum\_prox_{ij} + \beta_2 Cum\_traf\_safe_{ij} + \beta_3 Cum\_connect_{ij} + \beta_4 Cum\_nice_{ij} \\ & + \beta_5 Cum\_safe_{ij} + \beta_6 Girl_{ij} + \beta_7 EtH1_{ij} + \beta_8 EtH2_{ij} + \beta_9 EtH3_{ij} + \beta_{10} EtH4_{ij} \\ & + \beta_{11} EtH5_{ij} + \beta_{12} EtH6_{ij} + \beta_{13} EtH7_{ij} + \beta_{14} FSM_{ij} + \beta_{15} HealtH_{ij} + \beta_{16} FAS1_{ij} \\ & + \beta_{17} FAS2_{ij} + \beta_{18} Cum\_safe_{ij} * Girl_{ij} \end{aligned}$$

Models for trajectory of exposure and change in binary outcomes

To test the relationship between trajectories of perceptions (i.e. change between wave 3 and baseline) and change in physical activity, logistic regressions are estimated with GEE to account for the clustering at individual level *i*. Models adjust for time-invariant confounders (gender, ethnicity, baseline FSM), time-varying covariates (health status, family affluence), and a time trend. The exposure variables are continuous and time-invariant. Their role in the model is comparable to a baseline treatment. To assess the associations between trajectory of exposure and change in physical activity, an interaction term is added between time and the trajectory variable. The general form of the model is the same as for the pooled longitudinal analysis. The specific equation of the adjusted model is:

$$\boldsymbol{x}_{ij}'\boldsymbol{\beta} = \beta_0 + \beta_1 CHange\_prox_i + \beta_2 CHange\_traf\_safe_i + \beta_3 CHange\_connect_i + \beta_4 CHange\_nice_i + \beta_5 CHange\_safe_i + \beta_6 CHange\_prox_i * time_j + \beta_7 CHange\_traf\_safe_i * time_j + \beta_8 CHange\_connect_i * time_j + \beta_9 CHange\_nice_i * time_j + \beta_{10} CHange\_safe_i * time_j + \beta_{11} Girl_i + \beta_{12} EtH1_i + \beta_{13} EtH2_i + \beta_{14} EtH3_i + \beta_{15} EtH4_i + \beta_{16} EtH5_i + \beta_{17} EtH6_i + \beta_{18} EtH7_i + \beta_{19} FSM_{i1} + \beta_{20} HealtH_{ij} + \beta_{21} FAS1_{ij} + \beta_{22} FAS2_{ij} + \beta_{23} time_j$$

Where:

$CHange\_prox_i$= trajectory of change in perceived bus stop proximity

$CHange\_traf\_safe_i$= trajectory of change in perceived traffic safety

$CHange\_connect_i$= trajectory of change in perceived street connectivity

$CHange\_nice_i$= trajectory of change in enjoyment of neighbourhood

$CHange\_safe_i$= trajectory of change in perceived personal safety

Five additional models included a tree-way interaction term to assess whether gender moderates the association between trajectory of perception and change in physical activity. For example, the equation for a gender interaction with street connectivity is:

$$\boldsymbol{x}_{ij}'\boldsymbol{\beta} = \beta_0 + \beta_1 CHange\_prox_i + \beta_2 CHange\_traf\_safe_i + \beta_3 CHange\_connect_i + \beta_4 CHange\_nice_i + \beta_5 CHange\_safe_i + \beta_6 CHange\_prox_i * time_j + \beta_7 CHange\_traf\_safe_i * time_j + \beta_8 CHange\_connect_i * time_j + \beta_9 CHange\_nice_i * time_j + \beta_{10} CHange\_safe_i * time_j + \beta_{11} Girl_i + \beta_{12} EtH1_i + \beta_{13} EtH2_i + \beta_{14} EtH3_i + \beta_{15} EtH4_i + \beta_{16} EtH5_i + \beta_{17} EtH6_i + \beta_{18} EtH7_i + \beta_{19} FSM_{i1} + \beta_{20} HealtH_{ij} + \beta_{21} FAS1_{ij} + \beta_{22} FAS2_{ij} + \beta_{23} time_j + \beta_{24} Girl_i * time_j + \beta_{25} Girl_i * time_j * CHange\_connect_i$$

E.3 Selection of the working correlation structures in the GEE estimation process using the complete cases

To decide on the working correlation to use, I compared model-based and robust standard errors (SEs) of the parameters of the models for different working correlations structures. The working correlation of choice should be the one with smallest difference between the two types of SEs. For each hypothesis tested (each type of model) and each outcome, several specifications of the working correlation were fitted. For the pooled longitudinal models and models for trajectory of change, I used unstructured (i.e. allowing for different correlations across waves), exchangeable/compound symmetry (i.e. same correlation across waves), and autoregressive of the First order or AR1 (i.e. a decreasing correlation over time). For the models estimated with GEE accounting for clustering at school level (cross-sectional model), exchangeable and independent working correlation were applied. Comparisons of the SEs for each model of interest are in Table E.4-Table E.12 and summarised as follows

Pooled longitudinal models

Results from Table E.4-Table E.6 indicate that exchangeable and unstructured working correlations give better results. Exchangeable working correlations seem more appropriate for the first two outcomes (Table E.4 and Table E.5) but unstructured working correlation is slightly better for outdoor physical activity (Table E.6). In all three Tables, AR1 correlations lead to the greater differences between model-based and robust SEs.

Cross-sectional models for cumulative exposure

Difference between exchangeable and independent working correlations are marginal (Table E.7-Table E.9). Exchangeable working correlations have smallest difference between robust and model-based SEs for walking to school and walking for leisure outcomes (Table E.7 and Table E.8). For the outcome outdoor physical activity, an independent working correlation structure leads to smaller differences in the SEs for the main parameters (Table E.9). This suggests that the clustering effect at school level is almost negligible.

Models for trajectories of exposure and outcome

For the main parameters of interest, unstructured working correlation seems to be more appropriate (Table E.10-Table E.12). The differences between model-based and robust SEs are very similar for both specifications of the correlation structures. AR1 correlations lead to greater standard error (SE) differences.

Conclusion

Results indicate that the choice between unstructured and exchangeable working correlation does not seem to matter for the longitudinal models (pooled and trajectory). Results from the cross-sectional models for cumulative exposure indicate that clustering at school level does not have a great role; therefore independent correlation could also be used. Exchangeable working correlation is nevertheless used to stress on the correlation at school level. For all the longitudinal models, the more flexible – unstructured – working correlations are used.

Table E.4 Comparison of the parameters and standard errors of three different specifications of the working correlation matrix in the GEE estimation of the fully adjusted pooled longitudinal model for walking to school

parameter	b UN	b AR1	b EXC	SE UN Robust	SE UN Model	SE AR1 Robust	SE AR1 Model	SE EXC Robust	SE EXC Model	Diff SE UN	Diff SE AR1	Diff SE EXC
time	-0.036	-0.056	-0.034	0.037	0.038	0.044	0.050	0.037	0.038	-0.001	-0.006	-0.000
2.ibus_rr	-0.140	-0.251	-0.137	0.098	0.093	0.122	0.112	0.098	0.093	0.006	0.010	0.005
2.traffic	0.218	0.227	0.209	0.115	0.118	0.136	0.136	0.116	0.119	-0.004	-0.000	-0.003
3.traffic	0.180	0.130	0.178	0.114	0.118	0.135	0.136	0.116	0.119	-0.004	-0.001	-0.003
2.infra	0.095	0.121	0.096	0.089	0.089	0.108	0.103	0.089	0.089	0.000	0.004	-0.001
3.infra	0.189	0.188	0.181	0.110	0.111	0.132	0.127	0.110	0.111	-0.000	0.005	-0.001
2.nice3	0.080	0.015	0.073	0.087	0.092	0.105	0.107	0.088	0.092	-0.005	-0.002	-0.005
3.nice3	-0.086	-0.161	-0.099	0.099	0.102	0.121	0.120	0.099	0.103	-0.004	0.001	-0.004
2.n_safe2a	0.112	0.054	0.119	0.142	0.138	0.174	0.160	0.142	0.139	0.004	0.014	0.004
3.n_safe2a	0.037	-0.038	0.021	0.135	0.133	0.162	0.153	0.135	0.133	0.002	0.009	0.002
4.n_safe2a	0.073	0.010	0.060	0.138	0.134	0.166	0.155	0.138	0.135	0.003	0.011	0.003
5.n_safe2a	0.109	0.101	0.106	0.141	0.137	0.171	0.160	0.141	0.138	0.003	0.010	0.003
2.gender_r	0.085	0.029	0.086	0.092	0.092	0.113	0.109	0.092	0.092	-0.000	0.004	-0.000
2.d_eth_8cat	-0.549	-0.455	-0.543	0.188	0.186	0.232	0.220	0.188	0.186	0.002	0.012	0.002
3.d_eth_8cat	0.235	0.337	0.230	0.270	0.275	0.327	0.325	0.270	0.275	-0.005	0.001	-0.004
4.d_eth_8cat	-0.207	-0.204	-0.202	0.256	0.250	0.325	0.301	0.256	0.250	0.006	0.024	0.006
5.d_eth_8cat	0.270	0.232	0.271	0.175	0.176	0.203	0.199	0.175	0.176	-0.000	0.005	-0.000
6.d_eth_8cat	-0.939	-0.981	-0.950	0.222	0.221	0.273	0.262	0.222	0.221	0.001	0.012	0.001
7.d_eth_8cat	-0.416	-0.420	-0.416	0.174	0.177	0.219	0.218	0.174	0.177	-0.004	0.001	-0.004
8.d_eth_8cat	-0.326	-0.356	-0.330	0.135	0.136	0.159	0.156	0.135	0.136	-0.001	0.003	-0.001
2.health2	0.143	0.092	0.144	0.080	0.080	0.095	0.093	0.080	0.080	0.001	0.002	0.001

parameter	b UN	b AR1	b EXC	SE UN Robust	SE UN Model	SE AR1 Robust	SE AR1 Model	SE EXC Robust	SE EXC Model	Diff SE UN	Diff SE AR1	Diff SE EXC
2.fas_cat	-0.273	-0.211	-0.256	0.158	0.151	0.189	0.175	0.157	0.151	0.007	0.014	0.006
3.fas_cat	-0.245	-0.163	-0.235	0.165	0.159	0.195	0.185	0.163	0.159	0.005	0.010	0.004
2.fsm_ref_r	0.082	0.210	0.082	0.097	0.097	0.122	0.117	0.097	0.097	0.000	0.005	0.000
_cons	1.386	1.621	1.385	0.256	0.257	0.313	0.305	0.255	0.257	-0.002	0.008	-0.002

b - parameter of the logistic regression; SE - standard error of the parameter; EXC - exchangeable; UN - unstructured; AR1 - first-order auto-regressive ; Model – Model-based Standard Error produced by the GEE estimation; Robust – Cluster-Robust Standard Error; Diff – difference between Robust and Model-based Standard Errors

Table E.5 Comparison of the parameters and standard errors of three different specifications of the working correlation matrix in the GEE estimation of the fully adjusted pooled longitudinal model for walking for leisure

parameter	b UN	b AR1	b EXC	SE UN Robust	SE UN Model	SE AR1 Robust	SE AR1 Model	SE EXC Robust	SE EXC Model	Diff SE UN	Diff SE AR1	Diff SE EXC
time	-0.230	-0.202	-0.231	0.040	0.040	0.048	0.048	0.040	0.038	0.000	-0.000	0.002
2.ibus_rr	-0.132	-0.142	-0.134	0.082	0.084	0.095	0.098	0.083	0.085	-0.002	-0.003	-0.002
2.traffic	-0.111	-0.172	-0.103	0.119	0.115	0.134	0.130	0.119	0.116	0.003	0.004	0.003
3.traffic	-0.176	-0.201	-0.170	0.118	0.115	0.133	0.130	0.118	0.116	0.003	0.003	0.003
2.infra	0.100	0.142	0.103	0.088	0.088	0.100	0.101	0.088	0.089	-0.001	-0.001	-0.000
3.infra	0.133	0.143	0.129	0.107	0.106	0.122	0.121	0.108	0.107	0.001	0.001	0.001
2.nice3	-0.031	-0.077	-0.025	0.089	0.089	0.103	0.101	0.090	0.089	0.001	0.002	0.001
3.nice3	0.071	0.078	0.073	0.098	0.098	0.113	0.112	0.099	0.098	0.000	0.001	0.001
2.n_safe2a	0.286	0.234	0.279	0.136	0.135	0.154	0.154	0.137	0.136	0.001	-0.001	0.001
3.n_safe2a	0.080	0.116	0.072	0.134	0.131	0.150	0.148	0.134	0.132	0.002	0.001	0.002
4.n_safe2a	0.325	0.372	0.321	0.133	0.131	0.150	0.148	0.134	0.132	0.002	0.001	0.002
5.n_safe2a	0.204	0.292	0.198	0.137	0.135	0.156	0.154	0.138	0.136	0.002	0.002	0.002
2.gender_r	0.482	0.462	0.481	0.079	0.078	0.093	0.091	0.079	0.078	0.001	0.002	0.001

parameter	b UN	b AR1	b EXC	SE UN Robust	SE UN Model	SE AR1 Robust	SE AR1 Model	SE EXC Robust	SE EXC Model	Diff SE UN	Diff SE AR1	Diff SE EXC
2.d_eth_8cat	-0.362	-0.430	-0.359	0.161	0.157	0.192	0.184	0.161	0.157	0.004	0.008	0.004
3.d_eth_8cat	-0.398	-0.327	-0.399	0.200	0.201	0.235	0.231	0.201	0.202	-0.001	0.005	-0.001
4.d_eth_8cat	-0.687	-0.746	-0.694	0.199	0.210	0.246	0.252	0.200	0.211	-0.011	-0.005	-0.011
5.d_eth_8cat	-0.954	-1.014	-0.954	0.132	0.136	0.149	0.152	0.133	0.136	-0.004	-0.003	-0.003
6.d_eth_8cat	-0.889	-0.862	-0.912	0.213	0.210	0.254	0.253	0.214	0.211	0.004	0.001	0.003
7.d_eth_8cat	-0.949	-1.039	-0.944	0.158	0.160	0.192	0.199	0.158	0.161	-0.003	-0.008	-0.003
8.d_eth_8cat	-0.460	-0.555	-0.465	0.109	0.107	0.125	0.122	0.109	0.107	0.002	0.002	0.002
2.health2	0.004	0.050	0.006	0.073	0.073	0.085	0.083	0.074	0.073	0.001	0.002	0.001
2.fas_cat	0.049	-0.057	0.050	0.134	0.133	0.152	0.151	0.135	0.134	0.000	0.001	0.002
3.fas_cat	0.177	0.110	0.180	0.141	0.140	0.161	0.158	0.143	0.140	0.001	0.003	0.003
2.fsm_ref_r	0.162	0.172	0.156	0.083	0.082	0.098	0.096	0.083	0.082	0.001	0.002	0.001
_cons	-0.086	-0.021	-0.087	0.234	0.233	0.269	0.267	0.235	0.232	0.002	0.002	0.003

b - parameter of the logistic regression; SE - standard error of the parameter; EXC - exchangeable; UN - unstructured; AR1 - first-order auto-regressive ; Model – Model-based Standard Error produced by the GEE estimation; Robust – Cluster-Robust Standard Error; Diff – difference between Robust and Model-based Standard Errors

Table E.6 Comparison of the parameters and standard errors of three different specifications of the working correlation matrix in the GEE estimation of the fully adjusted pooled longitudinal model for outdoor physical activity

parameter	b UN	b AR1	b EXC	SE UN Robust	SE UN Model	SE AR1 Robust	SE AR1 Model	SE EXC Robust	SE EXC Model	Diff SE UN	Diff SE AR1	Diff SE EXC
time	-0.347	-0.314	-0.347	0.047	0.045	0.053	0.056	0.046	0.044	0.002	-0.002	0.002
2.ibus_rr	-0.023	-0.045	-0.020	0.097	0.100	0.112	0.116	0.098	0.100	-0.002	-0.004	-0.002
2.traffic	0.031	0.021	0.032	0.141	0.135	0.157	0.152	0.140	0.135	0.006	0.005	0.005
3.traffic	-0.088	-0.028	-0.084	0.144	0.135	0.162	0.152	0.144	0.135	0.010	0.010	0.010
2.infra	0.217	0.189	0.229	0.103	0.100	0.115	0.113	0.103	0.100	0.003	0.002	0.003

parameter	b UN	b AR1	b EXC	SE UN Robust	SE UN Model	SE AR1 Robust	SE AR1 Model	SE EXC Robust	SE EXC Model	Diff SE UN	Diff SE AR1	Diff SE EXC
3.infra	0.360	0.346	0.363	0.126	0.124	0.141	0.141	0.126	0.124	0.002	0.001	0.002
2.nice3	-0.014	0.154	-0.020	0.104	0.100	0.116	0.114	0.104	0.101	0.003	0.002	0.004
3.nice3	0.077	0.286	0.068	0.121	0.114	0.138	0.129	0.121	0.114	0.008	0.008	0.008
2.n_safe2a	0.120	0.090	0.121	0.152	0.153	0.172	0.173	0.152	0.152	-0.000	-0.001	-0.001
3.n_safe2a	-0.041	-0.058	-0.021	0.148	0.146	0.167	0.164	0.148	0.146	0.003	0.002	0.002
4.n_safe2a	0.059	0.002	0.065	0.144	0.147	0.160	0.166	0.144	0.147	-0.003	-0.005	-0.003
5.n_safe2a	0.131	0.071	0.141	0.153	0.154	0.174	0.176	0.152	0.154	-0.001	-0.002	-0.002
2.gender_r	-1.590	-1.625	-1.588	0.098	0.098	0.117	0.114	0.098	0.098	-0.000	0.003	-0.000
2.d_eth_8cat	0.320	0.239	0.322	0.190	0.192	0.229	0.224	0.190	0.192	-0.002	0.005	-0.002
3.d_eth_8cat	0.198	0.025	0.196	0.243	0.248	0.289	0.283	0.244	0.249	-0.005	0.006	-0.005
4.d_eth_8cat	0.928	0.848	0.921	0.295	0.298	0.359	0.372	0.295	0.298	-0.003	-0.014	-0.003
5.d_eth_8cat	0.062	-0.087	0.064	0.154	0.157	0.178	0.175	0.154	0.157	-0.002	0.003	-0.003
6.d_eth_8cat	0.086	-0.067	0.087	0.224	0.227	0.283	0.270	0.224	0.228	-0.003	0.013	-0.004
7.d_eth_8cat	0.562	0.251	0.563	0.183	0.193	0.221	0.228	0.183	0.193	-0.010	-0.007	-0.011
8.d_eth_8cat	0.271	0.071	0.272	0.133	0.130	0.155	0.148	0.133	0.130	0.003	0.008	0.003
2.health2	-0.008	0.060	-0.009	0.086	0.085	0.099	0.097	0.086	0.085	0.001	0.002	0.001
2.fas_cat	0.170	-0.047	0.173	0.156	0.149	0.177	0.175	0.156	0.149	0.007	0.002	0.007
3.fas_cat	0.337	0.106	0.347	0.166	0.158	0.189	0.186	0.166	0.158	0.007	0.004	0.008
2.fsm_ref_r	0.102	0.158	0.101	0.097	0.099	0.117	0.116	0.097	0.099	-0.002	0.002	-0.002
_cons	2.015	2.093	1.994	0.288	0.272	0.325	0.319	0.288	0.271	0.016	0.006	0.017

b - parameter of the logistic regression; SE - standard error of the parameter; EXC - exchangeable; UN - unstructured; AR1 - first-order auto-regressive ; Model – Model-based Standard Error produced by the GEE estimation; Robust – Cluster-Robust Standard Error; Diff – difference between Robust and Model-based Standard Errors

Table E.7 Comparison of the parameters and standard errors of three different specifications of the working correlation matrix in the GEE estimation of the fully adjusted cross-sectional model for cumulative exposure for walking to school

parameter	b EXC	b IND	SE EXC Robust	SE EXC Model	SE IND Robust	SE IND Model	Diff SE EXC	Diff SE IND
ibus_rr_sum	-0.063	-0.043	0.084	0.103	0.085	0.105	-0.019	-0.020
traffic_sum	0.006	0.012	0.060	0.068	0.059	0.070	-0.009	-0.011
infra_sum	0.068	0.070	0.072	0.064	0.071	0.065	0.008	0.006
nice3_sum	-0.109	-0.127	0.061	0.063	0.059	0.064	-0.002	-0.005
n_safe2a_sum	-0.018	-0.032	0.044	0.038	0.046	0.039	0.006	0.007
2.gender_r	0.088	0.055	0.278	0.176	0.280	0.176	0.102	0.104
2.d_eth_8cat	-0.185	-0.322	0.287	0.342	0.285	0.348	-0.054	-0.063
3.d_eth_8cat	0.604	0.723	0.539	0.487	0.624	0.518	0.052	0.106
4.d_eth_8cat	0.324	0.261	0.498	0.482	0.613	0.491	0.016	0.122
5.d_eth_8cat	0.591	0.656	0.284	0.305	0.261	0.314	-0.021	-0.053
6.d_eth_8cat	-0.761	-0.937	0.282	0.391	0.289	0.400	-0.108	-0.111
7.d_eth_8cat	-0.131	-0.338	0.350	0.338	0.353	0.341	0.012	0.013
8.d_eth_8cat	0.071	-0.093	0.262	0.234	0.224	0.236	0.028	-0.012
2.health2	-0.068	-0.115	0.170	0.170	0.175	0.174	-0.000	0.000
2.fas_cat	-0.705	-0.739	0.476	0.489	0.492	0.507	-0.013	-0.015
3.fas_cat	-0.522	-0.620	0.418	0.491	0.457	0.507	-0.073	-0.050
2.fsm_ref_r	0.159	0.225	0.165	0.188	0.167	0.193	-0.024	-0.026
_cons	2.606	2.796	1.065	0.950	1.059	0.954	0.115	0.105

b- parameter of the logistic regression; SE - standard error of the parameter; EXC - exchangeable; IND - independent; Model - Model-based Standard Error produced by the GEE estimation; Robust – Cluster-Robust Standard Error; Diff – difference between Robust and Model-based Standard Errors

Table E.8 Comparison of the parameters and standard errors of three different specifications of the working correlation matrix in the GEE estimation of the fully adjusted cross-sectional model for cumulative exposure for walking for leisure

parameter	b EXC	b IND	SE EXC Robust	SE EXC Model	SE IND Robust	SE IND Model	Diff SE EXC	Diff SE IND
ibus_rr_sum	0.101	0.103	0.095	0.092	0.096	0.092	0.004	0.004
traffic_sum	0.075	0.075	0.060	0.060	0.060	0.060	-0.000	-0.001
infra_sum	0.046	0.051	0.079	0.059	0.079	0.059	0.020	0.020
nice3_sum	-0.062	-0.066	0.063	0.057	0.062	0.057	0.006	0.006
n_safe2a_sum	-0.014	-0.016	0.038	0.034	0.038	0.034	0.004	0.005
2.gender_r	0.680	0.682	0.192	0.158	0.188	0.157	0.034	0.031
2.d_eth_8cat	-0.317	-0.297	0.407	0.323	0.407	0.322	0.084	0.084
3.d_eth_8cat	-0.384	-0.382	0.335	0.378	0.336	0.377	-0.043	-0.041
4.d_eth_8cat	-0.425	-0.420	0.360	0.403	0.350	0.402	-0.043	-0.053
5.d_eth_8cat	-1.119	-1.132	0.243	0.270	0.244	0.269	-0.026	-0.025
6.d_eth_8cat	-0.825	-0.814	0.389	0.410	0.392	0.409	-0.021	-0.018
7.d_eth_8cat	-1.234	-1.221	0.318	0.365	0.315	0.363	-0.047	-0.047
8.d_eth_8cat	-0.350	-0.349	0.173	0.202	0.177	0.201	-0.029	-0.024
2.health2	-0.011	-0.021	0.181	0.156	0.181	0.156	0.025	0.026
2.fas_cat	-0.152	-0.128	0.312	0.383	0.308	0.384	-0.071	-0.075
3.fas_cat	-0.036	-0.018	0.292	0.383	0.287	0.384	-0.091	-0.096
2.fsm_ref_r	0.160	0.157	0.154	0.169	0.151	0.169	-0.015	-0.017
_cons	-1.463	-1.476	0.924	0.802	0.925	0.802	0.123	0.123

b- parameter of the logistic regression; SE - standard error of the parameter; EXC - exchangeable; IND - independent; Model - Model-based Standard Error produced by the GEE estimation; Robust – Cluster-Robust Standard Error; Diff – difference between Robust and Model-based Standard Errors

Table E.9 Comparison of the parameters and standard errors of three different specifications of the working correlation matrix in the GEE estimation of the fully adjusted cross-sectional model for cumulative exposure for outdoor physical activity

parameter	b EXC	b IND	SE EXC Robust	SE EXC Model	SE IND Robust	SE IND Model	Diff SE EXC	Diff SE IND
ibus_rr_sum	0.101	0.109	0.116	0.093	0.115	0.093	0.023	0.022
traffic_sum	0.067	0.059	0.077	0.063	0.075	0.063	0.015	0.012
infra_sum	0.053	0.045	0.053	0.063	0.051	0.063	-0.010	-0.012
nice3_sum	0.061	0.056	0.051	0.060	0.050	0.060	-0.009	-0.010
n_safe2a_sum	0.003	0.004	0.031	0.035	0.032	0.036	-0.004	-0.004
2.gender_r	-1.773	-1.772	0.163	0.175	0.169	0.172	-0.012	-0.003
2.d_eth_8cat	0.110	0.126	0.291	0.345	0.304	0.347	-0.055	-0.043
3.d_eth_8cat	0.177	0.313	0.331	0.408	0.361	0.413	-0.077	-0.053
4.d_eth_8cat	1.119	1.199	0.454	0.532	0.509	0.542	-0.079	-0.033
5.d_eth_8cat	0.087	0.071	0.235	0.268	0.228	0.266	-0.033	-0.038
6.d_eth_8cat	-0.114	-0.095	0.362	0.413	0.362	0.414	-0.051	-0.052
7.d_eth_8cat	0.431	0.411	0.385	0.347	0.392	0.346	0.038	0.046
8.d_eth_8cat	0.245	0.274	0.181	0.221	0.185	0.220	-0.041	-0.035
2.health2	0.315	0.280	0.171	0.165	0.168	0.166	0.006	0.003
2.fas_cat	-0.442	-0.549	0.403	0.445	0.413	0.456	-0.043	-0.043
3.fas_cat	-0.562	-0.695	0.430	0.449	0.440	0.458	-0.018	-0.018
2.fsm_ref_r	0.171	0.226	0.181	0.180	0.186	0.180	0.001	0.006
_cons	-0.018	0.162	0.862	0.847	0.877	0.855	0.015	0.022

b- parameter of the logistic regression; SE - standard error of the parameter; EXC - exchangeable; IND - independent; Model - Model-based Standard Error produced by the GEE estimation; Robust – Cluster-Robust Standard Error; Diff – difference between Robust and Model-based Standard Errors

Table E.10 Comparison of the parameters and standard errors of three different specifications of the working correlation matrix in the GEE estimation of the fully adjusted model trajectories of walking to school

parameter	b UN	b AR1	b EXC	SE UN Robust	SE UN Model	SE AR1 Robust	SE AR1 Model	SE EXC Robust	SE EXC Model	Diff SE UN	Diff SE AR1	Diff SE EXC
time	0.008	-0.026	0.006	0.045	0.047	0.048	0.058	0.045	0.046	-0.003	-0.010	-0.002
ibus_rr_change	0.246	0.360	0.255	0.250	0.261	0.279	0.326	0.252	0.261	-0.011	-0.047	-0.009
traffic_change	0.062	0.148	0.058	0.162	0.163	0.180	0.198	0.163	0.162	-0.000	-0.018	0.001
infra_change	0.057	0.073	0.064	0.156	0.159	0.178	0.192	0.157	0.159	-0.003	-0.014	-0.002
nice3_change	0.114	0.233	0.123	0.140	0.141	0.160	0.174	0.140	0.140	-0.001	-0.014	-0.000
n_safe2a_change	-0.084	-0.092	-0.087	0.083	0.082	0.090	0.099	0.084	0.082	0.001	-0.009	0.002
c.ibus_rr_change#c.time	-0.106	-0.159	-0.113	0.110	0.110	0.119	0.141	0.111	0.108	-0.000	-0.022	0.003
c.traffic_change#c.time	0.008	-0.058	0.010	0.071	0.070	0.076	0.087	0.071	0.069	0.001	-0.011	0.003
c.infra_change#c.time	0.005	-0.021	0.000	0.064	0.068	0.072	0.084	0.064	0.067	-0.004	-0.012	-0.003
c.nice3_change#c.time	-0.055	-0.076	-0.062	0.058	0.060	0.063	0.076	0.058	0.059	-0.002	-0.012	-0.001
c.n_safe2a_change#c.time	0.000	0.010	0.002	0.035	0.035	0.037	0.043	0.036	0.034	0.000	-0.006	0.001
2.gender_r	0.098	0.018	0.098	0.123	0.124	0.134	0.129	0.123	0.124	-0.001	0.005	-0.001
2.d_eth_8cat	-0.540	-0.610	-0.531	0.261	0.259	0.283	0.266	0.262	0.259	0.002	0.017	0.003
3.d_eth_8cat	0.354	0.486	0.350	0.327	0.347	0.362	0.372	0.327	0.347	-0.020	-0.010	-0.020
4.d_eth_8cat	-0.163	-0.181	-0.160	0.357	0.336	0.389	0.349	0.357	0.336	0.021	0.040	0.021
5.d_eth_8cat	0.180	0.166	0.178	0.220	0.218	0.236	0.224	0.219	0.218	0.002	0.012	0.001
6.d_eth_8cat	-0.730	-0.876	-0.742	0.310	0.306	0.320	0.305	0.309	0.306	0.004	0.014	0.003
7.d_eth_8cat	-0.415	-0.424	-0.417	0.244	0.250	0.279	0.266	0.243	0.251	-0.007	0.013	-0.007
8.d_eth_8cat	-0.269	-0.288	-0.271	0.175	0.175	0.187	0.179	0.174	0.175	-0.000	0.008	-0.000
2.health2	0.115	0.051	0.119	0.104	0.104	0.111	0.109	0.104	0.104	0.000	0.002	0.001

parameter	b UN	b AR1	b EXC	SE UN Robust	SE UN Model	SE AR1 Robust	SE AR1 Model	SE EXC Robust	SE EXC Model	Diff SE UN	Diff SE AR1	Diff SE EXC
2.fas_cat	-0.347	-0.274	-0.337	0.216	0.199	0.225	0.208	0.212	0.198	0.017	0.017	0.014
3.fas_cat	-0.309	-0.232	-0.310	0.223	0.212	0.231	0.221	0.219	0.211	0.012	0.010	0.008
2.fsm_ref_r	0.216	0.324	0.217	0.137	0.137	0.151	0.144	0.137	0.137	0.000	0.007	0.000
_cons	1.582	1.638	1.576	0.268	0.258	0.284	0.274	0.265	0.257	0.010	0.010	0.008

b - parameter of the logistic regression; SE - standard error of the parameter; EXC - exchangeable; UN - unstructured; AR1 - first-order auto-regressive ; Model – Model-based Standard Error produced by the GEE estimation; Robust – Cluster-Robust Standard Error; Diff – difference between Robust and Model-based Standard Errors

Table E.11 Comparison of the parameters and standard errors of three different specifications of the working correlation matrix in the GEE estimation of the fully adjusted model trajectories of walking for leisure

parameter	b UN	b AR1	b EXC	SE UN Robust	SE UN Model	SE AR1 Robust	SE AR1 Model	SE EXC Robust	SE EXC Model	Diff SE UN	Diff SE AR1	Diff SE EXC
time	-0.261	-0.256	-0.257	0.049	0.050	0.054	0.054	0.050	0.047	-0.000	-0.001	0.003
ibus_rr_change	0.125	0.098	0.114	0.249	0.249	0.284	0.283	0.250	0.238	-0.000	0.000	0.013
traffic_change	-0.243	-0.334	-0.233	0.160	0.157	0.176	0.177	0.160	0.150	0.003	-0.001	0.010
infra_change	-0.060	-0.195	-0.047	0.157	0.155	0.173	0.171	0.157	0.148	0.002	0.002	0.009
nice3_change	0.101	0.163	0.101	0.139	0.138	0.154	0.153	0.140	0.131	0.001	0.001	0.008
n_safe2a_change	-0.036	-0.046	-0.034	0.079	0.081	0.087	0.089	0.079	0.077	-0.002	-0.002	0.002
c.ibus_rr_change#c.time	-0.073	-0.072	-0.076	0.112	0.114	0.127	0.130	0.113	0.107	-0.001	-0.002	0.006
c.traffic_change#c.time	0.076	0.124	0.070	0.075	0.072	0.082	0.081	0.076	0.068	0.003	0.001	0.007
c.infra_change#c.time	0.017	0.041	0.013	0.072	0.071	0.080	0.078	0.072	0.067	0.001	0.001	0.006
c.nice3_change#c.time	-0.072	-0.078	-0.071	0.064	0.063	0.070	0.070	0.064	0.059	0.001	0.000	0.005
c.n_safe2a_change#c.time	0.036	0.036	0.036	0.036	0.037	0.040	0.041	0.037	0.035	-0.000	-0.001	0.002

parameter	b UN	b AR1	b EXC	SE UN Robust	SE UN Model	SE AR1 Robust	SE AR1 Model	SE EXC Robust	SE EXC Model	Diff SE UN	Diff SE AR1	Diff SE EXC
2.gender_r	0.543	0.475	0.535	0.102	0.101	0.109	0.107	0.102	0.101	0.002	0.002	0.002
2.d_eth_8cat	-0.129	-0.111	-0.113	0.220	0.213	0.240	0.229	0.219	0.214	0.006	0.011	0.005
3.d_eth_8cat	-0.406	-0.342	-0.405	0.248	0.247	0.271	0.261	0.250	0.247	0.001	0.010	0.002
4.d_eth_8cat	-0.712	-0.586	-0.713	0.266	0.275	0.282	0.288	0.267	0.276	-0.010	-0.006	-0.009
5.d_eth_8cat	-0.908	-0.891	-0.909	0.163	0.167	0.172	0.175	0.164	0.168	-0.004	-0.002	-0.004
6.d_eth_8cat	-0.505	-0.639	-0.532	0.268	0.265	0.284	0.287	0.270	0.267	0.003	-0.002	0.003
7.d_eth_8cat	-0.962	-0.898	-0.954	0.217	0.223	0.235	0.244	0.218	0.224	-0.007	-0.009	-0.006
8.d_eth_8cat	-0.396	-0.438	-0.399	0.139	0.134	0.147	0.142	0.140	0.135	0.005	0.005	0.005
2.health2	-0.039	-0.019	-0.043	0.095	0.092	0.100	0.097	0.095	0.092	0.003	0.004	0.003
2.fas_cat	-0.008	-0.005	-0.005	0.162	0.168	0.169	0.176	0.167	0.169	-0.006	-0.007	-0.002
3.fas_cat	0.168	0.178	0.178	0.175	0.178	0.184	0.186	0.180	0.178	-0.002	-0.002	0.001
2.fsm_ref_r	0.181	0.191	0.173	0.110	0.109	0.117	0.116	0.111	0.110	0.001	0.002	0.001
_cons	0.009	0.036	0.003	0.215	0.214	0.225	0.225	0.218	0.212	0.001	-0.000	0.006

b - parameter of the logistic regression; SE - standard error of the parameter; EXC - exchangeable; UN - unstructured; AR1 - first-order auto-regressive ; Model – Model-based Standard Error produced by the GEE estimation; Robust – Cluster-Robust Standard Error; Diff – difference between Robust and Model-based Standard Errors

Table E.12 Comparison of the parameters and standard errors of three different specifications of the working correlation matrix in the GEE estimation of the fully adjusted model trajectories of outdoor physical activity

parameter	b UN	b AR1	b EXC	SE UN Robust	SE UN Model	SE AR1 Robust	SE AR1 Model	SE EXC Robust	SE EXC Model	Diff SE UN	Diff SE AR1	Diff SE EXC
time	-0.364	-0.345	-0.363	0.052	0.053	0.057	0.063	0.052	0.052	-0.000	-0.005	0.001
ibus_rr_change	0.007	0.220	0.008	0.280	0.300	0.324	0.365	0.280	0.297	-0.020	-0.041	-0.017
traffic_change	0.104	0.064	0.095	0.185	0.185	0.219	0.221	0.185	0.183	0.000	-0.002	0.002

parameter	b UN	b AR1	b EXC	SE UN Robust	SE UN Model	SE AR1 Robust	SE AR1 Model	SE EXC Robust	SE EXC Model	Diff SE UN	Diff SE AR1	Diff SE EXC
infra_change	-0.374	-0.473	-0.374	0.182	0.182	0.202	0.215	0.182	0.180	-0.001	-0.013	0.002
nice3_change	0.009	-0.014	0.015	0.165	0.161	0.189	0.190	0.165	0.160	0.004	-0.000	0.005
n_safe2a_change	-0.052	-0.023	-0.056	0.101	0.095	0.111	0.111	0.101	0.094	0.006	0.000	0.007
c.ibus_rr_change#c.time	0.034	-0.052	0.031	0.118	0.123	0.139	0.155	0.118	0.120	-0.004	-0.015	-0.002
c.traffic_change#c.time	-0.074	-0.059	-0.068	0.077	0.077	0.091	0.095	0.077	0.075	0.000	-0.003	0.001
c.infra_change#c.time	0.107	0.151	0.109	0.075	0.075	0.082	0.091	0.075	0.074	-0.000	-0.009	0.001
c.nice3_change#c.time	-0.025	0.009	-0.027	0.070	0.066	0.080	0.080	0.070	0.065	0.004	-0.000	0.005
c.n_safe2a_change#c.time	0.061	0.040	0.062	0.042	0.039	0.046	0.047	0.042	0.039	0.003	-0.001	0.004
2.gender_r	-1.518	-1.595	-1.520	0.128	0.126	0.140	0.133	0.128	0.126	0.002	0.007	0.002
2.d_eth_8cat	0.023	0.047	0.021	0.257	0.257	0.282	0.273	0.257	0.257	-0.001	0.009	0.000
3.d_eth_8cat	0.128	0.156	0.129	0.300	0.302	0.340	0.323	0.300	0.302	-0.002	0.017	-0.002
4.d_eth_8cat	1.094	0.884	1.087	0.379	0.418	0.381	0.441	0.379	0.417	-0.039	-0.060	-0.038
5.d_eth_8cat	0.032	-0.041	0.037	0.188	0.193	0.203	0.200	0.188	0.193	-0.005	0.003	-0.005
6.d_eth_8cat	0.109	0.001	0.110	0.293	0.305	0.326	0.318	0.293	0.305	-0.012	0.008	-0.012
7.d_eth_8cat	0.529	0.302	0.528	0.246	0.265	0.261	0.278	0.246	0.265	-0.019	-0.017	-0.019
8.d_eth_8cat	0.204	0.114	0.207	0.171	0.163	0.184	0.171	0.171	0.163	0.008	0.013	0.008
2.health2	0.092	0.130	0.088	0.108	0.106	0.117	0.113	0.108	0.106	0.002	0.004	0.002
2.fas_cat	0.109	0.004	0.104	0.209	0.195	0.221	0.210	0.211	0.195	0.014	0.011	0.016
3.fas_cat	0.221	0.111	0.219	0.222	0.208	0.234	0.222	0.224	0.208	0.015	0.011	0.016
2.fsm_ref_r	0.281	0.322	0.278	0.131	0.134	0.143	0.140	0.131	0.133	-0.003	0.003	-0.003
_cons	2.168	2.281	2.174	0.277	0.257	0.293	0.279	0.278	0.256	0.020	0.015	0.022

b - parameter of the logistic regression; SE - standard error of the parameter; EXC - exchangeable; UN - unstructured; AR1 - first-order auto-regressive ; Model – Model-based Standard Error produced by the GEE estimation; Robust – Cluster-Robust Standard Error; Diff – difference between Robust and Model-based Standard Errors

E.4 Results from the estimation of the models of chapter 6 with GEE with alternative the working correlation using the imputed datasets

Table E.13 Odds ratios (OR) of walking to school vs. not by perception of the neighbourhood environment, adjusting for potential confounders (3 waves of the ORiEL Study, n=2260)

Exposure		Unadjusted OR	Adjusted OR¹	95%CI	P-value parameter	P-value unadjusted	P-value adjusted¹	Gender interaction (p-value) ²
Bus stop proximity	Further away	1.00	1.00			0.173	0.223	0.857
	1-5 minutes	0.90	0.91	[0.78,1.06]	0.223			
Perceived traffic safety	Low	1.00	1.00			0.629	0.463	0.523
	Medium	1.09	1.11	[0.92,1.34]	0.265			
	High	1.08	1.12	[0.93,1.36]	0.232			
Perceived connectivity	Low	1.00	1.00			0.328	0.257	0.802
	Medium	1.10	1.11	[0.95,1.28]	0.179			
	High	1.13	1.16	[0.97,1.40]	0.111			
Nhood nice for walk/cycle	Strongly/slightly disagree	1.00	1.00			0.409	0.173	0.500
	Slightly agree	1.02	1.00	[0.86,1.17]	0.975			
	Strongly agree	0.94	0.88	[0.75,1.04]	0.144			
Feel safe	Strongly disagree	1.00	1.00			0.733	0.677	0.854
	Slightly disagree	1.15	1.14	[0.91,1.42]	0.243			
	Neither agree nor disagree	1.03	1.02	[0.82,1.27]	0.855			
	Slightly agree	1.05	1.06	[0.85,1.33]	0.601			
	Strongly agree	1.08	1.11	[0.88,1.40]	0.370			
Gender	Male	1.00	1.00			0.518	0.243	0.854
	Female	1.05	1.10	[0.94,1.29]	0.243			

Exposure		Unadjusted OR	Adjusted OR[1]	95%CI	P-value parameter	P-value unadjusted	P-value adjusted[1]	Gender interaction (p-value) [2]
Ethnicity	White: UK	1.00	1.00			<0.001	<0.001	0.487
	White: Mixed	0.62	0.61	[0.44,0.84]	0.003			
	Asian: Indian	1.12	1.15	[0.71,1.85]	0.577			
	Asian: Pakistani	0.87	0.89	[0.56,1.43]	0.639			
	Asian: Bangladeshi	1.32	1.33	[0.98,1.82]	0.071			
	Black: Caribbean	0.43	0.42	[0.29,0.60]	<0.001			
	Black: African	0.59	0.60	[0.45,0.80]	<0.001			
	Other	0.71	0.71	[0.57,0.90]	0.004			
Health	no condition	1.00	1.00			0.071	0.071	0.026
	1+ conditions(s)	1.13	1.13	[0.99,1.30]	0.071			
FAS Categories	Low	1.00	1.00			0.217	0.236	0.347
	Moderate	0.82	0.84	[0.66,1.07]	0.166			
	High	0.86	0.91	[0.71,1.17]	0.467			
Take FSM at W1	No	1.00	1.00			0.326	0.281	0.217
	Yes	1.08	1.09	[0.93,1.29]	0.281			
time		0.96	0.96	[0.90,1.01]	0.119	0.133	0.119	0.578

Results are from Generalised Estimating Equations to account for the dependency across repeated measurements (exchangeable working correlation matrix). [1] Adjusted for all variables of the table. [2] The adjusted model was replicated for each outcome with an additional interaction term between gender and the exposure.

Table E.14 Odds ratios (OR) of walking for leisure vs. not by perception of the neighbourhood environment, adjusting for potential confounders (3 waves of the ORiEL Study, n=2260)

Exposure		Unadjusted OR	Adjusted OR[1]	95%CI	P-value parameter	P-value unadjusted	P-value adjusted[1]	Gender interaction (p-value) [2]
Bus stop proximity	Further away	1.00	1.00			0.039	0.078	0.780
	1-5 minutes	0.87	0.89	[0.78,1.01]	0.078			

Exposure		Unadjusted OR	Adjusted OR[1]	95%CI	P-value parameter	P-value unadjusted	P-value adjusted[1]	Gender interaction (p-value) [2]
Perceived traffic safety	Low	1.00	1.00			0.385	0.295	0.664
	Medium	0.91	0.91	[0.75,1.10]	0.315			
	High	0.88	0.86	[0.71,1.04]	0.124			
Perceived connectivity	Low	1.00	1.00			0.192	0.308	0.884
	Medium	1.14	1.13	[0.96,1.32]	0.138			
	High	1.10	1.09	[0.90,1.31]	0.382			
Nhood nice for walk/cycle	Strongly/slightly disagree	1.00	1.00			0.309	0.506	0.387
	Slightly agree	1.01	1.02	[0.88,1.17]	0.817			
	Strongly agree	1.10	1.09	[0.92,1.29]	0.324			
Feel safe	Strongly disagree	1.00	1.00			0.053	0.025	0.881
	Slightly disagree	1.29	1.29	[1.03,1.63]	0.028			
	Neither agree nor disagree	1.08	1.09	[0.87,1.36]	0.472			
	Slightly agree	1.25	1.32	[1.05,1.66]	0.018			
	Strongly agree	1.11	1.17	[0.92,1.49]	0.192			
Gender	Male	1.00	1.00			<0.001	<0.001	0.881
	Female	1.60	1.58	[1.39,1.81]	<0.001			
Ethnicity	White: UK	1.00	1.00			<0.001	<0.001	0.136
	White: Mixed	0.70	0.66	[0.50,0.86]	0.002			
	Asian: Indian	0.53	0.51	[0.36,0.74]	<0.001			
	Asian: Pakistani	0.50	0.51	[0.37,0.72]	<0.001			
	Asian: Bangladeshi	0.35	0.35	[0.28,0.44]	<0.001			
	Black: Caribbean	0.44	0.41	[0.29,0.57]	<0.001			
	Black: African	0.42	0.42	[0.32,0.54]	<0.001			
	Other	0.58	0.56	[0.46,0.68]	<0.001			

Exposure		Unadjusted OR	Adjusted OR¹	95%CI	P-value parameter	P-value unadjusted	P-value adjusted¹	Gender interaction (p-value) ²
Health	no condition	1.00	1.00			0.223	0.434	0.787
	1+ conditions(s)	1.07	1.05	[0.93,1.18]	0.434			
FAS Categories	Low	1.00	1.00			0.211	0.140	0.621
	Moderate	0.94	1.06	[0.85,1.32]	0.618			
	High	1.04	1.18	[0.93,1.50]	0.166			
Take FSM at W1	No	1.00	1.00			0.884	0.147	0.558
	Yes	1.01	1.11	[0.97,1.27]	0.147			
time		0.80	0.79	[0.74,0.84]	<0.001	<0.001	<0.001	0.431

Results are from Generalised Estimating Equations to account for the dependency across repeated measurements (exchangeable working correlation matrix). [1] Adjusted for all variables of the table. [2] The adjusted model was replicated for each outcome with an additional interaction term between gender and the exposure.

Table E.15 Odds ratios (OR) of reporting at least one outdoor physical activity* vs. not by perception of the neighbourhood environment, adjusting for potential confounders (3 waves of the ORiEL Study, n=2260)

Exposure		Unadjusted OR	Adjusted OR¹	95%CI	P-value parameter	P-value unadjusted	P-value adjusted¹	Gender interaction (p-value) ²
Bus stop proximity	Further away	1.00	1.00			0.669	0.964	0.651
	1-5 minutes	0.97	1.00	[0.83,1.19]	0.964			
Perceived traffic safety	Low	1.00	1.00			0.510	0.176	0.011
	Medium	0.99	1.02	[0.81,1.28]	0.854			
	High	0.92	0.89	[0.71,1.13]	0.352			
Perceived connectivity	Low	1.00	1.00			0.266	0.079	0.647
	Medium	1.06	1.15	[0.97,1.37]	0.098			
	High	1.17	1.27	[1.03,1.56]	0.025			
Nhood nice for walk/cycle	Strongly/slightly disagree	1.00	1.00			0.037	0.272	0.694

Exposure		Unadjusted OR	Adjusted OR[1]	95%CI	P-value parameter	P-value unadjusted	P-value adjusted[1]	Gender interaction (p-value) [2]
	Slightly agree	0.94	0.95	[0.81,1.12]	0.550			
	Strongly agree	1.12	1.08	[0.90,1.30]	0.432			
Feel safe	Strongly disagree	1.00	1.00			0.324	0.531	0.738
	Slightly disagree	1.08	1.13	[0.87,1.47]	0.367			
	Neither agree nor disagree	0.96	0.97	[0.76,1.25]	0.821			
	Slightly agree	1.07	1.10	[0.85,1.42]	0.488			
	Strongly agree	1.15	1.10	[0.86,1.41]	0.465			
Gender	Male	1.00	1.00			<0.001	<0.001	0.738
	Female	0.23	0.22	[0.19,0.26]	<0.001			
Ethnicity	White: UK	1.00	1.00			0.002	0.011	0.183
	White: Mixed	1.16	1.30	[0.95,1.78]	0.107			
	Asian: Indian	1.42	1.43	[0.92,2.20]	0.109			
	Asian: Pakistani	2.05	1.95	[1.24,3.06]	0.004			
	Asian: Bangladeshi	1.19	1.08	[0.83,1.41]	0.551			
	Black: Caribbean	0.86	1.04	[0.72,1.50]	0.838			
	Black: African	1.59	1.56	[1.16,2.10]	0.003			
	Other	1.26	1.30	[1.04,1.62]	0.023			
Health	no condition	1.00	1.00			0.145	0.436	0.099
	1+ conditions(s)	0.91	0.95	[0.82,1.09]	0.436			
FAS Categories	Low	1.00	1.00			0.008	0.004	0.813
	Moderate	1.11	1.22	[0.94,1.58]	0.128			
	High	1.33	1.47	[1.12,1.93]	0.005			
Take FSM at W1	No	1.00	1.00			0.119	0.170	0.351
	Yes	1.13	1.12	[0.95,1.31]	0.170			

Exposure	Unadjusted OR	Adjusted OR[1]	95%CI	P-value parameter	P-value unadjusted	P-value adjusted[1]	Gender interaction (p-value) [2]
time	0.78	0.75	[0.70,0.80]	<0.001	<0.001	<0.001	0.007

Results are from Generalised Estimating Equations to account for the dependency across repeated measurements (exchangeable working correlation matrix). [1] Adjusted for all variables of the table. [2] The adjusted model was replicated for each outcome with an additional interaction term between gender and the exposure. * Outdoor physical activities include: basketball (or volleyball), blading, cricket, football, rounders, rugby and skating.

Table E.16 Odds ratios (OR) of walking to school vs. not at wave 3 by cumulated perception of the neighbourhood environment over the 3 waves, adjusting for potential confounders (n=2260)

Exposure	Unadjusted OR	Adjusted OR[1]	95%CI	P-value unadjusted	P-value adjusted[1]	Gender interaction (p-value) [2]
Cumulative bus stop proximity	0.95	0.95	[0.85,1.07]	0.360	0.383	0.835
Cumulative traffic safety	1.00	1.03	[0.95,1.12]	0.992	0.415	0.757
Cumulative favourable infrastructure	1.03	1.05	[0.95,1.15]	0.479	0.336	0.703
Cumulative nice neighbourhood	0.97	0.96	[0.88,1.04]	0.406	0.303	0.742
Cumulative personal safety	0.98	0.99	[0.95,1.03]	0.328	0.615	0.847

Results are from Generalised Estimating Equations to account for the clustering of individuals within schools (independent working correlation matrix). The cumulative exposure are continuous variables constructed as the sum of scores of each exposure over the 3 waves. A higher score indicates a perception of supportive environment for the specific exposure. [1] Adjusted for gender, ethnicity, health conditions (at wave 3), family affluence (at wave 3), baseline FSM and the other perception variables. [2] The adjusted model was replicated for each outcome with an additional interaction term between gender and the exposure.

Table E.17 Odds ratios (OR) of walking for leisure vs. not at wave 3 by cumulated perception of the neighbourhood environment over the 3 waves, adjusting for potential confounders (n=2260)

Exposure	Unadjusted OR	Adjusted OR[1]	95%CI	P-value unadjusted	P-value adjusted[1]	Gender interaction (p-value) [2]
Cumulative bus stop proximity	1.00	0.98	[0.86,1.12]	0.964	0.759	0.844
Cumulative traffic safety	1.02	1.04	[0.95,1.13]	0.602	0.371	0.792
Cumulative favourable infrastructure	1.04	1.05	[0.95,1.15]	0.416	0.350	0.422
Cumulative nice neighbourhood	0.98	0.99	[0.92,1.07]	0.566	0.844	0.802
Cumulative personal safety	0.98	0.99	[0.95,1.03]	0.219	0.762	0.906

Results are from Generalised Estimating Equations to account for the clustering of individuals within schools (independent working correlation matrix). The cumulative exposure are continuous variables constructed as the sum of scores of each exposure over the 3 waves. A higher score indicates a perception of supportive environment for the specific exposure. [1] Adjusted for gender, ethnicity, health conditions (at wave 3), family affluence (at wave 3) and baseline FSM. [2] The adjusted model was replicated for each outcome with an additional interaction term between gender and the exposure.

Table E.18 Odds ratios (OR) of reporting at least one outdoor physical activity* vs. not at wave 3 by cumulated perception of the neighbourhood environment over the 3 waves, adjusting for potential confounders (n=2260)

Exposure	Unadjusted OR	Adjusted OR[1]	95%CI	P-value unadjusted	P-value adjusted[1]	Gender interaction (p-value) [2]
Cumulative bus stop proximity	0.95	0.94	[0.83,1.07]	0.389	0.361	0.913
Cumulative traffic safety	1.02	1.00	[0.93,1.07]	0.414	0.929	0.526
Cumulative favourable infrastructure	0.99	1.03	[0.96,1.10]	0.790	0.413	0.778
Cumulative nice neighbourhood	1.03	1.01	[0.94,1.08]	0.208	0.768	0.504
Cumulative personal safety	1.05	1.03	[0.98,1.07]	0.004	0.244	0.885

Results are from Generalised Estimating Equations to account for the clustering of individuals within schools (independent working correlation matrix).

The cumulative exposure are continuous variables constructed as the sum of scores of each exposure over the 3 waves. A higher score indicates a perception of supportive environment for the specific exposure. [1] Adjusted for gender, ethnicity, health conditions (at wave 3), family affluence (at wave 3) and baseline FSM. [2] The adjusted model was replicated for each outcome with an additional interaction term between gender and the exposure. * Outdoor physical activities include: basketball (or volleyball), blading, cricket, football, rounders, rugby and skating.

Table E.19 Odds ratios (OR) of walking to school vs. not by change in perception of the neighbourhood environment since the baseline, adjusting for potential confounders (3 waves of the ORiEL Study n=2,260)

Exposure	Unadjusted OR	Adjusted OR[1]	95% CI	P-value unadjusted	P-value adjusted	Gender interaction (p-value) [2]
Change: Bus stop proximity	0.88	0.86	[0.62 , 1.20]	0.448	0.376	0.923
Change: Traffic safety	1.10	1.09	[0.87 , 1.35]	0.363	0.455	0.973
Change: Favourable infrastructure	0.96	0.96	[0.78 , 1.19]	0.709	0.715	0.869
Change: Nice neighbourhood	1.10	1.12	[0.92 , 1.37]	0.284	0.250	0.488
Change: Personal safety	0.99	0.97	[0.86 , 1.09]	0.809	0.589	0.971
Time x change interaction: Bus stop proximity	1.06	1.07	[0.93 , 1.22]	0.408	0.353	0.929
Time x change interaction: Traffic safety	0.96	0.97	[0.89 , 1.06]	0.353	0.527	0.436
Time x change interaction: Favourable infrastructure	1.01	1.02	[0.93 , 1.11]	0.837	0.722	0.867
Time x change interaction: Nice neighbourhood	0.95	0.95	[0.88 , 1.03]	0.189	0.229	0.563
Time x change interaction: Personal safety	0.99	1.00	[0.95 , 1.04]	0.628	0.913	0.960

Results are from Generalised Estimating Equations to account for the dependency across repeated measurements (exchangeable working correlation matrix).
Each exposure variable measures change since baseline on a continuous scale. Each unit represent an average change in exposure by one category between the baseline and the end of the study (+1 = improvement of the neighbourhood by one category on average). The time x change interaction assesses whether exposure change is associated with different trajectory of change in the outcome. [1] adjusted for time, gender, ethnicity, health conditions, family affluence and baseline FSM reporting. [2] The adjusted model was replicated for each outcome with the addition of 2 way- and 3 way- interactions between gender, change and time.

Table E.20 Odds ratios (OR) of walking for leisure vs. not by change in perception of the neighbourhood environment since the baseline, adjusting for potential confounders (3 waves of the ORiEL Study; n=2,260)

Exposure	Unadjusted OR	Adjusted OR[1]	95% CI	P-value unadjusted	P-value adjusted	Gender interaction (p-value) [2]
Change: Bus stop proximity	1.13	1.16	[0.84 , 1.61]	0.429	0.355	0.576
Change: Traffic safety	0.99	1.00	[0.81 , 1.22]	0.922	0.973	0.276
Change: Favourable infrastructure	1.01	1.01	[0.82 , 1.24]	0.939	0.945	0.613
Change: Nice neighbourhood	0.96	0.95	[0.80 , 1.14]	0.576	0.578	0.233
Change: Personal safety	1.00	1.02	[0.91 , 1.14]	0.985	0.709	0.439
Time x change interaction: Bus stop proximity	0.87	0.86	[0.74 , 1.00]	0.051	0.047	0.925
Time x change interaction: Traffic safety	0.99	0.98	[0.90 , 1.08]	0.744	0.715	0.326
Time x change interaction: Favourable infrastructure	1.00	1.00	[0.91 , 1.11]	0.954	0.965	0.255
Time x change interaction: Nice neighbourhood	1.02	1.02	[0.95 , 1.11]	0.655	0.580	0.268
Time x change interaction: Personal safety	1.00	1.00	[0.95 , 1.05]	0.985	0.951	0.996

Results are from Generalised Estimating Equations to account for the dependency across repeated measurements (exchangeable working correlation matrix). Each exposure variable measures change since baseline on a continuous scale. Each unit represent an average change in exposure by one category between the baseline and the end of the study (+1 = improvement of the neighbourhood by one category on average). The time x change interaction assesses whether exposure change is associated with different trajectory of change in the outcome. [1] adjusted for time, gender, ethnicity, health conditions, family affluence and baseline FSM reporting. [2] The adjusted model was replicated for each outcome with the addition of 2 way- and 3 way- interactions between gender, change and time.

Table E.21 Odds ratios (OR) of reporting at least one outdoor physical activity vs. not by change in perception of the neighbourhood environment since the baseline, adjusting for potential confounders (3 waves of the ORiEL Study; n=2,260)*

Exposure	Unadjusted OR	Adjusted OR[1]	95% CI	P-value unadjusted	P-value adjusted	Gender interaction (p-value) [2]
Change: Bus stop proximity	0.87	0.82	[0.53 , 1.27]	0.473	0.370	0.044
Change: Traffic safety	1.11	1.11	[0.85 , 1.45]	0.396	0.452	0.603
Change: Favourable infrastructure	0.80	0.78	[0.61 , 1.01]	0.045	0.056	0.423

Change: Nice neighbourhood	0.99	1.00	[0.82 , 1.23]	0.943	0.985	0.818
Change: Personal safety	1.02	1.02	[0.89 , 1.16]	0.790	0.808	0.758
Time x change interaction: Bus stop proximity	1.10	1.10	[0.93 , 1.31]	0.210	0.259	0.093
Time x change interaction: Traffic safety	0.94	0.94	[0.84 , 1.04]	0.245	0.228	0.835
Time x change interaction: Favourable infrastructure	1.07	1.07	[0.97 , 1.19]	0.119	0.178	0.091
Time x change interaction: Nice neighbourhood	1.02	1.02	[0.93 , 1.11]	0.605	0.723	0.501
Time x change interaction: Personal safety	1.01	1.01	[0.96 , 1.07]	0.660	0.751	0.961

Results are from Generalised Estimating Equations to account for the dependency across repeated measurements (exchangeable working correlation matrix).Each exposure variable measures change since baseline on a continuous scale. Each unit represent an average change in exposure by one category between the baseline and the end of the study (+1 = improvement of the neighbourhood by one category on average). The time x change interaction assesses whether exposure change is associated with different trajectory of change in the outcome. [1] adjusted for time, gender, ethnicity, health conditions, family affluence and baseline FSM reporting. [2] The adjusted model was replicated for each outcome with the addition of 2 way- and 3 way- interactions between gender, change and time. * Outdoor physical activities include: basketball (or volleyball), blading, cricket, football, rounders, rugby and skating.

E.5 Results from the complete case analysis of chapter 6

Table E.22 Odds ratios (OR) of walking to school vs. not by perception of the neighbourhood environment, adjusting for potential confounders (3 waves of the ORiEL Study, n=4,246 from 2,028 individuals)

Exposure		N cat	Unadjusted OR	Adjusted OR[1]	95%CI	P-value parameter	P-value unadjusted	P-value adjusted[1]	Gender interaction (p-value) [2]
Bus stop proximity	Further away	850	1.00	1.00			0.123	0.155	0.730
	1-5 minutes	3396	0.86	0.87	[0.72,1.05]	0.155			
Perceived traffic safety	Low	428	1.00	1.00			0.175	0.160	0.443
	Medium	1421	1.23	1.24	[0.99,1.56]	0.057			
	High	2397	1.16	1.20	[0.96,1.50]	0.115			
Perceived connectivity	Low	832	1.00	1.00			0.256	0.231	0.767
	Medium	2483	1.11	1.10	[0.92,1.31]	0.288			
	High	931	1.19	1.21	[0.97,1.50]	0.087			
Nhood nice for walk/cycle	Strongly/slightly disagree	1020	1.00	1.00			0.271	0.146	0.273
	Slightly agree	1669	1.11	1.08	[0.91,1.28]	0.360			
	Strongly agree	1557	0.99	0.92	[0.76,1.11]	0.382			
Feel safe	Strongly disagree	403	1.00	1.00			0.896	0.890	0.928
	Slightly disagree	669	1.15	1.12	[0.85,1.48]	0.428			
	Neither agree nor disagree	996	1.09	1.04	[0.80,1.35]	0.787			
	Slightly agree	1112	1.10	1.08	[0.82,1.41]	0.595			
	Strongly agree	1066	1.10	1.11	[0.85,1.47]	0.439			

Exposure		N cat	Unadjusted OR	Adjusted OR[1]	95%CI	P-value parameter	P-value unadjusted	P-value adjusted[1]	Gender interaction (p-value) [2]
Gender	Male	2288	1.00	1.00			0.716	0.358	-
	Female	1958	1.03	1.09	[0.91,1.30]	0.358			
Ethnicity	White: UK	779	1.00	1.00			<0.001	<0.001	0.660
	White: Mixed	345	0.60	0.58	[0.40,0.83]	0.003			
	Asian: Indian	185	1.23	1.27	[0.75,2.15]	0.383			
	Asian: Pakistani	175	0.80	0.81	[0.49,1.34]	0.419			
	Asian: Bangladeshi	700	1.32	1.31	[0.93,1.85]	0.124			
	Black: Caribbean	180	0.41	0.39	[0.25,0.60]	<0.001			
	Black: African	403	0.65	0.66	[0.47,0.93]	0.017			
	Other	1479	0.71	0.72	[0.55,0.94]	0.016			
Health	no condition	2472	1.00	1.00			0.129	0.076	0.278
	1+ conditions(s)	1774	1.13	1.15	[0.99,1.35]	0.076			
FAS Categories	Low	319	1.00	1.00			0.126	0.225	0.630
	Moderate	2182	0.74	0.76	[0.56,1.04]	0.084			
	High	1745	0.74	0.78	[0.57,1.08]	0.137			
Take FSM at W1	No	2738	1.00	1.00			0.340	0.395	0.375
	Yes	1508	1.09	1.09	[0.90,1.31]	0.395			
time		.	0.96	0.96	[0.90,1.04]	0.331	0.262	0.331	0.599

Results are from Generalised Estimating Equations to account for the dependency across repeated measurements (unstructured working correlation matrix). [1] Adjusted for all variables of the table. [2] The adjusted model was replicated for each outcome with an additional interaction term between gender and the exposure.

Table E.23 Odds ratios (OR) of walking for leisure vs. not by perception of the neighbourhood environment, adjusting for potential confounders (3 waves of the ORiEL Study, n= 4,128 from 2,005)

Exposure		N cat	Unadjusted OR	Adjusted OR[1]	95%CI	P-value parameter	P-value unadjusted	P-value adjusted[1]	Gender interaction (p-value) [2]
Bus stop proximity	Further away	826	1.00	1.00			0.100	0.109	0.512
	1-5 minutes	3302	0.88	0.88	[0.75,1.03]	0.109			
Perceived traffic safety	Low	422	1.00	1.00			0.439	0.293	0.665
	Medium	1382	0.90	0.89	[0.71,1.13]	0.348			
	High	2324	0.87	0.84	[0.67,1.06]	0.134			
Perceived connectivity	Low	799	1.00	1.00			0.203	0.418	0.841
	Medium	2416	1.15	1.10	[0.93,1.31]	0.257			
	High	913	1.18	1.14	[0.93,1.41]	0.214			
Nhood nice for walk/cycle	Strongly/slightly disagree	988	1.00	1.00			0.276	0.460	0.871
	Slightly agree	1625	0.96	0.97	[0.81,1.16]	0.733			
	Strongly agree	1515	1.08	1.07	[0.89,1.30]	0.470			
Feel safe	Strongly disagree	396	1.00	1.00			0.064	0.024	0.904
	Slightly disagree	635	1.29	1.33	[1.02,1.74]	0.036			
	Neither agree nor disagree	963	1.06	1.08	[0.83,1.41]	0.551			
	Slightly agree	1092	1.29	1.38	[1.07,1.80]	0.015			
	Strongly agree	1042	1.15	1.23	[0.94,1.60]	0.138			
Gender	Male	2214	1.00	1.00			<0.001	<0.001	-
	Female	1914	1.64	1.62	[1.39,1.89]	<0.001			
Ethnicity	White: UK	763	1.00	1.00			<0.001	<0.001	0.073
	White: Mixed	327	0.75	0.70	[0.51,0.95]	0.025			

Exposure		N cat	Unadjusted OR	Adjusted OR[1]	95%CI	P-value parameter	P-value unadjusted	P-value adjusted[1]	Gender interaction (p-value) [2]
	Asian: Indian	177	0.68	0.67	[0.45,0.99]	0.046			
	Asian: Pakistani	176	0.48	0.50	[0.34,0.74]	0.001			
	Asian: Bangladeshi	691	0.39	0.39	[0.30,0.50]	<0.001			
	Black: Caribbean	178	0.45	0.41	[0.27,0.62]	<0.001			
	Black: African	377	0.39	0.39	[0.28,0.53]	<0.001			
	Other	1439	0.65	0.63	[0.51,0.78]	<0.001			
Health	no condition	2400	1.00	1.00			0.693	0.955	0.566
	1+ conditions(s)	1728	1.03	1.00	[0.87,1.16]	0.955			
FAS Categories	Low	311	1.00	1.00			0.196	0.166	0.443
	Moderate	2123	0.93	1.05	[0.81,1.36]	0.714			
	High	1694	1.06	1.19	[0.91,1.57]	0.209			
Take FSM at W1	No	2657	1.00	1.00			0.574	0.050	0.642
	Yes	1471	1.05	1.18	[1.00,1.38]	0.050			
time		.	0.81	0.79	[0.73,0.86]	<0.001	<0.001	<0.001	0.893

Results are from Generalised Estimating Equations to account for the dependency across repeated measurements (unstructured working correlation matrix). [1] Adjusted for all variables of the table. [2] The adjusted model was replicated for each outcome with an additional interaction term between gender and the exposure.

Table E.24 Odds ratios (OR) of reporting at least one outdoor physical activity vs. not by perception of the neighbourhood environment, adjusting for potential confounders (3 waves of the ORiEL Study, n= 3,974 from 1,980 individuals)*

Exposure		N cat	Unadjusted OR	Adjusted OR[1]	95%CI	P-value parameter	P-value unadjusted	P-value adjusted[1]	Gender interaction (p-value) [2]
Bus stop proximity	Further away	783	1.00	1.00			0.749	0.817	0.776
	1-5 minutes	3191	0.97	0.98	[0.81,1.18]	0.817			
Perceived traffic safety	Low	403	1.00	1.00			0.828	0.370	0.008
	Medium	1338	1.00	1.03	[0.78,1.36]	0.825			
	High	2233	0.95	0.92	[0.69,1.22]	0.543			
Perceived connectivity	Low	770	1.00	1.00			0.095	0.016	0.601
	Medium	2332	1.09	1.24	[1.02,1.52]	0.035			
	High	872	1.27	1.43	[1.12,1.83]	0.004			
Nhood nice for walk/cycle	Strongly/slightly disagree	953	1.00	1.00			0.128	0.638	0.945
	Slightly agree	1566	0.97	0.99	[0.80,1.21]	0.889			
	Strongly agree	1455	1.14	1.08	[0.85,1.37]	0.524			
Feel safe	Strongly disagree	382	1.00	1.00			0.261	0.551	0.785
	Slightly disagree	614	1.06	1.13	[0.84,1.52]	0.430			
	Neither agree nor disagree	933	0.97	0.96	[0.72,1.28]	0.780			
	Slightly agree	1052	1.05	1.06	[0.80,1.41]	0.684			
	Strongly agree	993	1.22	1.14	[0.85,1.54]	0.391			
Gender	Male	2153	1.00	1.00			<0.001	<0.001	-
	Female	1821	0.21	0.20	[0.17,0.25]	<0.001			
Ethnicity	White: UK	735	1.00	1.00			0.001	0.007	0.109
	White: Mixed	316	1.21	1.38	[0.95,2.00]	0.093			

Exposure		N cat	Unadjusted OR	Adjusted OR[1]	95%CI	P-value parameter	P-value unadjusted	P-value adjusted[1]	Gender interaction (p-value) [2]
	Asian: Indian	171	1.25	1.22	[0.76,1.96]	0.415			
	Asian: Pakistani	169	2.75	2.53	[1.42,4.51]	0.002			
	Asian: Bangladeshi	675	1.23	1.06	[0.79,1.44]	0.688			
	Black: Caribbean	171	0.85	1.09	[0.70,1.69]	0.702			
	Black: African	357	1.71	1.75	[1.23,2.51]	0.002			
	Other	1380	1.26	1.31	[1.01,1.70]	0.042			
Health	no condition	2309	1.00	1.00			0.431	0.922	0.745
	1+ conditions(s)	1665	0.94	0.99	[0.84,1.17]	0.922			
FAS Categories	Low	302	1.00	1.00			0.103	0.053	0.462
	Moderate	2042	1.07	1.18	[0.87,1.61]	0.277			
	High	1630	1.25	1.40	[1.01,1.94]	0.042			
Take FSM at W1	No	2562	1.00	1.00			0.143	0.295	0.616
	Yes	1412	1.14	1.11	[0.92,1.34]	0.295			
time			0.74	0.71	[0.65,0.77]	<0.001	<0.001	<0.001	0.056

Results are from Generalised Estimating Equations to account for the dependency across repeated measurements (unstructured working correlation matrix). [1] Adjusted for all variables of the table. [2] The adjusted model was replicated for each outcome with an additional interaction term between gender and the exposure. * Outdoor physical activities include: basketball (or volleyball), blading, cricket, football, rounders, rugby and skating.

Table E.25 Odds ratios (OR) of walking to school vs. not at wave 3 by cumulated perception of the neighbourhood environment over the 3 waves, adjusting for potential confounders (n=865)

Exposure	Unadjusted OR	Adjusted OR[1]	95%CI	P-value unadjusted	P-value adjusted[1]	Gender interaction (p-value) [2]
Cumulative bus stop proximity	0.91	0.94	[0.80,1.11]	0.284	0.457	0.088
Cumulative traffic safety	0.93	1.01	[0.90,1.13]	0.195	0.916	0.263
Cumulative favourable infrastructure	1.06	1.07	[0.93,1.23]	0.419	0.345	0.390
Cumulative nice neighbourhood	0.91	0.90	[0.79,1.01]	0.096	0.076	0.473
Cumulative personal safety	0.95	0.98	[0.90,1.07]	0.233	0.682	0.485

Results are from Generalised Estimating Equations to account for the clustering of individuals within schools (exchangeable working correlation matrix). The cumulative exposure are continuous variables constructed as the sum of scores of each exposure over the 3 waves. A higher score indicates a perception of supportive environment for the specific exposure. [1] Adjusted for gender, ethnicity, health conditions (at wave 3), family affluence (at wave 3), baseline FSM and the other perception variables. [2] The adjusted model was replicated for each outcome with an additional interaction term between gender and the exposure.

Table E.26 Odds ratios (OR) of walking for leisure vs. not at wave 3 by cumulated perception of the neighbourhood environment over the 3 waves, adjusting for potential confounders (n=860)

Exposure	Unadjusted OR	Adjusted OR[1]	95%CI	P-value unadjusted	P-value adjusted[1]	Gender interaction (p-value) [2]
Cumulative bus stop proximity	1.07	1.11	[0.92,1.33]	0.433	0.289	0.732
Cumulative traffic safety	1.01	1.08	[0.96,1.21]	0.838	0.210	0.615
Cumulative favourable infrastructure	1.02	1.05	[0.90,1.22]	0.756	0.565	0.459
Cumulative nice neighbourhood	0.95	0.94	[0.83,1.06]	0.250	0.324	0.270
Cumulative personal safety	0.96	0.99	[0.92,1.06]	0.211	0.717	0.815

Results are from Generalised Estimating Equations to account for the clustering of individuals within schools (exchangeable working correlation matrix). The cumulative exposure are continuous variables constructed as the sum of scores of each exposure over the 3 waves. A higher score indicates a perception of supportive environment for the specific exposure. ¹ Adjusted for gender, ethnicity, health conditions (at wave 3), family affluence (at wave 3) and baseline FSM. ² The adjusted model was replicated for each outcome with an additional interaction term between gender and the exposure.

Table E.27 Odds ratios (OR) of reporting at least one outdoor physical activity* vs. not at wave 3 by cumulated perception of the neighbourhood environment over the 3 waves, adjusting for potential confounders (n= 839)

Exposure	Unadjusted OR	Adjusted OR¹	95%CI	P-value unadjusted	P-value adjusted¹	Gender interaction (p-value) ²
Cumulative bus stop proximity	1.13	1.11	[0.88,1.39]	0.222	0.385	0.015
Cumulative traffic safety	1.09	1.07	[0.92,1.24]	0.224	0.388	0.235
Cumulative favourable infrastructure	1.03	1.05	[0.95,1.17]	0.423	0.315	0.565
Cumulative nice neighbourhood	1.05	1.06	[0.96,1.17]	0.139	0.234	0.171
Cumulative personal safety	1.06	1.00	[0.94,1.07]	0.060	0.912	0.943

Results are from Generalised Estimating Equations to account for the clustering of individuals within schools (exchangeable working correlation matrix). The cumulative exposure are continuous variables constructed as the sum of scores of each exposure over the 3 waves. A higher score indicates a perception of supportive environment for the specific exposure. ¹ Adjusted for gender, ethnicity, health conditions (at wave 3), family affluence (at wave 3) and baseline FSM. ² The adjusted model was replicated for each outcome with an additional interaction term between gender and the exposure. * Outdoor physical activities include: basketball (or volleyball), blading, cricket, football, rounders, rugby and skating.

Table E.28 Odds ratios (OR) of walking to school vs. not by change in perception of the neighbourhood environment since the baseline, adjusting for potential confounders (3 waves of the ORiEL Study n= 2,703 from 1,027 individuals)

Exposure	Unadjusted OR	Adjusted OR¹	95% CI	P-value unadjusted	P-value adjusted	Gender interaction (p-value) ²
Change: Bus stop proximity	1.08	1.28	[0.78 , 2.09]	0.682	0.325	0.130
Change: Traffic safety	1.20	1.06	[0.77 , 1.46]	0.141	0.704	0.462
Change: Favourable infrastructure	0.97	1.06	[0.78 , 1.44]	0.814	0.714	0.858

Change: Nice neighbourhood	1.10	1.12	[0.85 , 1.47]	0.348	0.415	0.703
Change: Personal safety	0.99	0.92	[0.78 , 1.08]	0.862	0.312	0.109
Time x change interaction: Bus stop proximity	0.97	0.90	[0.73 , 1.12]	0.663	0.338	0.063
Time x change interaction: Traffic safety	0.94	1.01	[0.88 , 1.16]	0.224	0.909	0.095
Time x change interaction: Favourable infrastructure	1.00	1.01	[0.89 , 1.14]	0.986	0.936	0.672
Time x change interaction: Nice neighbourhood	0.94	0.95	[0.84 , 1.06]	0.125	0.339	0.996
Time x change interaction: Personal safety	0.98	1.00	[0.93 , 1.07]	0.527	0.994	0.584

Results are from Generalised Estimating Equations to account for the dependency across repeated measurements (unstructured working correlation matrix). Each exposure variable measures change since baseline on a continuous scale. Each unit represent an average change in exposure by one category between the baseline and the end of the study (+1 = improvement of the neighbourhood by one category on average). The time x change interaction assesses whether exposure change is associated with different trajectory of change in the outcome. [1] adjusted for time, gender, ethnicity, health conditions, family affluence and baseline FSM reporting. [2] The adjusted model was replicated for each outcome with the addition of 2 way- and 3 way- interactions between gender, change and time.

Table E.29 Odds ratios (OR) of walking for leisure vs. not by change in perception of the neighbourhood environment since the baseline, adjusting for potential confounders (3 waves of the ORiEL Study; n=2,622 from 1,023 individuals)

Exposure	Unadjusted OR	Adjusted OR[1]	95% CI	P-value unadjusted	P-value adjusted	Gender interaction (p-value) [2]
Change: Bus stop proximity	1.15	1.13	[0.70 , 1.84]	0.442	0.616	0.512
Change: Traffic safety	0.94	0.78	[0.57 , 1.07]	0.598	0.129	0.175
Change: Favourable infrastructure	1.01	0.94	[0.69 , 1.28]	0.957	0.703	0.983
Change: Nice neighbourhood	0.98	1.11	[0.84 , 1.45]	0.866	0.468	0.338
Change: Personal safety	0.98	0.96	[0.83 , 1.13]	0.787	0.648	0.373
Time x change interaction: Bus stop proximity	0.87	0.93	[0.75 , 1.16]	0.075	0.518	0.998
Time x change interaction: Traffic safety	1.00	1.08	[0.93 , 1.25]	0.936	0.313	0.237
Time x change interaction: Favourable infrastructure	0.99	1.02	[0.88 , 1.17]	0.834	0.809	0.893
Time x change interaction: Nice neighbourhood	1.00	0.93	[0.82 , 1.05]	0.946	0.257	0.298

Time x change interaction: Personal safety	1.00	1.04	[0.96 , 1.11]	0.975	0.329	0.700

Results are from Generalised Estimating Equations to account for the dependency across repeated measurements (unstructured working correlation matrix). Each exposure variable measures change since baseline on a continuous scale. Each unit represent an average change in exposure by one category between the baseline and the end of the study (+1 = improvement of the neighbourhood by one category on average). The time x change interaction assesses whether exposure change is associated with different trajectory of change in the outcome. [1] adjusted for time, gender, ethnicity, health conditions, family affluence and baseline FSM reporting. [2] The adjusted model was replicated for each outcome with the addition of 2 way- and 3 way- interactions between gender, change and time.

Table E.30 Odds ratios (OR) of reporting at least one outdoor physical activity* vs. not by change in perception of the neighbourhood environment since the baseline, adjusting for potential confounders (3 waves of the ORiEL Study; n=2,534 from 1,021 individuals)

Exposure	Unadjusted OR	Adjusted OR[1]	95% CI	P-value unadjusted	P-value adjusted	Gender interaction (p-value) [2]
Change: Bus stop proximity	0.93	1.01	[0.58 , 1.74]	0.709	0.981	0.218
Change: Traffic safety	1.13	1.11	[0.77 , 1.59]	0.346	0.572	0.002
Change: Favourable infrastructure	0.70	0.69	[0.48 , 0.98]	0.010	0.039	0.908
Change: Nice neighbourhood	0.92	1.01	[0.73 , 1.40]	0.434	0.955	0.530
Change: Personal safety	1.07	0.95	[0.78 , 1.16]	0.336	0.606	0.242
Time x change interaction: Bus stop proximity	1.10	1.03	[0.82 , 1.30]	0.245	0.774	0.305
Time x change interaction: Traffic safety	0.94	0.93	[0.80 , 1.08]	0.258	0.334	0.008
Time x change interaction: Favourable infrastructure	1.11	1.11	[0.96 , 1.29]	0.058	0.151	0.892
Time x change interaction: Nice neighbourhood	1.06	0.98	[0.85 , 1.12]	0.203	0.723	0.415
Time x change interaction: Personal safety	1.00	1.06	[0.98 , 1.15]	0.926	0.148	0.419

Results are from Generalised Estimating Equations to account for the dependency across repeated measurements (unstructured working correlation matrix). Each exposure variable measures change since baseline on a continuous scale. Each unit represent an average change in exposure by one category between the baseline and the end of the study (+1 = improvement of the neighbourhood by one category on average). The time x change interaction assesses whether exposure change is associated with different trajectory of change in the outcome. [1] adjusted for time, gender, ethnicity, health conditions, family affluence and baseline FSM reporting. [2] The adjusted model was replicated for each outcome with the addition of 2 way- and 3 way- interactions between gender, change and time. * Outdoor physical activities include: basketball (or volleyball), blading, cricket, football, rounders, rugby and skating.

Appendix F Supplementary material for chapter 7

F.1 Analysis of missingness for chapter 7

This appendix presents results from analyses of the missing data for chapter 7. The analyses were conducted in order to inform: i) the validity of the complete case analysis; ii) the plausibility of the MAR assumption; and iii) the selection of the auxiliary variables of the imputation model. Analyses focus on variables not previously studied in chapter 6 (cf. E.1 Analysis of missingness for chapter 6) and are restricted to the four more common ethnic groups: White UK, White Mixed, Bangladeshi, Black African. Note that these analyses are only informative and should be interpreted with caution as some assumptions might be violated in some of the models (e.g. clustering at individual level, normality in the error terms).

Validity of complete case analysis

Table F.1 indicate that walking to school has significant bivariate associations with missingness of neighbourhood-level (LSOA) ethnic density and distance to school, which are based on the reporting of individual address by respondents. The strength of evidence of associations weakens in the adjusted models for neighbourhood-level ethnic density. As in the preceding chapter, walking for leisure is most likely not associated with missingness of the covariates of the models, as indicated both in adjusted and unadjusted models. The odds of outdoor physical activity are associated with missingness on household composition in both adjusted and unadjusted models.

Overall, these results indicate that a complete case analysis might lead to some bias. Due to widespread item missingness, this analysis cannot be fully conclusive however. It is unclear whether weaker associations in the fully adjusted models are themselves biased (because of the change in the sample) or if they indicate that the complete case analysis is still valid once controlling for all relevant variables (i.e. once adjusted for covariates, missingness does not depend that much on the outcomes). Given that some significant associations remain in the adjusted models, the results overall indicate that a complete case analysis is very likely to be biased, which rules out the MCAR assumption.

Table F.1 Assessment of complete case analysis validity: unadjusted and adjusted ORs of item response for each covariate with missing values by outcome variable (adjusted and unadjusted results; n = 1,160; 3,480 measurements)

Covariate	N missing	% missing	Outcome	N	OR	Pvalue	N*	OR*	Pvalue*
Ethnic density LSOA	292	8.4	Walk to school	3325	1.60	0.001	2846	1.35	0.076
			Walk for leisure	3150	0.89	0.413	2704	0.81	0.207
			Outdoor PA	3003	0.98	0.918	2589	1.15	0.469
Household composition	32	0.9	Walk to school	3325	0.88	0.799	2863	0.98	0.975
			Walk for leisure	3150	1.41	0.479	2717	1.07	0.915
			Outdoor PA	3003	1.96	0.143	2602	2.47	0.152
Time lived in neighbourhood	282	8.1	Walk to school	3325	1.17	0.345	2846	1.16	0.421
			Walk for leisure	3150	0.88	0.418	2704	0.79	0.196
			Outdoor PA	3003	0.53	0.005	2589	0.79	0.337
Distance to school	297	8.5	Walk to school	3325	1.63	0.001	3325	1.63	0.001

*Results from logistic regressions, adjusted for gender, ethnicity, health, family affluence, baseline FSM, school-level ethnic density and household composition (except for the model with household composition missingness) Response is coded 1 and missingness 0.

Plausibility of the MAR mechanism

In addition to analyses of MAR mechanism performed in chapter 6 (E.1 Analysis of missingness for chapter 6), I investigated whether missingness on new variables with high missingness - neighbourhood-level ethnic density, distance to school and time lived in the neighbourhood - could be predicted using almost fully observed variables (Table F.2). Predictors used were (almost) fully observed variables from the model of interest (school-level ethnic density, gender, ethnicity, family affluence, free school meals, household composition) and auxiliary variables *a priori* hypothesised to be associated with the probability of missingness: school, country of birth, language spoken at home, self-rated health, mental health (WEMWBS total score).

Amongst the (almost) fully observed variables of the model of interest, ethnicity, school, country of birth, language spoken at home and mental health were good predictors of missingness for at least two out of the three the variables examined (Table F.2). Gender and FSM were also a good predictor of missingness on time lived in the neighbourhood.

This analysis indicates that at least some of the variables are predictive of missingness, which supports the plausibility of the MAR assumption. Variables with more missing values are also likely to predict missingness on the variables of the models of interest so that an imputation model with the wide range of variables considered will further strengthen the plausibility of the assumption. However, it is never possible to rule out MNAR, and it might be that even accounting for all these variables, the missingness mechanism depends on unmeasured variables.

Table F.2 Assessment of the MAR assumption: (almost) fully observed predictors of item missingness for the additional variables with high levels of missing values.

Missingness variable	Predictor	p-value
Ethnic density LSOA	Gender	0.922
	Ethnicity	0.001
	school	<0.001
	FAS Categories	0.167
	Take FSM at W1	0.377
	Country of Birth	0.009
	language at home	0.014
	self-rated health	0.321
	household composition	0.473
	School-level ethnic density	0.637
	Log of total PA	0.717
	Mental Health (WEMWBS)	0.057
Time lived in neighbourhood	Gender	0.002
	Ethnicity	0.065
	school	0.010
	FAS Categories	0.556
	Take FSM at W1	0.004
	Country of Birth	0.926
	language at home	0.354
	self-rated health	0.276
	household composition	0.801
	School-level ethnic density	0.540
	Log of total PA	0.348
	Mental Health (WEMWBS)	0.257
Distance to school	Gender	0.845
	Ethnicity	0.002
	school	<0.001
	FAS Categories	0.108
	Take FSM at W1	0.180
	Country of Birth	0.007
	language at home	0.016
	self-rated health	0.286
	household composition	0.400
	School-level ethnic density	0.432
	Log of total PA	0.907
	Mental Health (WEMWBS)	0.074

Results from logistic regressions.

Selecting variables for the imputation model

The imputation model should include variables of the models of interest and relevant auxiliary variables. The later should be included only if they are likely to reduce bias and/or to increase efficiency (Carpenter & Kenward 2012). Variables predictive of the chance of missing values identified above should be included in the imputation model only if they also predict the underlying missing values, in which case, they are likely to reduce bias and improve efficiency. Auxiliary variables should however be excluded if they do not predict the underlying values themselves. Variables associated with the underlying values - but not the chance of missing values - should be included because they will improve efficiency, although they are not going to reduce bias.

Table F.3 reports linear and logistic regression results of associations between the three additional variables with missing values (neighbourhood-level ethnic density(continuous), time lived in the neighbourhood(binary), and log distance to school (continuous)) and almost fully observed variables of the model of interest, as well as auxiliary variables. Neighbourhood-level ethnic density is well predicted by ethnicity, school, FSM, country of birth, self-rated health, school-level ethnic density, and to a lower extent and mental health. Time lived in the neighbourhood is predicted by ethnicity, school, FSM, country of birth, household composition and total PA, and, to some extent, school-level ethnic density. Distance to school (log) is predicted by ethnicity, school, FSM, country of birth, school-level ethnic density and log of total PA.

Additional analysis (not presented here) of a potential auxiliary variables with more missing values – same-ethnicity friends (measured at wave 3 and recoded as many vs. few) – further indicates that the variable could be included in the imputation model to increase precision. Same-ethnicity friends was a potential predictor of neighbourhood-level ethnic density (unadjusted p-value < 0.001, adjusted p-value = 0.104). It was however not a predictor of missing values on the ethnic density variable (unadjusted p-value = 0.737). It was therefore considered in the initial imputation model, but left out of the final imputation model for parsimony purposes.

Summary

Overall, these analyses combined with those of the previous chapter (E.1 Analysis of missingness for chapter 6), indicates that an imputation model with the auxiliary variables considered – country of birth, language spoken at home, self-rated health, total physical activity, mental health – are very likely to reduce bias and improve efficiency compared to a complete case analysis. Covariates of the model of interest with more missing values are also expected to reduce bias and improve efficiency.

Table F.3 Associations between variables with missing values and auxiliary variables, adjusted for all auxiliary variables and gender, ethnicity, school, FSM, household composition, and FAS category.

Variable with missing values	Predictor	p-value
Ethnic density LSOA	Gender	0.338
	Ethnicity	<0.001
	school	<0.001
	FAS Categories	0.135
	Take FSM at W1	0.017
	Country of Birth	<0.001
	language at home	0.624
	self-rated health	0.009
	household composition	0.321
	School-level ethnic density	<0.001
	Log of total PA	0.045
	Mental Health (WEMWBS)	0.070
Time lived in neighbourhood	Gender	0.150
	Ethnicity	0.002
	school	<0.001
	FAS Categories	0.007
	Take FSM at W1	0.001
	Country of Birth	<0.001
	language at home	0.794
	self-rated health	0.885
	household composition	0.019
	School-level ethnic density	0.079
	Log of total PA	<0.001
	Mental Health (WEMWBS)	0.409
Distance to school (log)	Gender	0.441
	Ethnicity	<0.001
	school	<0.001
	FAS Categories	0.499
	Take FSM at W1	0.010
	Country of Birth	0.009
	language at home	0.148
	self-rated health	0.508
	household composition	0.473
	School-level ethnic density	0.036
	Log of total PA	<0.001
	Mental Health (WEMWBS)	0.478

Results from linear and logistic regression models.

F.2 Model equations of chapter 7

The partially adjusted and fully adjusted model equations of chapter 7 are described in this appendix. The models account for time-invariant (gender, baseline FSM) and time-varying confounders (health condition, family affluence, household composition and time lived in the neighbourhood). A time trend was included to reflect the general decrease in physical activity during adolescence. The models for walking to school also account for the log distance to school. The logistic models estimated with GEE to account for clustering at individual level *i* are expressed as follows:

$$logit\{\Pr(Y_{ij} = 1|\boldsymbol{x_{ij}})\} = \boldsymbol{x'_{ij}\beta}$$

Where:

i= individual

j= repeated measures

Y_{ij} = physical activity outcome (walking to school, walking for leisure or outdoor physical activity) for individual *i* at occasion *j*

$\boldsymbol{x_{ij}}$ = a matrix representing the variables included in the model for all individuals at each occasion

$\boldsymbol{\beta}$ = a vector representing the coefficients of the model, including a constant

The following equations describe the form taken by $\boldsymbol{x'_{ij}\beta}$ in three types of models fitted.

1. Partially adjusted model for school-level ethnic density

$$\boldsymbol{x'_{ij}\beta} = \beta_0 + \beta_1 ScHool\_etH\_dens_i + \beta_2 EtH2_i + \beta_3 EtH3_i + \beta_4 EtH4_i + \beta_5 EtH2_i * ScHool\_etH\_dens_i + \beta_6 EtH3_i * ScHool\_etH\_dens_i + \beta_7 Eth4_i * ScHool\_etH\_dens_i + \beta_8 Girl_i + \beta_9 FSM_{i1} + \beta_{10} HealtH_{ij} + \beta_{11} FAS1_{ij} + \beta_{12} FAS2_{ij} + \beta_{13} HH\_comp_{ij} + \beta_{14} Nb\_time_{ij} + \beta_{15} Time_{ij} \ (+ \beta_{16} ScHool\_dist_{ij})$$

2. Partially adjusted model for neighbourhood-level ethnic density

$$\boldsymbol{x'_{ij}\beta} = \beta_0 + \beta_1 Nb\_etH\_dens_{ij} + \beta_2 EtH2_i + \beta_3 EtH3_i + \beta_4 EtH4_i + \beta_5 EtH2_i * Nb\_etH\_dens_{ij} + \beta_6 EtH3_i * Nb\_etH\_dens_{ij} + \beta_7 EtH4_i * Nb\_etH\_dens_{ij} + \beta_8 Girl_i + \beta_9 FSM_{i1} + \beta_{10} HealtH_{ij} + \beta_{11} FAS1_{ij} + \beta_{12} FAS2_{ij} + \beta_{13} HH\_comp_{ij} + \beta_{14} Nb\_time_{ij} + \beta_{15} Time_{ij} \ (+ \beta_{16} ScHool\_dist_{ij})$$

3. Fully adjusted model for school-level ethnic density and neighbourhood-level ethnic density

$$\boldsymbol{x'_{ij}\beta} = \beta_0 + \beta_1 ScHool\_etH\_dens_i + \beta_2 Nb\_etH\_dens_{ij} + \beta_3 EtH2_i + \beta_4 EtH3_i + \beta_5 EtH4_i + \beta_6 EtH2_i * ScHool\_etH\_dens_i + \beta_7 EtH3_i * ScHool\_etH\_dens_i + \beta_8 EtH4_i * ScHool\_etH\_dens_i + \beta_9 EtH2_i * Nb\_etH\_dens_{ij} + \beta_{10} EtH3_i * Nb\_etH\_dens_{ij} + \beta_{11} EtH4_i * Nb\_etH\_dens_{ij} + \beta_{12} Girl_i + \beta_{13} FSM_{i1} + \beta_{14} HealtH_{ij} + \beta_{15} FAS1_{ij} + \beta_{16} FAS2_{ij} + \beta_{17} HH\_comp_{ij} + \beta_{18} Nb\_time_{ij} + \beta_{19} Time_{ij} \ (+ \beta_{20} ScHool\_dist_{ij})$$

Where:

$ScHool\_etH\_dens_i$= School-level own ethnic density (time-invariant)

$Nb\_etH\_dens_{ij}$= Neighbourhood-level (LSOA) own ethnic density (time-varying if changed residence)

$EtH2_i$,…, $EtH4_i$= Ethnicity dummy variables (reference category: White UK; time invariant)

$Girl_i$= Dummy variable for girls (time invariant)

FSM_{i1}= Baseline free school meals (reference category: no free school meal)

$HealtH_{ij}$ = Health conditions dummy variable (reference category: no condition)

$FAS2_{ij}, FAS3_{ij}$= Family affluence dummy variables (reference category: low)

HH_comp_{ij}= Household composition dummy variable (reference category: live with both parents)

Nb_time_{ij}= Time lived in the neighbourhood (reference category: more than 5 years)

$Time_{ij}$= Continuous variable indicating the wave (1, 2 or 3). Measurement time is considered equivalent across all individuals at each wave

$ScHool\_dist_{ij}$= Log distance to school (time-varying if changed residence)

F.3 Results from the estimation of the models of chapter 7 with GEE with alternative the working correlation using the imputed datasets

Table F.4 Ethnic group specific odds ratios (OR) of walking to school vs. not by own-group ethnic density* (3 waves of the ORiEL Study, n= 1,160)

Exposure	Unadjusted OR	Partially Adjusted OR[1]	95% CI	P-value	Fully Adjusted OR[2]	95% CI	p-value
School-level ethnic density				<0.001			<0.001
White: UK	1.08	1.08	[0.96 , 1.21]	0.183	1.11	[0.94 , 1.30]	0.206
White: Mixed	0.52	0.51	[0.34 , 0.75]	0.001	0.44	[0.28 , 0.69]	0.001
Asian: Bangladeshi	1.19	1.19	[1.09 , 1.31]	<0.001	1.12	[0.96 , 1.32]	0.143
Black: African	0.58	0.58	[0.45 , 0.75]	<0.001	0.60	[0.45 , 0.79]	<0.001
Neighbourhood-level ethnic density				0.003			0.508
White: UK	1.01	1.01	[0.88 , 1.16]	0.903	0.96	[0.81 , 1.14]	0.651
White: Mixed	0.96	0.95	[0.62 , 1.44]	0.805	1.34	[0.82 , 2.21]	0.244
Asian: Bangladeshi	1.31	1.31	[1.13 , 1.50]	<0.001	1.15	[0.91 , 1.46]	0.235
Black: African	0.81	0.80	[0.60 , 1.08]	0.142	0.92	[0.67 , 1.26]	0.615

Results are estimated with Generalised Estimating Equations models to account for the dependency across repeated measurements (exchangeable working correlation matrix). Interaction terms between the own-group ethnic density variable and ethnicity were used and ethnic group specific ORs were obtained. *Own-group density assessed as change per 10 percentage points. [1] Adjusted for time, gender, health conditions, family affluence, baseline FSM, household composition, time lived in the neighbourhood and distance to school. [2] Adjusted for time, gender, health conditions, family affluence, baseline FSM, household composition, time lived in the neighbourhood, distance to school, the other ethnic density variable and its interaction with ethnicity.

Table F.5 Ethnic group specific odds ratios (OR) of walking for leisure vs. not by own-group ethnic density (3 waves of the ORiEL Study, n= 1,160)*

Exposure	Unadjusted OR	Partially Adjusted OR[1]	95% CI	P-value	Fully Adjusted OR[2]	95% CI	p-value
School-level ethnic density				0.398			0.858
White: UK	0.99	0.99	[0.89 , 1.10]	0.832	0.96	[0.86 , 1.08]	0.505
White: Mixed	0.90	0.86	[0.61 , 1.22]	0.397	0.93	[0.64 , 1.36]	0.705
Asian: Bangladeshi	0.94	0.95	[0.90 , 1.01]	0.112	0.97	[0.89 , 1.05]	0.443
Black: African	1.12	1.14	[0.86 , 1.51]	0.371	1.07	[0.78 , 1.47]	0.684
Neighbourhood-level ethnic density				0.308			0.622
White: UK	1.03	1.02	[0.94 , 1.12]	0.584	1.04	[0.95 , 1.15]	0.378
White: Mixed	0.82	0.82	[0.57 , 1.18]	0.279	0.85	[0.57 , 1.26]	0.411
Asian: Bangladeshi	0.92	0.94	[0.85 , 1.03]	0.189	0.97	[0.84 , 1.12]	0.666
Black: African	1.18	1.18	[0.91 , 1.54]	0.209	1.16	[0.87 , 1.55]	0.318

Results are estimated with Generalised Estimating Equations to account for the dependency across repeated measurements (exchangeable working correlation matrix). Interaction terms between the own-group ethnic density variable and ethnicity were used and ethnic group specific ORs were obtained. *Own-group density assessed as change per 10 percentage points. [1] Adjusted for time, gender, health conditions, family affluence, baseline FSM, household composition and time lived in the neighbourhood. [2] Adjusted for time, gender, health conditions, family affluence, baseline FSM, household composition, time lived in the neighbourhood, the other ethnic density variable and its interaction with ethnicity.

Table F.6 Ethnic group specific odds ratios (OR) of outdoor PA vs. not by own-group ethnic density* (3 waves of the ORiEL Study, n= 1,160)

Exposure	Unadjusted OR	Partially Adjusted OR[1]	95%	CI	P-value	Fully Adjusted OR[2]	95%	CI	p-value
School-level ethnic density					0.071				0.551
White: UK	0.86	0.87	[0.77 ,	0.97]	0.016	0.94	[0.82 ,	1.08]	0.402
White: Mixed	0.97	1.05	[0.68 ,	1.61]	0.831	1.03	[0.64 ,	1.65]	0.896
Asian: Bangladeshi	1.05	1.02	[0.95 ,	1.09]	0.561	1.03	[0.94 ,	1.14]	0.511
Black: African	0.79	0.78	[0.58 ,	1.04]	0.092	0.79	[0.57 ,	1.10]	0.160
Neighbourhood-level ethnic density					0.032				0.271
White: UK	0.84	0.85	[0.76 ,	0.94]	0.001	0.87	[0.77 ,	0.98]	0.020
White: Mixed	1.07	1.05	[0.70 ,	1.58]	0.813	1.04	[0.66 ,	1.61]	0.876
Asian: Bangladeshi	1.04	1.01	[0.91 ,	1.12]	0.857	0.98	[0.85 ,	1.13]	0.744
Black: African	0.90	0.88	[0.67 ,	1.17]	0.385	0.96	[0.70 ,	1.31]	0.792

Results are estimated with Generalised Estimating Equations to account for the dependency across repeated measurements (exchangeable working correlation matrix). Interaction terms between the own-group ethnic density variable and ethnicity were used and ethnic group specific ORs were obtained. *Own-group density assessed as change per 10 percentage points. [1] Adjusted for time, gender, health conditions, family affluence, baseline FSM, household composition and time lived in the neighbourhood. [2] Adjusted for time, gender, health conditions, family affluence, baseline FSM, household composition, time lived in the neighbourhood, the other ethnic density variable and its interaction with ethnicity.

F.4 Results from stratified analyses by ethnic group using the imputed datasets

Table F.7 Ethnic group specific odds ratios (OR) of walking to school vs. not by own-group ethnic density* (3 waves of the ORiEL Study, n= 1,160)

Exposure	Unadjusted OR	Partially Adjusted OR[1]	95% CI	P-value	Fully Adjusted OR[2]	95% CI	p-value
School-level ethnic density							
White: UK	1.08	1.09	[0.97 , 1.23]	0.128	1.11	[0.95 , 1.31]	0.185
White: Mixed	0.54	0.49	[0.32 , 0.73]	0.001	0.42	[0.26 , 0.69]	0.001
Asian: Bangladeshi	1.20	1.20	[1.09 , 1.33]	<0.001	1.13	[0.97 , 1.33]	0.111
Black: African	0.58	0.57	[0.44 , 0.75]	<0.001	0.60	[0.44 , 0.80]	0.001
Neighbourhood-level ethnic density							
White: UK	1.01	1.02	[0.89 , 1.17]	0.755	0.97	[0.82 , 1.16]	0.746
White: Mixed	0.94	0.93	[0.59 , 1.46]	0.746	1.32	[0.77 , 2.26]	0.310
Asian: Bangladeshi	1.31	1.30	[1.13 , 1.51]	<0.001	1.15	[0.91 , 1.44]	0.242
Black: African	0.78	0.78	[0.58 , 1.05]	0.101	0.90	[0.65 , 1.24]	0.517

Results are estimated with Generalised Estimating Equations to account for the dependency across repeated measurements (unstructured working correlation matrix). *Own-group density assessed as change per 10 percentage points. [1] Adjusted for time, gender, health conditions, family affluence, baseline FSM, household composition, time lived in the neighbourhood and distance to school. [2] Adjusted for time, gender, health conditions, family affluence, baseline FSM, household composition, time lived in the neighbourhood, distance to school, and the other ethnic density variable.

Table F.8 Ethnic group specific odds ratios (OR) of walking for leisure vs. not by own-group ethnic density (3 waves of the ORiEL Study, n= 1,160)*

Exposure	Unadjusted OR	Partially Adjusted OR¹	95%	CI	P-value	Fully Adjusted OR²	95%	CI	p-value
School-level ethnic density									
White: UK	0.99	0.99	[0.89	, 1.09	] 0.829	0.96	[0.86	, 1.08	] 0.491
White: Mixed	0.91	0.87	[0.62	, 1.23	] 0.439	0.96	[0.65	, 1.42	] 0.847
Asian: Bangladeshi	0.94	0.95	[0.89	, 1.01	] 0.089	0.97	[0.89	, 1.06	] 0.488
Black: African	1.12	1.15	[0.86	, 1.53	] 0.336	1.08	[0.78	, 1.50	] 0.643
Neighbourhood-level ethnic density									
White: UK	1.03	1.03	[0.94	, 1.12	] 0.540	1.05	[0.95	, 1.15	] 0.352
White: Mixed	0.83	0.79	[0.54	, 1.15	] 0.215	0.80	[0.52	, 1.22	] 0.304
Asian: Bangladeshi	0.91	0.92	[0.83	, 1.02	] 0.107	0.95	[0.82	, 1.10	] 0.479
Black: African	1.17	1.19	[0.91	, 1.55	] 0.205	1.16	[0.86	, 1.56	] 0.328

Results are estimated with Generalised Estimating Equations to account for the dependency across repeated measurements (unstructured working correlation matrix). *Own-group density assessed as change per 10 percentage points. ¹ Adjusted for time, gender, health conditions, family affluence, baseline FSM, household composition and time lived in the neighbourhood. ² Adjusted for time, gender, health conditions, family affluence, baseline FSM, household composition, time lived in the neighbourhood, and the other ethnic density variable.

Table F.9 Ethnic group specific odds ratios (OR) of outdoor PA vs. not. by own-group ethnic density* (3 waves of the ORiEL Study, n= 1,160)

Exposure	Unadjusted OR	Partially Adjusted OR[1]	95%	CI	P-value	Fully Adjusted OR[2]	95%	CI	p-value
School-level ethnic density									
White: UK	0.86	0.86	[0.76	, 0.96]	0.010	0.93	[0.82	, 1.07]	0.306
White: Mixed	0.99	0.99	[0.65	, 1.50]	0.951	1.00	[0.63	, 1.57]	0.994
Asian: Bangladeshi	1.05	1.02	[0.94	, 1.10]	0.658	1.03	[0.93	, 1.13]	0.627
Black: African	0.79	0.76	[0.56	, 1.02]	0.068	0.76	[0.55	, 1.06]	0.106
Neighbourhood-level ethnic density									
White: UK	0.84	0.84	[0.76	, 0.93]	0.001	0.87	[0.78	, 0.97]	0.014
White: Mixed	1.07	0.97	[0.63	, 1.48]	0.887	0.97	[0.61	, 1.55]	0.904
Asian: Bangladeshi	1.04	1.01	[0.90	, 1.13]	0.895	0.98	[0.85	, 1.14]	0.815
Black: African	0.92	0.89	[0.67	, 1.19]	0.437	0.98	[0.72	, 1.35]	0.919

Results are estimated with Generalised Estimating Equations to account for the dependency across repeated measurements (unstructured working correlation matrix). *Own-group density assessed as change per 10 percentage points. [1] Adjusted for time, gender, health conditions, family affluence, baseline FSM, household composition and time lived in the neighbourhood. [2] Adjusted for time, gender, health conditions, family affluence, baseline FSM, household composition, time lived in the neighbourhood, and the other ethnic density variable.

F.5 Results from stratified analyses by ethnic group using ethnic density tertiles and the imputed datasets

Table F.10 Ethnicity-stratified odds ratios (OR) of walking to school vs. not by school-level own-group ethnic density tertile (3 waves of the ORiEL Study, n= 1,160)

School-level ethnic density		Unadjusted OR	Partially Adjusted OR[1]	95% CI	P-value param.	p-value	Fully Adjusted OR[2]	95% CI	p-value param.	p-value
White: UK	Low*	1.00	1.00			0.006				0.008
	Medium	0.50	0.52	[0.32 , 0.83]	0.007		0.49	[0.30 , 0.80]	0.004	
	High	0.94	0.96	[0.57 , 1.62]	0.890		0.84	[0.46 , 1.54]	0.584	
White: Mixed	Low*	1.00	1.00			<0.001				<0.001
	Medium	0.26	0.23	[0.11 , 0.45]	<0.001		0.19	[0.09 , 0.39]	<0.001	
	High	0.36	0.30	[0.14 , 0.62]	0.001		0.22	[0.09 , 0.51]	<0.001	
Asian: Bangladeshi	Low*	1.00	1.00			<0.001				<0.001
	Medium	6.43	6.43	[3.38 , 12.24]	<0.001		7.18	[3.30 , 15.62]	<0.001	
	High	2.40	2.39	[1.29 , 4.42]	0.006		2.57	[1.10 , 6.00]	0.029	
Black: African	Low*	1.00	1.00			0.001				0.002
	Medium	0.69	0.69	[0.40 , 1.17]	0.169		0.71	[0.40 , 1.27]	0.250	
	High	0.39	0.37	[0.22 , 0.64]	<0.001		0.38	[0.22 , 0.67]	0.001	

Results are from logistic regression models estimated with Generalised Estimating Equations to account for the dependency across repeated measurements (unstructured working correlation matrix). *Own-group density assessed as change per 10 percentage points. [1] Adjusted for time, gender, health conditions, family affluence, baseline FSM, household composition, time lived in the neighbourhood and distance to school. [2] Adjusted for time, gender, health conditions, family affluence, baseline FSM, household composition, time lived in the neighbourhood, distance to school, and the other ethnic density variable. *ref. category

Table F.11 Ethnicity-stratified odds ratios (OR) of walking to school vs. not by neighbourhood-level own-group ethnic density tertile (3 waves of the ORiEL Study, n= 1,160)

Neighbourhood-level ethnic density		Unadjusted OR	Partially Adjusted OR[1]	95%	CI	P-value param.	p-value	Fully Adjusted OR[2]	95%	CI	p-value param.	p-value
White: UK	Low*	1.00	1.00				0.577	1.00				0.603
	Medium	1.09	1.14	[0.70 ,	1.85]	0.605		1.24	[0.74 ,	2.07]	0.417	
	High	1.23	1.31	[0.80 ,	2.16]	0.287		1.33	[0.74 ,	2.37]	0.337	
White: Mixed	Low*	1.00	1.00				0.979	1.00				0.375
	Medium	0.97	0.95	[0.46 ,	1.95]	0.888		1.37	[0.65 ,	2.90]	0.407	
	High	1.01	1.01	[0.49 ,	2.11]	0.970		1.80	[0.80 ,	4.02]	0.152	
Asian: Bangladeshi	Low*	1.00	1.00				0.010	1.00				0.017
	Medium	0.96	0.96	[0.57 ,	1.62]	0.879		0.50	[0.25 ,	1.00]	0.049	
	High	2.76	2.72	[1.35 ,	5.45]	0.005		1.17	[0.46 ,	3.01]	0.742	
Black: African	Low*	1.00	1.00				0.574	1.00				0.871
	Medium	0.90	0.87	[0.48 ,	1.60]	0.656		0.87	[0.46 ,	1.65]	0.669	
	High	0.73	0.73	[0.42 ,	1.27]	0.268		0.86	[0.48 ,	1.54]	0.606	

Results are from logistic regression models estimated with Generalised Estimating Equations to account for the dependency across repeated measurements (unstructured working correlation matrix). *Own-group density assessed as change per 10 percentage points. [1] Adjusted for time, gender, health conditions, family affluence, baseline FSM, household composition, time lived in the neighbourhood and distance to school. [2] Adjusted for time, gender, health conditions, family affluence, baseline FSM, household composition, time lived in the neighbourhood, distance to school, and the other ethnic density variable. *ref. category

Table F.12 Ethnicity-stratified odds ratios (OR) of walking for leisure vs. not by school-level own-group ethnic density tertile (3 waves of the ORiEL Study, n= 1,160)

School-level ethnic density		Unadjusted OR	Partially Adjusted OR[1]	95% CI	P-value param.	p-value	Fully Adjusted OR[2]	95% CI	p-value param.	p-value
White: UK	Low*	1.00	1.00			0.461	1.00			0.465
	Medium	0.82	0.81	[0.56 , 1.17]	0.257		0.80	[0.55 , 1.16]	0.232	
	High	0.99	0.98	[0.67 , 1.43]	0.912		0.93	[0.62 , 1.40]	0.720	
White: Mixed	Low*	1.00	1.00			0.359	1.00			0.396
	Medium	1.26	1.20	[0.73 , 1.97]	0.468		1.34	[0.79 , 2.27]	0.273	
	High	0.86	0.79	[0.43 , 1.44]	0.438		0.95	[0.49 , 1.86]	0.886	
Asian: Bangladeshi	Low*	1.00	1.00			0.085	1.00			0.261
	Medium	0.77	0.76	[0.52 , 1.10]	0.150		0.82	[0.53 , 1.26]	0.364	
	High	0.54	0.60	[0.37 , 0.96]	0.032		0.65	[0.38 , 1.09]	0.103	
Black: African	Low*	1.00	1.00			0.407	1.00			0.638
	Medium	0.95	1.08	[0.65 , 1.79]	0.757		1.04	[0.62 , 1.73]	0.889	
	High	1.30	1.40	[0.85 , 2.33]	0.187		1.28	[0.75 , 2.21]	0.364	

Results are from logistic regression models estimated with Generalised Estimating Equations to account for the dependency across repeated measurements (unstructured working correlation matrix). *Own-group density assessed as change per 10 percentage points. [1] Adjusted for time, gender, health conditions, family affluence, baseline FSM, household composition, and time lived in the neighbourhood. [2] Adjusted for time, gender, health conditions, family affluence, baseline FSM, household composition, time lived in the neighbourhood, and the other ethnic density variable. *ref. category

Table F.13 Ethnicity-stratified odds ratios (OR) of walking for leisure vs. not by neighbourhood-level own-group ethnic density tertile (3 waves of the ORiEL Study, n= 1,160)

Neighbourhood-level ethnic density		Unadjusted OR	Partially Adjusted OR[1]	95%	CI	P-value param.	p-value	Fully Adjusted OR[2]	95%	CI	p-value param.	p-value
White: UK	Low*	1.00	1.00				0.818	1.00				0.831
	Medium	0.96	0.97	[0.67 ,	1.40]	0.861		1.00	[0.69 ,	1.46]	0.998	
	High	1.10	1.09	[0.75 ,	1.57]	0.660		1.11	[0.75 ,	1.66]	0.597	
White: Mixed	Low*	1.00	1.00				0.461	1.00				0.520
	Medium	0.90	0.86	[0.49 ,	1.51]	0.604		0.83	[0.46 ,	1.47]	0.518	
	High	0.76	0.70	[0.40 ,	1.22]	0.206		0.69	[0.37 ,	1.28]	0.241	
Asian: Bangladeshi	Low*	1.00	1.00				0.241	1.00				0.821
	Medium	0.77	0.80	[0.52 ,	1.23]	0.316		0.91	[0.58 ,	1.45]	0.701	
	High	0.67	0.70	[0.47 ,	1.06]	0.091		0.85	[0.53 ,	1.39]	0.527	
Black: African	Low*	1.00	1.00				0.335	1.00				0.491
	Medium	0.94	0.96	[0.55 ,	1.66]	0.873		0.96	[0.56 ,	1.67]	0.896	
	High	1.32	1.37	[0.82 ,	2.30]	0.233		1.31	[0.76 ,	2.24]	0.331	

Results are from logistic regression models estimated with Generalised Estimating Equations to account for the dependency across repeated measurements (unstructured working correlation matrix). *Own-group density assessed as change per 10 percentage points. [1] Adjusted for time, gender, health conditions, family affluence, baseline FSM, household composition, and time lived in the neighbourhood. [2] Adjusted for time, gender, health conditions, family affluence, baseline FSM, household composition, time lived in the neighbourhood, and the other ethnic density variable. *ref. category

Table F.14 Ethnicity-stratified odds ratios (OR) of outdoor PA vs. not by school-level own-group ethnic density tertile (3 waves of the ORiEL Study, n= 1,160)

School-level ethnic density		Unadjusted OR	Partially Adjusted OR[1]	95%	CI	P-value param.	p-value	Fully Adjusted OR[2]	95%	CI	p-value param.	p-value
White: UK	Low*	1.00	1.00				0.025	1.00				0.156
	Medium	0.59	0.58	[0.38 ,	0.91]	0.016		0.65	[0.41 ,	1.01]	0.057	
	High	0.57	0.58	[0.37 ,	0.92]	0.020		0.73	[0.44 ,	1.20]	0.216	
White: Mixed	Low*	1.00	1.00				0.979	1.00				0.983
	Medium	0.93	0.95	[0.52 ,	1.74]	0.879		0.99	[0.53 ,	1.87]	0.981	
	High	0.92	0.93	[0.47 ,	1.88]	0.850		0.94	[0.43 ,	2.04]	0.873	
Asian: Bangladeshi	Low*	1.00	1.00				0.676	1.00				0.678
	Medium	0.92	0.98	[0.63 ,	1.51]	0.923		1.02	[0.62 ,	1.69]	0.937	
	High	1.86	1.24	[0.70 ,	2.18]	0.461		1.27	[0.68 ,	2.38]	0.448	
Black: African	Low*	1.00	1.00				0.023	1.00				0.019
	Medium	1.42	1.29	[0.71 ,	2.35]	0.394		1.33	[0.72 ,	2.43]	0.362	
	High	0.64	0.58	[0.34 ,	0.99]	0.045		0.57	[0.33 ,	0.98]	0.041	

Results are from logistic regression models estimated with Generalised Estimating Equations to account for the dependency across repeated measurements (unstructured working correlation matrix). *Own-group density assessed as change per 10 percentage points. [1] Adjusted for time, gender, health conditions, family affluence, baseline FSM, household composition, and time lived in the neighbourhood. [2] Adjusted for time, gender, health conditions, family affluence, baseline FSM, household composition, time lived in the neighbourhood, and the other ethnic density variable. *ref. category

Table F.15 Ethnicity-stratified odds ratios (OR) of outdoor PA vs. not by neighbourhood-level own-group ethnic density tertile (3 waves of the ORiEL Study, n= 1,160)

Neighbourhood-level ethnic density		Unadjusted OR	Partially Adjusted OR[1]	95%	CI	P-value param.	p-value	Fully Adjusted OR[2]	95%	CI	p-value param.	p-value
White: UK	Low*	1.00	1.00				0.018	1.00				0.097
	Medium	0.68	0.66	[0.43 ,	1.02]	0.061		0.72	[0.46 ,	1.12]	0.145	
	High	0.51	0.53	[0.34 ,	0.82]	0.004		0.59	[0.37 ,	0.95]	0.029	
White: Mixed	Low*	1.00	1.00				0.638	1.00				0.646
	Medium	0.71	0.76	[0.41 ,	1.40]	0.374		0.76	[0.41 ,	1.43]	0.401	
	High	1.00	0.94	[0.49 ,	1.78]	0.840		0.96	[0.47 ,	1.97]	0.910	
Asian: Bangladeshi	Low*	1.00	1.00				0.581	1.00				0.581
	Medium	0.96	0.84	[0.52 ,	1.33]	0.451		0.80	[0.49 ,	1.33]	0.399	
	High	1.24	1.05	[0.64 ,	1.74]	0.839		0.98	[0.55 ,	1.78]	0.959	
Black: African	Low*	1.00	1.00				0.889	1.00				0.756
	Medium	0.93	0.90	[0.50 ,	1.63]	0.727		0.81	[0.44 ,	1.47]	0.483	
	High	0.96	0.88	[0.51 ,	1.51]	0.637		0.97	[0.56 ,	1.70]	0.926	

Results are from logistic regression models estimated with Generalised Estimating Equations to account for the dependency across repeated measurements (unstructured working correlation matrix). *Own-group density assessed as change per 10 percentage points. [1] Adjusted for time, gender, health conditions, family affluence, baseline FSM, household composition, and time lived in the neighbourhood. [2] Adjusted for time, gender, health conditions, family affluence, baseline FSM, household composition, time lived in the neighbourhood, and the other ethnic density variable. *ref. category

F.6 Results from the complete case analysis of chapter 7

Table F.16 Ethnic group specific odds ratios (OR) of walking to school vs. not by own-group ethnic density* (3 waves of the ORiEL Study, n= 2,489 observations from 1,051 individuals)

Exposure	Unadjusted OR	Partially Adjusted OR[1]	95% CI	P-value	Fully Adjusted OR[2]	95% CI	p-value
School-level ethnic density				<0.001			<0.001
White: UK	1.12	1.12	[0.99 , 1.27]	0.065	1.13	[0.96 , 1.33]	0.147
White: Mixed	0.50	0.48	[0.31 , 0.76]	0.002	0.41	[0.24 , 0.69]	0.001
Asian: Bangladeshi	1.18	1.18	[1.07 , 1.31]	0.001	1.15	[0.97 , 1.37]	0.117
Black: African	0.46	0.46	[0.34 , 0.63]	<0.001	0.46	[0.33 , 0.65]	<0.001
Neighbourhood-level ethnic density				0.003			0.824
White: UK	1.01	1.06	[0.92 , 1.21]	0.434	0.99	[0.83 , 1.19]	0.933
White: Mixed	0.96	0.88	[0.54 , 1.45]	0.622	1.41	[0.77 , 2.58]	0.259
Asian: Bangladeshi	1.31	1.24	[1.07 , 1.43]	0.004	1.06	[0.83 , 1.37]	0.627
Black: African	0.81	0.80	[0.58 , 1.10]	0.172	1.01	[0.71 , 1.45]	0.951

Results are from logistic regression models estimated with Generalised Estimating Equations to account for the dependency across repeated measurements (unstructured working correlation matrix). Interaction terms between the own-group ethnic density variable and ethnicity were used and ethnic group specific ORs were obtained.
*Own-group density assessed as change per 10 percentage points. [1] Adjusted for time, gender, health conditions, family affluence, baseline FSM, household composition, time lived in the neighbourhood and distance to school. [2] Adjusted for time, gender, health conditions, family affluence, baseline FSM, household composition, time lived in the neighbourhood, distance to school, the other ethnic density variable and its interaction with ethnicity.

Table F.17 Ethnic group specific odds ratios (OR) of walking for leisure vs. not by own-group ethnic density (3 waves of the ORiEL Study, n= 2,397 observations from 1,032 individuals)*

Exposure	Unadjusted OR	Partially Adjusted OR[1]	95%	CI	P-value	Fully Adjusted OR[2]	95%	CI	p-value
School-level ethnic density					0.7616				0.990
White: UK	1.00	1.00	[0.90	, 1.12]	0.948	0.98	[0.86	, 1.12]	0.764
White: Mixed	0.90	0.83	[0.56	, 1.24]	0.365	0.92	[0.61	, 1.39]	0.704
Asian: Bangladeshi	0.95	0.97	[0.91	, 1.04]	0.354	0.99	[0.90	, 1.09]	0.805
Black: African	1.04	1.07	[0.77	, 1.49]	0.682	1.00	[0.70	, 1.44]	0.996
Neighbourhood-level ethnic density					0.411				0.616
White: UK	1.03	1.03	[0.93	, 1.13]	0.608	1.04	[0.93	, 1.16]	0.534
White: Mixed	0.77	0.76	[0.49	, 1.16]	0.201	0.79	[0.50	, 1.23]	0.297
Asian: Bangladeshi	0.93	0.95	[0.85	, 1.05]	0.305	0.96	[0.82	, 1.12]	0.587
Black: African	1.19	1.18	[0.86	, 1.60]	0.303	1.18	[0.84	, 1.64]	0.339

Results are from logistic regression models estimated with Generalised Estimating Equations to account for the dependency across repeated measurements (unstructured working correlation matrix). Interaction terms between the own-group ethnic density variable and ethnicity were used and ethnic group specific ORs were obtained. *Own-group density assessed as change per 10 percentage points. [1] Adjusted for time, gender, health conditions, family affluence, baseline FSM, household composition and time lived in the neighbourhood. [2] Adjusted for time, gender, health conditions, family affluence, baseline FSM, household composition, time lived in the neighbourhood, the other ethnic density variable and its interaction with ethnicity.

Table F.18 Ethnic group specific odds ratios (OR) of outdoor PA vs. not by own-group ethnic density (3 waves of the ORiEL Study, n= 2,300 observations from 1,021 individuals)*

Exposure	Unadjusted OR	Partially Adjusted OR[1]	95%	CI	P-value	Fully Adjusted OR[2]	95%	CI	p-value
School-level ethnic density					0.406				0.899
White: UK	0.91	0.92	[0.81 ,	1.04]	0.191	0.98	[0.84 ,	1.15]	0.831
White: Mixed	0.80	0.89	[0.57 ,	1.40]	0.623	0.95	[0.58 ,	1.55]	0.839
Asian: Bangladeshi	1.05	1.02	[0.94 ,	1.10]	0.627	1.01	[0.91 ,	1.12]	0.875
Black: African	0.80	0.79	[0.56 ,	1.12]	0.181	0.83	[0.57 ,	1.21]	0.328
Neighbourhood-level ethnic density					0.176				0.463
White: UK	0.87	0.89	[0.79 ,	1.00]	0.041	0.90	[0.79 ,	1.02]	0.103
White: Mixed	0.90	0.83	[0.54 ,	1.27]	0.387	0.85	[0.53 ,	1.36]	0.490
Asian: Bangladeshi	1.08	1.04	[0.92 ,	1.16]	0.562	1.03	[0.88 ,	1.20]	0.746
Black: African	0.82	0.84	[0.60 ,	1.16]	0.290	0.90	[0.62 ,	1.28]	0.548

Results are from logistic regression models estimated with Generalised Estimating Equations to account for the dependency across repeated measurements (unstructured working correlation matrix). Interaction terms between the own-group ethnic density variable and ethnicity were used and ethnic group specific ORs were obtained.
*Own-group density assessed as change per 10 percentage points. [1] Adjusted for time, gender, health conditions, family affluence, baseline FSM, household composition and time lived in the neighbourhood. [2] Adjusted for time, gender, health conditions, family affluence, baseline FSM, household composition, time lived in the neighbourhood, the other ethnic density variable and its interaction with ethnicity.

Appendix G Supplementary material for chapter 8

G.1 Analysis of missingness for chapter 8

This appendix presents results from a preliminary analysis of the missing data for analyses of social support and neighbourhood trust. The analyses were conducted in order to inform i) the validity of the complete case analysis, ii) the plausibility of the MAR assumption, and iii) the selection of the auxiliary variables of the imputation model. Analyses are restricted to waves 2 and 3 and do not repeat missing data analysis of variables already studied in preceding chapters. Note that these analyses are only informative and should be interpreted with caution as some assumptions might be violated in some of the models (e.g. clustering at individual level, normality in the error terms).

Validity of complete case analysis

Table G.1 indicates that walking to school has significant bivariate associations with missingness of neighbourhood trust, and some association with the friend domain of social support. The strength of evidence and of the associations weakens in the adjusted model. Walking for leisure is most likely not associated with missingness of the covariates of the models, as indicated in adjusted and unadjusted models. The odds of outdoor physical activity are associated with missingness on all social support variables, and remains strongly associated with the family component of social support in the unadjusted model. Similar pattern of association are observed for pay and play phyisical activity, which is strongly associated with missingness on all three indicators of social support in both adjusted and unadjusted model. There is also some indication of association with missingness on the neighbourhood trust variable in the unadjusted model.

These results indicate that a complete case analysis might lead to some bias. Due to widespread item missingness, this analysis cannot be fully conclusive however. It is unclear whether weaker associations in the fully adjusted models are themselves biased (because of the change in the analytical sample) or if they indicate that the complete case analysis is still valid once controlling for all relevant variables (i.e. once adjusted for covariates, missingness does not depend that much on the outcomes). Given that some significant associations remain in the adjusted models, the results overall indicate that a complete case analysis is very likely to be biased, which rules out the MCAR assumption.

Table G.1Assessment of complete case analysis validity: unadjusted and adjusted ORs of item response for each covariate with missing values by outcome variable (adjusted and unadjusted results; n = 2,260; 4,520 measurements)

Covariate	N missing	% missing	Outcome	N	OR	Pvalue	N*	OR*	Pvalue*
social support - family	887	19.6	Walk to school	4377	1.10	0.268	3590	1.05	0.648
			Walk for leisure	4250	1.06	0.466	3506	1.07	0.500
			Outdoor PA	4061	0.68	<0.001	3376	0.75	0.019
			Pay and Play PA	4103	0.78	0.004	3397	0.76	0.005
social support - sig. other	908	20.1	Walk to school	4377	1.18	0.062	3608	1.12	0.251
			Walk for leisure	4250	1.07	0.409	3521	1.09	0.373
			Outdoor PA	4061	0.75	0.003	3388	0.83	0.103
			Pay and Play PA	4103	0.80	0.008	3410	0.79	0.013
social support - friend	898	19.9	Walk to school	4377	1.16	0.102	3590	1.13	0.232
			Walk for leisure	4250	1.05	0.598	3506	1.04	0.726
			Outdoor PA	4061	0.74	0.002	3376	0.82	0.089
			Pay and Play PA	4103	0.73	<0.001	3397	0.74	0.002
Neighbourhood Trust	598	13.2	Walk to school	4377	1.27	0.019	3590	1.18	0.175
			Walk for leisure	4250	1.04	0.672	3506	0.95	0.687
			Outdoor PA	4061	0.85	0.145	3376	0.95	0.708
			Pay and Play PA	4103	0.86	0.119	3397	0.87	0.221

*Results from logistic regressions, adjusted for gender, ethnicity, health, family affluence, FSM, and household composition. Response is coded 1 and missingness 0. PA – physical activity.

Plausibility of the MAR mechanism

I investigated whether missingness on “new” variables with high missingness – social support, neighbourhood trust and pay and play physical activity - could be predicted using almost fully observed variables (Table G.2). Predictors used were (almost) fully observed variables from the model of interest (gender, ethnicity, family affluence, free school meals, household composition) and auxiliary variables *a priori* hypothesised to be associated with the probability of missingness: school, country of birth, language spoken at home, self-rated health, mental health.

Amongst the (almost) fully observed variables of the model of interest, gender and mental health good predictors of missingness for the two variables examined (Table G.2).

Given that at least some of the variables are predictive of missingness, the plausibility of the MAR assumption is supported. Variables with more missing values are also likely to predict missingness on the variables of the models of interest. An imputation model with the wide range of variables considered will further strengthen the plausibility of the assumption. However, it is never possible to rule out MNAR, and it might be that even accounting for all these variables, the missingness mechanism depends on unmeasured variables.

Table G.2 Assessment of the MAR assumption: (almost) fully observed predictors of item missingness for the additional variables with high levels of missing values.

Missingness variable	Predictor	p-value
social support - family	Gender	<0.001
	Ethnicity	0.002
	school	<0.001
	FAS Categories	0.174
	FSM	0.002
	Country of Birth	0.077
	language at home	0.742
	self-rated health	0.960
	household composition	0.871
	Log of total PA	0.064
	Mental Health (WEMWBS)	0.008
social support – sig. other	Gender	<0.001
	Ethnicity	0.004
	school	<0.001
	FAS Categories	0.058
	FSM	<0.001
	Country of Birth	0.156
	language at home	0.836
	self-rated health	0.874
	household composition	0.442
	Log of total PA	0.100
	Mental Health (WEMWBS)	0.004
social support - friend	Gender	<0.001
	Ethnicity	0.007
	school	<0.001
	FAS Categories	0.179
	FSM	<0.001
	Country of Birth	0.176
	language at home	0.892
	self-rated health	0.976
	household composition	0.819
	Log of total PA	0.068
	Mental Health (WEMWBS)	0.026

Results from logistic regressions.

Table G.3 Assessment of the MAR assumption: (almost) fully observed predictors of item missingness for the additional variables with high levels of missing values (continued)

Missingness variable	Predictor	p-value
Neighbourhood trust	Gender	<0.001
	Ethnicity	0.048
	school	<0.001
	FAS Categories	0.363
	FSM	0.018
	Country of Birth	0.907
	language at home	0.217
	self-rated health	0.629
	household composition	0.530
	Log of total PA	0.409
	Mental Health (WEMWBS)	0.001
Pay and play physical activity	Gender	<0.001
	Ethnicity	0.022
	school	<0.001
	FAS Categories	0.201
	FSM	0.574
	Country of Birth	0.872
	language at home	0.236
	self-rated health	0.392
	household composition	0.069
	Log of total PA	0.026
	Mental Health (WEMWBS)	0.691

Results from logistic regressions.

Selecting variables for the imputation model

The imputation model should include variables of the models of interest and relevant auxiliary variables. The later should be included only if they are likely to reduce bias and/or to increase efficiency (Carpenter & Kenward 2012). Variables predictive of the chance of missing values identified above should be included in the imputation model only if they also predict the underlying missing values, in which case, they are likely to reduce bias and improve efficiency. Auxiliary variables should however be excluded if they do not predict the underlying values themselves. Variables associated with the underlying values - but not the chance of missing values - should be included because they will improve efficiency, although they are not going to reduce bias.

Table G.3 reports linear and multinomial logistic regression results of associations between the "new" variables with missing values (social support scales, neighbourhood trust and pay and play physical activity) and almost fully observed variables of the model of interest, as well as auxiliary variables. Social support scales are well predicted by gender, ethnicity, school, and mental health. FSM and family affluence also seem to predict family and significant other scales of social support. Neighbourhood trust is predicted by gender, ethnicity, school self-rated health, total physical activity as well as mental health. There is some indication that country of birth predicts neighbourhood trust as well. Finally, pay and play physical activity is predicted by gender, school, family affluence, household composition and total physical activity.

Additional analyses (not presented here) of two potential auxiliary variables with more missing values – parental support and neighbourhood satisfaction – further indicate that these variables should be included in the imputation model. Parental support is shown to be a strong predictor of family social support in adjusted and unadjusted models (R-squared = 0.17). There is also indication that it predicts its missingness (p=0.021), but that level of evidence decrease in the fully adjusted model (p=0.152). Neighbourhood satisfaction (used as a summary score with three response categories) is a strong predictor of neighbourhood trust (R-squared in unadjusted model = 0.1053) and its missingness in both adjusted and unadjusted models (p<0.001).

School-level ethnic density was finally additionally tested as a predictor of missingness and values of neighbourhood trust and social support but there was no indication that it would improve the imputation model, based on the fully adjusted models used.

Summary

Overall, these analyses combined with those of the previous chapters show that an imputation model with the auxiliary variables considered – country of birth, language at home, self-rated health, total physical activity, mental health, parental support, neighbourhood satisfaction and BMI – are very likely to reduce bias and improve efficiency compared to a complete case analysis. Covariates of the model of interest with more missing values are also expected to reduce bias and improve efficiency.

Table G.4 Associations between variables with missing values and auxiliary variables, adjusted for all variables in the table

Missingness variable	Predictor	p-value
social support - family	Gender	<0.001
	Ethnicity	0.001
	school	0.002
	FAS Categories	0.076
	FSM	0.078
	Country of Birth	0.104
	language at home	0.472
	self-rated health	0.219
	household composition	0.984
	Log of total PA	0.641
	Mental Health (WEMWBS)	<0.001
social support – sig. other	Gender	<0.001
	Ethnicity	0.009
	school	<0.001
	FAS Categories	0.107
	FSM	0.049
	Country of Birth	0.999
	language at home	0.066
	self-rated health	0.941
	household composition	0.570
	Log of total PA	0.752
	Mental Health (WEMWBS)	<0.001
social support - friend	Gender	<0.001
	Ethnicity	<0.001
	school	<0.001
	FAS Categories	0.738
	FSM	0.583
	Country of Birth	0.580
	language at home	0.520
	self-rated health	0.936
	household composition	0.629
	Log of total PA	0.375
	Mental Health (WEMWBS)	<0.001

Results from linear models.

Table G.5 Associations between variables with missing values and auxiliary variables, adjusted for all variables in table (continued)

Missingness variable	Predictor	p-value
Neighbourhood trust	Gender	<0.001
	Ethnicity	0.001
	school	0.004
	FAS Categories	0.530
	FSM	0.321
	Country of Birth	0.082
	language at home	0.575
	self-rated health	<0.001
	household composition	0.478
	Log of total PA	<0.001
	Mental Health (WEMWBS)	<0.001
Pay and play physical activity	Gender	<0.001
	Ethnicity	0.389
	school	0.002
	FAS Categories	<0.001
	FSM	0.114
	Country of Birth	0.133
	language at home	0.939
	self-rated health	0.859
	household composition	0.022
	Log of total PA	<0.001
	Mental Health (WEMWBS)	0.296

Results from multinomial logistic regressions.

G.2 Model equations of chapter 8

Pooled longitudinal models

Separate models are fitted for each of the four binary physical activity outcomes. The models each include one of the exposure variables (neighbourhood trust, social support from family, friends or significant others) and account for time-invariant (gender, ethnicity) and time-varying confounders (health condition, family affluence, FSM, household composition, and time lived in the neighbourhood). A time trend is included to reflect the general decrease in physical activity during adolescence. Logistic regression models are fitted with GEE using unstructured working correlation to account for clustering across repeated measurements. The adjusted logistic model is expressed as follows:

$$logit\{\Pr(Y_{ij} = 1|\boldsymbol{x_{ij}})\} = \boldsymbol{x'_{ij}\beta}$$

Where:

i= individual

j= repeated measurements

Y_{ij} = physical activity outcome (walking to school, walking for leisure, outdoor physical activity or pay and play physical activity) for individual *i* at occasion *j*

$\boldsymbol{x_{ij}}$ = a matrix representing the variables included in the model for all individuals at each occasion

$\boldsymbol{\beta}$ = a vector representing the coefficients of the model, including a constant

In the adjusted model, $\boldsymbol{x'_{ij}\beta}$ takes the following form:

$\boldsymbol{x'_{ij}\beta} = \beta_0 + \beta_1 Exposure\_cat2_{ij} + \cdots + \beta_3 Exposure\_catm_{ij} + \beta_4 Girl_i + \beta_5 EtH2_i + \beta_6 EtH3_i + \beta_7 EtH4_i + \beta_8 EtH5_i + \beta_9 EtH6_i + \beta_{10} EtH7_i + \beta_{11} EtH8_i + \beta_{12} FSM_{ij} + \beta_{13} HealtH_{ij} + \beta_{14} FAS2_{ij} + \beta_{15} FAS3_{ij} + \beta_{16} HHcomp_{ij} + \beta_{17} Nb\_time_{ij} + \beta_{18} time_j$

Where:

$Exposure\_cat2_{ij}$,..., $Exposure\_catm_{ij}$ = dummy variables representing m-1 categories of the exposure variable of interest (3 dummy variables for neighbourhood trust and 2 dummy variables for the social support variables)

$Girl_i$= dummy variable for girls (time invariant)

$EtH2_i$,..., $EtH8_i$= Ethnicity dummy variables (reference category: White UK; time invariant)

FSM_{ij}= Free school meal status (reference category: no free school meal)

$HealtH_{ij}$ = Health conditions dummy variable (reference category: no condition)

$FAS2_{ij}$, $FAS3_{ij}$= Family affluence dummy variables (reference category: low)

HH_comp_{ij}= Household composition dummy variable (reference category: live with both parents)

Nb_time_{ij}= Time lived in the neighbourhood (reference category: more than 5 years)

$Time_{ij}$= dummy variable for wave 3.

In the models where the exposure variable is treated as a dose-response, the equation is:

$\boldsymbol{x}'_{ij}\boldsymbol{\beta} = \beta_0 + \beta_1 Exposure_{ij} + \beta_2 Girl_i + \beta_3 EtH2_i + \beta_4 EtH3_i + \beta_5 EtH4_i + \beta_6 EtH5_i + \beta_7 EtH6_i + \beta_8 EtH7_i + \beta_9 EtH8_i + \beta_{10} FSM_{ij} + \beta_{11} HealtH_{ij} + \beta_{12} FAS2_{ij} + \beta_{13} FAS3_{ij} + \beta_{14} HHcomp_{ij} + \beta_{15} Nb\_time_{ij} + \beta_{16} time_j$

Where $Exposure_{ij}$ is one of the exposure variables treated as continuous.

In the models testing whether gender is a moderator, interactions terms between gender and each exposure were included. The two types of models fitted are:

$\boldsymbol{x}'_{ij}\boldsymbol{\beta} = \beta_0 + \beta_1 Exposure\_cat2_{ij} + \cdots + \beta_3 Exposure\_catm_{ij} + \beta_4 Girl_i + \beta_5 EtH2_i + \beta_6 EtH3_i + \beta_7 EtH4_i + \beta_8 EtH5_i + \beta_9 EtH6_i + \beta_{10} EtH7_i + \beta_{11} EtH8_i + \beta_{12} FSM_{ij} + \beta_{13} HealtH_{ij} + \beta_{14} FAS2_{ij} + \beta_{15} FAS3_{ij} + \beta_{16} HHcomp_{ij} + \beta_{17} Nb\_time_{ij} + \beta_{18} time_j + \beta_{19} Exposure\_cat2_{ij} * Girl_i + \cdots + \beta_{21} Exposure\_catm_{ij} * Girl_i$

And

$\boldsymbol{x}'_{ij}\boldsymbol{\beta} = \beta_0 + \beta_1 Exposure_{ij} + \beta_2 Girl_i + \beta_3 Eth2_i + \beta_4 EtH3_i + \beta_5 EtH4_i + \beta_6 EtH5_i + \beta_7 EtH6_i + \beta_8 EtH7_i + \beta_9 EtH8_i + \beta_{10} FSM_{ij} + \beta_{11} HealtH_{ij} + \beta_{12} FAS2_{ij} + \beta_{13} FAS3_{ij} + \beta_{14} HHcomp_{ij} + \beta_{15} Nb\_time_{ij} + \beta_{16} time_{j+} \beta_{17} Exposure_{ij} * Girl_i$

Models for changes in exposures and outcomes using proportional odds models

Models are fitted to explore the association between changes in the outcomes and changes in the exposure variables. For each measure of change in the outcome (ordinal variable), separate models each include one of the measures of change in the exposure variables (change in neighbourhood trust, social support from family, friends and significant other) and account for confounders at wave 2 (gender, ethnicity, health condition, family affluence, FSM, household composition, and time lived in the neighbourhood). Proportional odds models are fitted with GEE using independence working correlation to account for clustering at school level. The adjusted proportional odds model is expressed as follows:

$$logit\{\Pr(Y^*_{ij} \le k|\boldsymbol{x_{ij}})\} = \alpha_k + \boldsymbol{x}'_{ij}\boldsymbol{\beta}$$

Where:

i= individual

j=school

Y^*_{ij} = ordinal variable indicating whether the physical activity outcome (walking to school, walking for leisure, outdoor physical activity or pay and play physical activity) decreased, remained constant or decreased for individual i and school *j*

k = values taken by the ordinal outcome variables. In this analysis, the model is fully described using *k* = 1 and 2 because the ordinal variables take 3 possible values.

$\boldsymbol{x_{ij}}$ = a matrix representing the variables included in the model for all individuals *i* in each school *j*

α_k= a separate constant defined for each cumulative logit

$\boldsymbol{\beta}$ = a vector representing the coefficients of the model

In the adjusted model, $\boldsymbol{x'_{ij}\beta}$ takes the following form:

$\boldsymbol{x'_{ij}\beta} = \beta_1 Exposure\_cHange_{ij} + \beta_2 Girl_{ij} + \beta_3 EtH2_{ij} + \beta_4 EtH3_{ij} + \beta_5 EtH4_{ij} + \beta_6 EtH5_{ij} + \beta_7 EtH6_{ij} + \beta_8 EtH7_{ij} + \beta_9 EtH8_{ij} + \beta_{10} FSM_{ij} + \beta_{11} HealtH_{ij} + \beta_{12} FAS2_{ij} + \beta_{13} FAS3_{ij} + \beta_{14} HHcomp_{ij} + \beta_{15} Nb\_time_{ij}$

Where:

$Exposure\_cHange_{ij}$ = continuous variable indicating change in one of the exposure variables over time (neighbourhood trust, or any of the three social support measures)

FSM_{ij}= Free school meal status at wave 2(reference category: no free school meal)

$HealtH_{ij}$ = Health conditions dummy variable at wave 2(reference category: no condition)

$FAS2_{ij}, FAS3_{ij}$= Family affluence dummy variables at wave 2 (reference category: low)

HH_comp_{ij}= Household composition dummy variable at wave 2 (reference category: live with both parents)

Nb_time_{ij}= Time lived in the neighbourhood at wave 2(reference category: more than 5 years)

Additional models are fitted to test whether gender is a moderator. These models simply add an interaction term between the exposure change variable and gender.

G.3 Results from the models of chapter 8 using the 3-wave balanced panel and the imputed datasets

This appendix presents some results from sensitivity analyses. The main results were restricted to adolescents that were interviewed at the three ORiEL waves. Analysis could be conducted on 2,257 out of the 2,260 individuals of the 3-wave balanced panel (due to the absence of wave identified in the imputed datasets). Overall, results are similar to the main analyses. Differences in the effect sizes are observed for walking for leisure and outdoor physical activity.

Table G.6 Odds ratios (OR) of walking to school vs. not by neighbourhood trust and social support, adjusting for potential confounders (waves 2 and 3* of the ORiEL Study, n=2,257*)

Exposure		Unadjusted OR	Adjusted OR[1]	95%CI	P-value parameter	P-value unadjusted	P-value adjusted[1]	Gender interaction (p-value) [2]
Neighbourhood Trust	Not at all	1.00	1.00			0.324	0.410	0.305
	A little	1.02	0.99	[0.76,1.29]	0.954			
	Some	1.15	1.09	[0.85,1.40]	0.508			
	A lot	0.99	0.92	[0.70,1.22]	0.581			
Social support - friend	low	1.00	1.00			0.196	0.144	0.389
	medium	1.12	1.10	[0.92,1.31]	0.301			
	high	0.96	0.91	[0.77,1.09]	0.307			
Social support – family	low	1.00	1.00			0.770	0.663	0.147
	medium	0.96	0.95	[0.78,1.17]	0.652			
	high	0.93	0.92	[0.76,1.11]	0.364			
Social support - sig. other	low	1.00	1.00			0.943	0.961	0.263
	medium	0.97	0.97	[0.80,1.19]	0.793			
	high	1.00	0.99	[0.83,1.17]	0.872			

Results are from Generalised Estimating Equations to account for the dependency across repeated measurements (unstructured working correlation matrix). [1] Adjusted for gender, ethnicity, health condition, FSM, family affluence, time lived in the neighbourhood, household composition and time. [2] The adjusted model was replicated for each outcome with an additional interaction term between gender and the exposure.

Table G.7 Odds ratios (OR) of change in walking to school predicted by change in neighbourhood trust and social support, adjusting for potential confounders at baseline (n=2,257)

Exposure	Unadjusted OR	Adjusted OR[1]	95% CI	P-value adjusted[1]	Gender interaction (p-value) [2]
Neighbourhood Trust	0.99	1.00	[0.89, 1.11]	0.943	0.169
Social support - friend	0.98	0.98	[0.87, 1.11]	0.772	0.398
Social support – family	1.00	0.99	[0.88, 1.13]	0.906	0.642
Social support - sig. other	1.03	1.02	[0.91, 1.14]	0.716	0.088

Results are from proportional odds model estimated with Generalised Estimating Equations to account for the clustering of individuals within schools (independent working correlation matrix). The proportional odds assumptions were not violated for the parameters of interest. Results are displayed as ORs of improvement in walking to school status (being either constant vs. decrease or increase vs. constant) per unit increase in the original scale of neighbourhood trust and tertile change in social support. OR > 1 indicate an improvement in the outcome as a response to an improvement in the exposure. [1] Adjusted for gender, ethnicity, health condition, FSM, family affluence, time lived in the neighbourhood and household composition at wave 2. [2] The adjusted model was replicated for each outcome with an additional interaction term between gender and the exposure.

Table G.8 Odds ratios (OR) of walking for leisure vs. not by neighbourhood trust and social support, adjusting for potential confounders (waves 2 and 3* of the ORiEL Study, n=2,257*)

Exposure		Unadjusted OR	Adjusted OR[1]	95%CI	P-value parameter	P-value unadjusted	P-value adjusted[1]	Gender interaction (p-value) [2]
Neighbourhood Trust	Not at all	1.00	1.00			0.079	0.175	0.944
	A little	1.38	1.33	[1.03,1.71]	0.029			
	Some	1.30	1.29	[1.01,1.65]	0.044			

Exposure		Unadjusted OR	Adjusted OR¹	95%CI	P-value parameter	P-value unadjusted	P-value adjusted¹	Gender interaction (p-value) ²
	A lot	1.21	1.24	[0.95,1.63]	0.120			
Social support - friend	low	1.00	1.00			0.001	0.034	0.366
	medium	1.29	1.23	[1.03,1.46]	0.020			
	high	1.34	1.20	[1.01,1.43]	0.034			
Social support – family	low	1.00	1.00			<0.001	0.001	0.614
	medium	1.23	1.22	[1.01,1.47]	0.041			
	high	1.44	1.38	[1.16,1.64]	0.001			
Social support - sig. other	low	1.00	1.00			0.001	0.021	0.524
	medium	1.22	1.14	[0.96,1.35]	0.124			
	high	1.40	1.27	[1.07,1.50]	0.006			

Results are from Generalised Estimating Equations to account for the dependency across repeated measurements (unstructured working correlation matrix). ¹ Adjusted for gender, ethnicity, health condition, FSM, family affluence, time lived in the neighbourhood, household composition and time. ² The adjusted model was replicated for each outcome with an additional interaction term between gender and the exposure.

Table G.9 Odds ratios (OR) of change in walking for leisure predicted by change in neighbourhood trust and social support, adjusting for potential confounders at baseline (n=2,257)

Exposure	Unadjusted OR	Adjusted OR¹	95% CI	P-value adjusted¹	Gender interaction (p-value) ²
Neighbourhood Trust	1.06	1.06	[0.97 , 1.15]	0.184	0.554
Social support - friend	1.12	1.12	[1.02 , 1.22]	0.016	0.421
Social support – family	1.10	1.10	[0.99 , 1.21]	0.065	0.416
Social support - sig. other	1.07	1.06	[0.97 , 1.17]	0.209	0.267

Results are from proportional odds model estimated with Generalised Estimating Equations to account for the clustering of individuals within schools (independent working correlation matrix). The proportional odds assumptions were not violated for the parameters of interest. Results are displayed as ORs of improvement in walking for leisure status (being either constant vs. decrease or increase vs. constant) per unit increase in the original scale of neighbourhood trust and tertile change in social support. OR > 1 indicate an improvement in the outcome as a response to an improvement in the exposure. [1] Adjusted for gender, ethnicity, health condition, FSM, family affluence, time lived in the neighbourhood and household composition at wave 2. [2] The adjusted model was replicated for each outcome with an additional interaction term between gender and the exposure.

Table G.10 Odds ratios (OR) of outdoor PA vs. not by neighbourhood trust and social support, adjusting for potential confounders (waves 2 and 3* of the ORiEL Study, n=2,257*)

Exposure		Unadjusted OR	Adjusted OR[1]	95%CI	P-value parameter	P-value unadjusted	P-value adjusted[1]	Gender interaction (p-value) [2]
Neighbourhood Trust	Not at all	1.00	1.00			<0.001	0.115	0.333
	A little	1.02	0.96	[0.73,1.24]	0.734			
	Some	1.15	1.04	[0.81,1.34]	0.762			
	A lot	1.64	1.28	[0.94,1.75]	0.116			
Social support - friend	low	1.00	1.00			0.375	0.473	0.025
	medium	0.96	1.12	[0.92,1.37]	0.259			
	high	0.88	1.10	[0.90,1.33]	0.347			
Social support – family	low	1.00	1.00			0.619	0.540	0.081
	medium	1.05	1.10	[0.90,1.35]	0.339			
	high	1.09	1.10	[0.91,1.33]	0.334			
Social support - sig. other	low	1.00	1.00			0.700	0.460	0.245
	medium	0.96	1.11	[0.91,1.36]	0.285			
	high	0.93	1.11	[0.93,1.33]	0.256			

Results are from Generalised Estimating Equations to account for the dependency across repeated measurements (unstructured working correlation matrix). [1] Adjusted for gender, ethnicity, health condition, FSM, family affluence, time lived in the neighbourhood, household composition and time. [2] The adjusted model was replicated for each outcome with an additional interaction term between gender and the exposure.

Table G.11 Odds ratios (OR) of change in outdoor PA predicted by change in neighbourhood trust and social support, adjusting for potential confounders at baseline (**n=2,257*****)***

Exposure	Unadjusted OR	Adjusted OR¹	95%		CI		P-value adjusted¹	Gender interaction (p-value) ²
Neighbourhood Trust	0.99	0.99	[0.91	,	1.07	]	0.767	0.574
Social support - friend	1.00	1.00	[0.90	,	1.12	]	0.935	0.411
Social support – family	0.95	0.94	[0.85	,	1.05	]	0.254	0.275
Social support - sig. other	1.01	1.00	[0.89	,	1.12	]	0.990	0.723

Results are from proportional odds model estimated with Generalised Estimating Equations to account for the clustering of individuals within schools (independent working correlation matrix). The proportional odds assumptions were not violated for the parameters of interest. Results are displayed as ORs of improvement in outdoor PA status (being either constant vs. decrease or increase vs. constant) per unit increase in the original scale of neighbourhood trust and tertile change in social support. OR > 1 indicate an improvement in the outcome as a response to an improvement in the exposure. ¹ Adjusted for gender, ethnicity, health condition, FSM, family affluence, time lived in the neighbourhood and household composition at wave 2. ² The adjusted model was replicated for each outcome with an additional interaction term between gender and the exposure.

Table G.12 Odds ratios (OR) of Pay and Play PA vs. not by neighbourhood trust and social support, adjusting for potential confounders (waves 2 and 3 *****of the ORiEL Study, n=2,257**)***

Exposure		Unadjusted OR	Adjusted OR¹	95%CI	P-value parameter	P-value unadjusted	P-value adjusted¹	Gender interaction (p-value) ²
Neighbourhood Trust	Not at all	1.00	1.00			0.004	0.012	0.185
	A little	0.98	0.89	[0.70,1.13]	0.327			
	Some	1.07	0.99	[0.78,1.25]	0.926			
	A lot	1.39	1.24	[0.96,1.62]	0.102			
Social support - friend	low	1.00	1.00			0.979	0.789	0.490
	medium	1.02	1.01	[0.86,1.19]	0.887			
	high	1.01	0.96	[0.81,1.13]	0.597			

Exposure		Unadjusted OR	Adjusted OR[1]	95%CI	P-value parameter	P-value unadjusted	P-value adjusted[1]	Gender interaction (p-value) [2]
Social support – family	low	1.00	1.00			0.715	0.913	0.777
	medium	1.01	0.99	[0.84,1.17]	0.911			
	high	1.06	0.97	[0.82,1.15]	0.698			
Social support - sig. other	low	1.00	1.00			0.760	0.950	0.797
	medium	1.01	0.97	[0.82,1.15]	0.757			
	high	1.06	1.00	[0.84,1.18]	0.956			

Results are from Generalised Estimating Equations to account for the dependency across repeated measurements (unstructured working correlation matrix).[1] Adjusted for gender, ethnicity, health condition, FSM, family affluence, time lived in the neighbourhood, household composition and time. [2] The adjusted model was replicated for each outcome with an additional interaction term between gender and the exposure.

***Table G.13 Odds ratios (OR) of change in Pay and Play PA predicted by change in neighbourhood trust and social support, adjusting for potential confounders at baseline* (n=2,257)**

Exposure	Unadjusted OR	Adjusted OR[1]	95% CI	P-value adjusted[1]	Gender interaction (p-value) [2]
Neighbourhood Trust	1.06	1.05	[0.95 , 1.16]	0.316	0.186
Social support - friend	0.97	0.97	[0.89 , 1.05]	0.440	0.689
Social support – family	0.97	0.96	[0.87 , 1.06]	0.462	0.493
Social support - sig. other	0.97	0.97	[0.88 , 1.07]	0.502	0.423

Results are from proportional odds model estimated with Generalised Estimating Equations to account for the clustering of individuals within schools (independent working correlation matrix). The proportional odds assumptions were not violated for the parameters of interest. Results are displayed as ORs of improvement in Pay and Play PA status (being either constant vs. decrease or increase vs. constant) per unit increase in the original scale of neighbourhood trust and tertile change in social support. OR > 1 indicate an improvement in the outcome as a response to an improvement in the exposure. [1] Adjusted for gender, ethnicity, health condition, FSM, family affluence, time lived in the neighbourhood and household composition at wave 2. [2] The adjusted model was replicated for each outcome with an additional interaction term between gender and the exposure.

G.4 Results from the estimation of the pooled longitudinal models of chapter 8 with GEE with alternative the working correlation using the imputed datasets

Table G.14 Odds ratios (OR) of walking to school vs. not by neighbourhood trust and social support, adjusting for potential confounders (waves 2 and 3 **of the ORiEL Study, n=2,644*)***

Exposure		Unadjusted OR	Adjusted OR[1]	95%CI	P-value parameter	P-value unadjusted	P-value adjusted[1]	Gender interaction (p-value) [2]
Neighbourhood Trust	Not at all	1.00	1.00			0.296	0.507	0.521
	A little	1.02	0.98	[0.77,1.25]	0.888			
	Some	1.17	1.10	[0.87,1.38]	0.424			
	A lot	1.06	0.98	[0.75,1.28]	0.888			
Social support - friend	low	1.00	1.00			0.253	0.175	0.267
	medium	1.10	1.07	[0.91,1.27]	0.415			
	high	0.95	0.91	[0.77,1.08]	0.260			
Social support – family	low	1.00	1.00			0.753	0.684	0.067
	medium	0.95	0.95	[0.79,1.14]	0.588			
	high	0.94	0.93	[0.78,1.10]	0.391			
Social support - sig. other	low	1.00	1.00			0.916	0.932	0.278
	medium	0.97	0.97	[0.81,1.16]	0.722			
	high	1.00	0.98	[0.83,1.16]	0.839			

Results are from Generalised Estimating Equations to account for the dependency across repeated measurements (exchangeable working correlation matrix).[1] Adjusted for gender, ethnicity, health condition, FSM, family affluence, time lived in the neighbourhood, household composition and time. [2] The adjusted model was replicated for each outcome with an additional interaction term between gender and the exposure.

Table G.15 Odds ratios (OR) of walking for leisure vs. not by neighbourhood trust and social support, adjusting for potential confounders (waves 2 and 3 **of the ORiEL Study, n=2,644*****)***

Exposure		Unadjusted OR	Adjusted OR[1]	95%CI	P-value parameter	P-value unadjusted	P-value adjusted[1]	Gender interaction (p-value) [2]
Neighbourhood Trust	Not at all	1.00	1.00			0.193	0.265	0.909
	A little	1.28	1.25	[0.99,1.58]	0.065			
	Some	1.25	1.26	[1.00,1.57]	0.048			
	A lot	1.20	1.23	[0.96,1.58]	0.102			
Social support - friend	low	1.00	1.00			0.001	0.091	0.503
	medium	1.24	1.17	[1.00,1.37]	0.055			
	high	1.31	1.16	[0.99,1.37]	0.069			
Social support – family	low	1.00	1.00			<0.001	0.004	0.577
	medium	1.20	1.20	[1.00,1.43]	0.047			
	high	1.38	1.32	[1.12,1.56]	0.001			
Social support - sig. other	low	1.00	1.00			0.001	0.055	0.425
	medium	1.18	1.11	[0.95,1.30]	0.191			
	high	1.34	1.21	[1.03,1.43]	0.020			

Results are from Generalised Estimating Equations to account for the dependency across repeated measurements (exchangeable working correlation matrix). [1] Adjusted for gender, ethnicity, health condition, FSM, family affluence, time lived in the neighbourhood, household composition and time. [2] The adjusted model was replicated for each outcome with an additional interaction term between gender and the exposure.

Table G.16 Odds ratios (OR) of outdoor PA vs. not by neighbourhood trust and social support, adjusting for potential confounders (waves 2 and 3* of the ORiEL Study, n=2,644*)

Exposure		Unadjusted OR	Adjusted OR[1]	95%CI	P-value parameter	P-value unadjusted	P-value adjusted[1]	Gender interaction (p-value) [2]
Neighbourhood Trust	Not at all	1.00	1.00			<0.001	0.099	0.679
	A little	1.03	0.98	[0.77,1.24]	0.839			
	Some	1.16	1.08	[0.86,1.37]	0.502			
	A lot	1.60	1.29	[0.97,1.70]	0.077			
Social support - friend	low	1.00	1.00			0.164	0.751	0.027
	medium	0.91	1.06	[0.89,1.27]	0.515			
	high	0.86	1.06	[0.89,1.26]	0.522			
Social support – family	low	1.00	1.00			0.844	0.813	0.183
	medium	1.01	1.05	[0.88,1.26]	0.571			
	high	1.04	1.05	[0.88,1.25]	0.575			
Social support - sig. other	low	1.00	1.00			0.273	0.880	0.358
	medium	0.90	1.03	[0.86,1.24]	0.763			
	high	0.89	1.04	[0.89,1.23]	0.603			

Results are from Generalised Estimating Equations to account for the dependency across repeated measurements (exchangeable working correlation matrix). [1] Adjusted for gender, ethnicity, health condition, FSM, family affluence, time lived in the neighbourhood, household composition and time. [2] The adjusted model was replicated for each outcome with an additional interaction term between gender and the exposure.

Table G.17 Odds ratios (OR) of pay and play physical activity vs. not by neighbourhood trust and social support, adjusting for potential confounders (waves 2 and 3 **of the ORiEL Study, n=2,644*****)***

Exposure		Unadjusted OR	Adjusted OR¹	95%CI	P-value parameter	P-value unadjusted	P-value adjusted¹	Gender interaction (p-value) ²
Neighbourhood Trust	Not at all	1.00	1.00			0.005	0.026	0.700
	A little	1.03	0.95	[0.76,1.20]	0.690			
	Some	1.10	1.03	[0.83,1.28]	0.767			
	A lot	1.40	1.27	[0.99,1.63]	0.055			
Social support - friend	low	1.00	1.00			0.975	0.873	0.537
	medium	1.00	1.00	[0.86,1.17]	0.995			
	high	1.01	0.96	[0.83,1.13]	0.646			
Social support – family	low	1.00	1.00			0.624	0.966	0.467
	medium	1.00	0.99	[0.84,1.16]	0.880			
	high	1.07	0.98	[0.83,1.16]	0.806			
Social support - sig. other	low	1.00	1.00			0.761	0.874	0.871
	medium	0.99	0.96	[0.82,1.13]	0.626			
	high	1.05	1.00	[0.85,1.17]	0.951			

Results are from Generalised Estimating Equations to account for the dependency across repeated measurements (exchangeable working correlation matrix). ¹ Adjusted for gender, ethnicity, health condition, FSM, family affluence, time lived in the neighbourhood, household composition and time. ² The adjusted model was replicated for each outcome with an additional interaction term between gender and the exposure.

G.5 Results from proportional odds models and partial proportional odds models of chapter 8 fitted with MLE, using the imputed datasets

Results of the within individual change models of chapter 8 were reproduced using (partial) proportional odds models without accounting for clustering at school-level. Given that the proportional odds assumption was not met for some of the confounders, results were also reproduced using partial proportional odds models. Separate models were used for walking to school (allowing the parameters to vary across the outcome values for ethnicity and time lived in the neighbourhood) and the other outcomes (allowing the parameters to vary across the outcome values for gender, household composition, FSM and FAS score). For the coefficients of interests, results were similar across the two types of models fitted and very similar to the original GEE results.

Table G.18 Odds ratios (OR) of change in walking to school predicted by change in neighbourhood trust and social support, adjusting for potential confounders at baseline (*n=2,644*)

Exposure	Unadjusted OR	Adjusted OR	95% CI	P-value adjusted[1]	Gender interaction (p-value) [2]
Neighbourhood Trust	1.02	1.03	[0.92 , 1.15]	0.605	0.145
Social support - friend	0.97	0.97	[0.87 , 1.08]	0.575	0.157
Social support – family	1.01	1.00	[0.89 , 1.13]	0.956	0.529
Social support - sig. other	1.03	1.02	[0.92 , 1.14]	0.694	0.071

Results are from proportional odds. The proportional odds assumptions were not violated for the parameters of interest. Results are displayed as ORs of improvement in walking to school status (being either constant vs. decrease or increase vs. constant) per unit increase in the original scale of neighbourhood trust and tertile change in social support. OR > 1 indicate an improvement in the outcome as a response to an improvement in the exposure. [1] Adjusted for gender, ethnicity, health condition, FSM, family affluence, time lived in the neighbourhood, and household composition at wave 2. [2] The adjusted model was replicated for each outcome with an additional interaction term between gender and the exposure.

Table G.19 Odds ratios (OR) of change in walking to school predicted by change in neighbourhood trust and social support, adjusting for potential confounders at baseline (**n=2,644*****)***

Exposure	Adjusted OR	95% CI	P-value adjusted[1]	Gender interaction (p-value) [2]
Neighbourhood Trust	1.03	[0.92 , 1.14]	0.613	0.148
Social support - friend	0.97	[0.87 , 1.08]	0.564	0.156
Social support – family	1.00	[0.89 , 1.13]	0.972	0.526
Social support - sig. other	1.02	[0.92 , 1.14]	0.697	0.071

Results are from partial proportional odds. The proportional odds assumptions were not violated for the parameters of interest, however, due to violation of the assumptions for some of the confounders, non-proportional odds were allowed for ethnicity and time lived in the neighbourhood. Results are displayed as ORs of improvement in walking to school status (being either constant vs. decrease or increase vs. constant) per unit increase in the original scale of neighbourhood trust and tertile change in social support. OR > 1 indicate an improvement in the outcome as a response to an improvement in the exposure. [1] Adjusted for gender, ethnicity, health condition, FSM, family affluence, time lived in the neighbourhood, and household composition at wave 2. [2] The adjusted model was replicated for each outcome with an additional interaction term between gender and the exposure.

Table G.20 Odds ratios (OR) of change in walking for leisure predicted by change in neighbourhood trust and social support, adjusting for potential confounders at baseline (**n=2,644*****)***

Exposure	Unadjusted OR	Adjusted OR	95% CI	P-value adjusted[1]	Gender interaction (p-value) [2]
Neighbourhood Trust	1.07	1.07	[0.98 , 1.17]	0.156	0.876
Social support - friend	1.11	1.11	[1.01 , 1.22]	0.037	0.447
Social support – family	1.07	1.07	[0.97 , 1.19]	0.189	0.489
Social support - sig. other	1.05	1.04	[0.95 , 1.15]	0.364	0.167

Results are from proportional odds. The proportional odds assumptions were not violated for the parameters of interest. Results are displayed as ORs of improvement in walking for leisure status (being either constant vs. decrease or increase vs. constant) per unit increase in the original scale of neighbourhood trust and tertile change in social support. OR > 1 indicate an improvement in the outcome as a response to an improvement in the exposure. [1] Adjusted for gender, ethnicity, health condition, FSM, family affluence, time lived in the neighbourhood, and household composition at wave 2. [2] The adjusted model was replicated for each outcome with an additional interaction term between gender and the exposure.

*Table G.21 Odds ratios (OR) of change in walking for leisure predicted by change in neighbourhood trust and social support, adjusting for potential confounders at baseline (***n=2,644***)*

Exposure	Adjusted OR	95% CI	P-value adjusted[1]	Gender interaction (p-value) [2]
Neighbourhood Trust	1.07	[0.98, 1.17]	0.149	0.812
Social support - friend	1.11	[1.01, 1.22]	0.036	0.367
Social support – family	1.07	[0.97, 1.19]	0.184	0.540
Social support - sig. other	1.05	[0.95, 1.15]	0.359	0.191

Results are from partial proportional odds. The proportional odds assumptions were not violated for the parameters of interest, however, due to violation of the assumptions for some of the confounders, non-proportional odds were allowed for gender, FSM, family affluence and household composition. Results are displayed as ORs of improvement in walking for leisure status (being either constant vs. decrease or increase vs. constant) per unit increase in the original scale of neighbourhood trust and tertile change in social support. OR > 1 indicate an improvement in the outcome as a response to an improvement in the exposure. [1] Adjusted for gender, ethnicity, health condition, FSM, family affluence, time lived in the neighbourhood, and household composition at wave 2. [2] The adjusted model was replicated for each outcome with an additional interaction term between gender and the exposure.

*Table G.22 Odds ratios (OR) of change in outdoor PA predicted by change in neighbourhood trust and social support, adjusting for potential confounders at baseline (***n=2,644***)*

Exposure	Unadjusted OR	Adjusted OR	95% CI	P-value adjusted[1]	Gender interaction (p-value) [2]
Neighbourhood Trust	0.99	0.99	[0.90, 1.09]	0.834	0.641
Social support - friend	1.01	1.01	[0.91, 1.12]	0.867	0.315
Social support – family	0.97	0.97	[0.87, 1.08]	0.543	0.556
Social support - sig. other	1.01	1.00	[0.90, 1.12]	0.947	0.785

Results are from proportional odds. The proportional odds assumptions were not violated for the parameters of interest. Results are displayed as ORs of improvement in outdoor PA status (being either constant vs. decrease or increase vs. constant) per unit increase in the original scale of neighbourhood trust and tertile change in social support. OR > 1 indicate an improvement in the outcome as a response to an improvement in the exposure. [1] Adjusted for gender, ethnicity, health condition, FSM, family affluence, time lived in the neighbourhood, and household composition at wave 2. [2] The adjusted model was replicated for each outcome with an additional interaction term between gender and the exposure.

Table G.23 Odds ratios (OR) of change in outdoor PA predicted by change in neighbourhood trust and social support, adjusting for potential confounders at baseline (n=2,644)

Exposure	Adjusted OR	95% CI	P-value adjusted[1]	Gender interaction (p-value) [2]
Neighbourhood Trust	0.99	[0.89 , 1.09]	0.815	0.590
Social support - friend	1.01	[0.91 , 1.13]	0.830	0.293
Social support – family	0.97	[0.87 , 1.08]	0.546	0.690
Social support - sig. other	1.00	[0.90 , 1.12]	0.950	0.762

Results are from partial proportional odds. The proportional odds assumptions were not violated for the parameters of interest, however, due to violation of the assumptions for some of the confounders, non-proportional odds were allowed for gender, FSM, family affluence and household composition. Results are displayed as ORs of improvement in outdoor PA status (being either constant vs. decrease or increase vs. constant) per unit increase in the original scale of neighbourhood trust and tertile change in social support. OR > 1 indicate an improvement in the outcome as a response to an improvement in the exposure. [1] Adjusted for gender, ethnicity, health condition, FSM, family affluence, time lived in the neighbourhood, and household composition at wave 2. [2] The adjusted model was replicated for each outcome with an additional interaction term between gender and the exposure.

Table G.24 Odds ratios (OR) of change in in Pay and Play PA predicted by change in neighbourhood trust and social support, adjusting for potential confounders at baseline (n=2,644)

Exposure	Unadjusted OR	Adjusted OR	95% CI	P-value adjusted[1]	Gender interaction (p-value) [2]
Neighbourhood Trust	1.06	1.06	[0.97 , 1.16]	0.201	0.099
Social support - friend	0.99	0.99	[0.91 , 1.08]	0.845	0.695
Social support – family	0.98	0.98	[0.88 , 1.09]	0.691	0.275
Social support - sig. other	0.98	0.98	[0.89 , 1.08]	0.672	0.340

Results are from proportional odds. The proportional odds assumptions were not violated for the parameters of interest. Results are displayed as ORs of improvement in Pay and Play PA status (being either constant vs. decrease or increase vs. constant) per unit increase in the original scale of neighbourhood trust and tertile change in social support. OR > 1 indicate an improvement in the outcome as a response to an improvement in the exposure. [1] Adjusted for gender, ethnicity, health condition, FSM, family affluence, time lived in the neighbourhood, and household composition at wave 2. [2] The adjusted model was replicated for each outcome with an additional interaction term between gender and the exposure.

Table G.25 Odds ratios (OR) of change in Pay and Play PA predicted by change in neighbourhood trust and social support, adjusting for potential confounders at baseline (*n=2,644*)

Exposure	Adjusted OR		95%		CI		P-value adjusted[1]	Gender interaction (p-value) [2]
Neighbourhood Trust	1.06	[	0.97	,	1.16	]	0.201	0.095
Social support - friend	0.99	[	0.91	,	1.08	]	0.837	0.689
Social support – family	0.98	[	0.88	,	1.09	]	0.696	0.274
Social support - sig. other	0.98	[	0.89	,	1.08	]	0.665	0.346

Results are from partial proportional odds. The proportional odds assumptions were not violated for the parameters of interest, however, due to violation of the assumptions for some of the confounders, non-proportional odds were allowed for gender, FSM, family affluence and household composition. Results are displayed as ORs of improvement in Pay and Play PA status (being either constant vs. decrease or increase vs. constant) per unit increase in the original scale of neighbourhood trust and tertile change in social support. OR > 1 indicate an improvement in the outcome as a response to an improvement in the exposure. [1] Adjusted for gender, ethnicity, health condition, FSM, family affluence, time lived in the neighbourhood, and household composition at wave 2. [2] The adjusted model was replicated for each outcome with an additional interaction term between gender and the exposure.

G.6 Results from the models of chapter 8 further adjusted for BMI for walking for leisure and pay and play physical activity using the imputed datasets

In the literature on social support and physical activity, authors sometimes treat BMI as a confounder, under the assumption that BMI is both associated with social support and the physical activity outcomes. In the ORiEL study, there is some evidence that BMI is associated with walking for leisure and Pay and Play PA, as well as with family social support, in models that adjust for other potential confounders. In this appendix, I reproduce results of chapter 8 for the outcomes walking for leisure and pay and play physical activity and further adjust for BMI.

Table G.26 Odds ratios (OR) of walking for leisure vs. not by neighbourhood trust and social support, adjusting for potential confounders and BMI (waves 2 and 3* of the ORiEL Study, n=2,644*)

Exposure		Adjusted OR¹	95%CI	P-value parameter	P-value unadjusted	P-value adjusted¹	Gender interaction (p-value) ²
Neighbourhood Trust	Not at all	1.00			0.193	0.265	0.909
	A little	1.25	[0.99,1.58]	0.065			
	Some	1.26	[1.00,1.57]	0.048			
	A lot	1.23	[0.96,1.58]	0.102			
Social support - friend	low	1.00			0.001	0.091	0.503
	medium	1.17	[1.00,1.37]	0.055			
	high	1.16	[0.99,1.37]	0.069			
Social support – family	low	1.00			<0.001	0.004	0.577
	medium	1.20	[1.00,1.43]	0.047			
	high	1.32	[1.12,1.56]	0.001			
Social support - sig. other	low	1.00			0.001	0.055	0.425
	medium	1.11	[0.95,1.30]	0.191			
	high	1.21	[1.03,1.43]	0.020			

Results are from Generalised Estimating Equations to account for the dependency across repeated measurements (unstructured working correlation matrix).

¹ Adjusted for gender, ethnicity, health condition, FSM, family affluence, time lived in the neighbourhood, household composition, BMI and time.

² The adjusted model was replicated for each outcome with an additional interaction term between gender and the exposure.

Table G.27 Odds ratios (OR) of change in walking for leisure predicted by change in neighbourhood trust and social support, adjusting for potential confounders at baseline (*n=2,644*)

Exposure	Adjusted OR	95% CI	P-value adjusted[1]	Gender interaction (p-value) [2]
Neighbourhood Trust	1.07	[0.99 , 1.15]	0.112	0.865
Social support - friend	1.11	[1.01 , 1.21]	0.024	0.415
Social support – family	1.07	[0.97 , 1.19]	0.186	0.508
Social support - sig. other	1.04	[0.96 , 1.13]	0.351	0.164

Results are from proportional odds model estimated with Generalised Estimating Equations to account for the clustering of individuals within schools (independent working correlation matrix). The proportional odds assumptions were not violated for the parameters of interest. Results are displayed as ORs of improvement in walking for leisure status (being either constant vs. decrease or increase vs. constant) per unit increase in the original scale of neighbourhood trust and tertile change in social support. OR > 1 indicate an improvement in the outcome as a response to an improvement in the exposure. [1] Adjusted for gender, ethnicity, health condition, FSM, family affluence, time lived in the neighbourhood household composition and BMI at wave 2. [2] The adjusted model was replicated for each outcome with an additional interaction term between gender and the exposure.

Table G.28 Odds ratios (OR) of Pay and Play PA vs. not by neighbourhood trust and social support, adjusting for potential confounders and BMI (waves 2 and 3* of the ORiEL Study, n=2,644*)

Exposure		Adjusted OR[1]	95%CI	P-value parameter	P-value unadjusted	P-value adjusted[1]	Gender interaction (p-value) [2]
Neighbourhood Trust	Not at all	1.00			0.005	0.026	0.700
	A little	0.95	[0.76,1.20]	0.690			
	Some	1.03	[0.83,1.28]	0.767			
	A lot	1.27	[0.99,1.63]	0.055			
Social support - friend	low	1.00			0.975	0.873	0.537
	medium	1.00	[0.86,1.17]	0.995			
	high	0.96	[0.83,1.13]	0.646			
Social support – family	low	1.00			0.624	0.966	0.467

Exposure		Adjusted OR¹	95%CI	P-value parameter	P-value unadjusted	P-value adjusted¹	Gender interaction (p-value) ²
	medium	0.99	[0.84,1.16]	0.880			
	high	0.98	[0.83,1.16]	0.806			
Social support - sig. other	low	1.00			0.761	0.874	0.871
	medium	0.96	[0.82,1.13]	0.626			
	high	1.00	[0.85,1.17]	0.951			

Results are from Generalised Estimating Equations to account for the dependency across repeated measurements (unstructured working correlation matrix). ¹ Adjusted for gender, ethnicity, health condition, FSM, family affluence, time lived in the neighbourhood, household composition, BMI and time. ² The adjusted model was replicated for each outcome with an additional interaction term between gender and the exposure.

Table G.29 Odds ratios (OR) of change in Pay and Play PA predicted by change in neighbourhood trust and social support, adjusting for potential confounders at baseline (**n=2,644*****)***

Exposure	Adjusted OR¹	95% CI	P-value adjusted¹	Gender interaction (p-value) ²
Neighbourhood Trust	1.06	[0.96 , 1.18]	0.220	0.072
Social support - friend	0.99	[0.92 , 1.07]	0.847	0.664
Social support – family	0.98	[0.89 , 1.08]	0.696	0.286
Social support - sig. other	0.98	[0.90 , 1.08]	0.744	0.280

Results are from proportional odds model estimated with Generalised Estimating Equations to account for the clustering of individuals within schools (independent working correlation matrix). The proportional odds assumptions were not violated for the parameters of interest. Results are displayed as ORs of improvement in Pay and Play Pa status (being either constant vs. decrease or increase vs. constant) per unit increase in the original scale of neighbourhood trust and tertile change in social support. OR > 1 indicate an improvement in the outcome as a response to an improvement in the exposure. ¹ Adjusted for gender, ethnicity, health condition, FSM, family affluence, time lived in the neighbourhood household composition and BMI at wave 2. ² The adjusted model was replicated for each outcome with an additional interaction term between gender and the exposure.

G.7 Results from the complete case analysis of chapter 8

Table G.30 Odds ratios (OR) of walking to school vs. not by potential socio-demographic and health confounders (waves 2 and 3 of the ORiEL Study, n=3,075 from 2,058 individuals)

Potential confounder		OR	Adjusted OR[1]	95%CI	P-value parameter	P-value unadjusted	P-value adjusted[1]
Gender	Male	1.00	1.00			0.229	0.064
	Female	1.12	1.20	[0.99,1.46]	0.064		
Ethnicity	White: UK	1.00	1.00			<0.001	0.001
	White: Mixed	0.79	0.86	[0.57,1.29]	0.458		
	Asian: Indian	1.03	1.19	[0.67,2.10]	0.558		
	Asian: Pakistani	0.86	0.93	[0.56,1.54]	0.783		
	Asian: Bangladeshi	1.42	1.43	[1.00,2.06]	0.051		
	Black: Caribbean	0.45	0.48	[0.30,0.76]	0.002		
	Black: African	0.60	0.71	[0.49,1.04]	0.076		
	Other	0.73	0.85	[0.64,1.13]	0.271		
Health	no condition	1.00	1.00			0.309	0.377
	1+ conditions(s)	1.09	1.08	[0.91,1.30]	0.377		
FAS Categories	Low	1.00	1.00			0.397	0.322
	Moderate	0.79	0.77	[0.53,1.11]	0.162		
	High	0.77	0.74	[0.50,1.10]	0.134		
Take FSM	No	1.00	1.00			0.088	0.031
	Yes	1.18	1.25	[1.02,1.54]	0.031		
Time lived in neighbourhood	>6 years	1.00	1.00			<0.001	<0.001
	<= 5 years	0.51	0.52	[0.43,0.63]	<0.001		
Household composition	Both Parents	1.00	1.00			0.013	0.112

Potential confounder		OR	Adjusted OR[1]	95%CI	P-value parameter	P-value unadjusted	P-value adjusted[1]
	Other	0.79	0.85	[0.69,1.04]	0.112		
time		0.85	0.86	[0.75,0.98]	0.030	0.015	0.030

Results are from Generalised Estimating Equations to account for the dependency across repeated measurements (unstructured working correlation matrix).[1] Adjusted for all other variables of the table

Table G.31 Odds ratios (OR) of walking to school vs. not by neighbourhood trust and social support, adjusting for potential confounders **(waves 2 and 3 of the ORiEL Study, n=3,075 from 2,058 individuals)**

Exposure		Unadjusted OR	Adjusted OR[1]	95%CI	P-value parameter	P-value unadjusted	P-value adjusted[1]	Gender interaction (p-value) [2]
Neighbourhood Trust	Not at all	1.00	1.00			0.115	0.383	0.559
	A little	0.95	0.89	[0.67,1.19]	0.434			
	Some	1.19	1.06	[0.80,1.40]	0.696			
	A lot	1.08	0.95	[0.69,1.31]	0.753			
Social support - friend	low	1.00	1.00			0.373	0.223	0.522
	medium	1.12	1.09	[0.90,1.33]	0.372			
	high	0.98	0.91	[0.74,1.12]	0.386			
Social support – family	low	1.00	1.00			0.563	0.396	0.111
	medium	0.94	0.92	[0.74,1.15]	0.477			
	high	0.89	0.86	[0.70,1.07]	0.174			
Social support - sig. other	low	1.00	1.00			0.868	0.802	0.030^

Exposure		Unadjusted OR	Adjusted OR[1]	95%CI	P-value parameter	P-value unadjusted	P-value adjusted[1]	Gender interaction (p-value) [2]
	medium	0.99	1.02	[0.82,1.25]	0.884			
	high	0.95	0.95	[0.77,1.17]	0.637			

Results are from Generalised Estimating Equations to account for the dependency across repeated measurements (unstructured working correlation matrix).[1] Adjusted for gender, ethnicity, health condition, FSM, family affluence, time lived in the neighbourhood, household composition and time. [2] The adjusted model was replicated for each outcome with an additional interaction term between gender and the exposure.^ None of the gender-specific associations was significant. In the absence of significant results, the exposures were not modelled in a dose-response fashion.

Table G.32 Odds ratios (OR) of walking to school predicted by change in neighbourhood trust and social support, adjusting for potential confounders at baseline (*n=1,161*)

Exposure	Unadjusted OR	Adjusted OR[1]	95% CI	P-value adjusted[1]	Gender interaction (p-value) [2]
Neighbourhood Trust	1.09	1.08	[0.94 , 1.25]	0.260	0.256
Social support - friend	1.03	1.03	[0.86 , 1.23]	0.752	0.107
Social support – family	1.07	1.05	[0.88 , 1.25]	0.563	0.630
Social support - sig. other	1.04	1.04	[0.91 , 1.18]	0.587	0.182

Results are from proportional odds model estimated with Generalised Estimating Equations to account for the clustering of individuals within schools (independent working correlation matrix). The proportional odds assumptions were not violated for the parameters of interest. Results are displayed as ORs of improvement in walking to school status (being either constant vs. decrease or increase vs. constant) per unit increase in the original scale of neighbourhood trust and tertile change in social support. OR > 1 indicate an improvement in the outcome as a response to an improvement in the exposure. [1] Adjusted for gender, ethnicity, health condition, FSM, family affluence, time lived in the neighbourhood and household composition at wave 2. [2] The adjusted model was replicated for each outcome with an additional interaction term between gender and the exposure.

Table G.33 **Odds ratios (OR) of walking for leisure vs. not by potential socio-demographic and health (waves 2 and 3 of the ORiEL Study, n=3,043 from 2,043 individuals)**

Potential confounder		OR	Adjusted OR[1]	95%CI	P-value parameter	P-value unadjusted	P-value adjusted[1]
Gender	Male	1.00	1.00			<0.001	<0.001
	Female	1.73	1.73	[1.46,2.05]	<0.001		
Ethnicity	White: UK	1.00	1.00			<0.001	<0.001
	White: Mixed	0.74	0.73	[0.52,1.04]	0.080		
	Asian: Indian	0.61	0.65	[0.41,1.03]	0.068		
	Asian: Pakistani	0.51	0.57	[0.37,0.88]	0.012		
	Asian: Bangladeshi	0.35	0.39	[0.29,0.52]	<0.001		
	Black: Caribbean	0.42	0.39	[0.24,0.64]	<0.001		
	Black: African	0.34	0.36	[0.26,0.51]	<0.001		
	Other	0.62	0.64	[0.51,0.81]	<0.001		
Health	no condition	1.00	1.00			0.378	0.784
	1+ conditions(s)	1.07	1.02	[0.87,1.21]	0.784		
FAS Categories	Low	1.00	1.00			0.024	0.054
	Moderate	1.00	1.03	[0.75,1.43]	0.845		
	High	1.23	1.26	[0.90,1.77]	0.185		
Take FSM	No	1.00	1.00			0.707	0.713
	Yes	0.97	1.04	[0.86,1.25]	0.713		
Time lived in neighbourhood	>6 years	1.00	1.00			0.278	0.590
	<= 5 years	0.91	0.95	[0.80,1.13]	0.590		
Household composition	Both Parents	1.00	1.00			0.025	0.105
	Other	1.22	1.17	[0.97,1.40]	0.105		
time		0.80	0.78	[0.68,0.90]	<0.001	0.001	<0.001

Results are from Generalised Estimating Equations to account for the dependency across repeated measurements (unstructured working correlation matrix).[1] Adjusted for all other variables of the table

***Table G.34 Odds ratios (OR) of walking for leisure vs. not by neighbourhood trust and social support, adjusting for potential confounders* (waves 2 and 3 of the ORiEL Study, n=3,043 from 2,043 individuals)**

Exposure		Unadjusted OR	Adjusted OR[1]	95%CI	P-value parameter	P-value unadjusted	P-value adjusted[1]	Gender interaction (p-value) [2]
Neighbourhood Trust	Not at all	1.00	1.00			0.364	0.676	0.957
	A little	1.14	1.10	[0.83,1.45]	0.507			
	Some	1.15	1.14	[0.87,1.50]	0.343			
	A lot	0.98	1.03	[0.75,1.40]	0.862			
	Trend*	0.99	1.01	[0.92,1.10]	0.877	0.732	0.877	0.917
Social support - friend	low	1.00	1.00			0.364	0.676	0.957
	medium	1.14	1.10	[0.83,1.45]	0.507			
	high	1.15	1.14	[0.87,1.50]	0.343			
	Trend*	1.16	1.08	[0.98,1.19]	0.102	0.001	0.102	0.413
Social support – family	low	1.00	1.00			0.001	0.009	0.600
	medium	1.32	1.30	[1.06,1.60]	0.012			
	high	1.40	1.33	[1.10,1.61]	0.003			
	Trend*	1.17	1.14	[1.04,1.26]	0.005	0.001	0.005	0.338
Social support - sig. other	low	1.00	1.00			<0.001	0.017	0.578
	medium	1.29	1.18	[0.98,1.43]	0.084			

Exposure		Unadjusted OR	Adjusted OR[1]	95%CI	P-value parameter	P-value unadjusted	P-value adjusted[1]	Gender interaction (p-value) [2]
	high	1.48	1.31	[1.09,1.58]	0.005			
	Trend*	1.22	1.14	[1.04,1.26]	0.005	<0.001	0.005	0.410

Results are from Generalised Estimating Equations to account for the dependency across repeated measurements (unstructured working correlation matrix).[1] Adjusted for gender, ethnicity, health condition, FSM, family affluence, time lived in the neighbourhood, household composition and time. [2] The adjusted model was replicated for each outcome with an additional interaction term between gender and the exposure.

Table G.35 Odds ratios (OR) of walking for leisure predicted by change in neighbourhood trust and social support, adjusting for potential confounders at baseline (*n=1,141*)

Exposure	Unadjusted OR	Adjusted OR[1]	95% CI	P-value adjusted[1]	Gender interaction (p-value) [2]
Neighbourhood Trust	1.00	1.00	[0.89 , 1.12]	0.965	0.288
Social support - friend	1.13	1.12	[1.03 , 1.23]	0.009	0.563
Social support – family	1.09	1.10	[0.98 , 1.24]	0.092	0.360
Social support - sig. other	1.09	1.09	[0.98 , 1.21]	0.099	0.030

Results are from proportional odds model estimated with Generalised Estimating Equations to account for the clustering of individuals within schools (independent working correlation matrix). The proportional odds assumptions were not violated for the parameters of interest. Results are displayed as ORs of improvement in walking for leisure status (being either constant vs. decrease or increase vs. constant) per unit increase in the original scale of neighbourhood trust and tertile change in social support. OR > 1 indicate an improvement in the outcome as a response to an improvement in the exposure. [1] Adjusted for gender, ethnicity, health condition, FSM, family affluence, time lived in the neighbourhood and household composition at wave 2. [2] The adjusted model was replicated for each outcome with an additional interaction term between gender and the exposure.

Table G.36 **Odds ratios (OR) of outdoor PA vs. not by potential socio-demographic and health confounders (waves 2 and 3 of the ORiEL Study, n=2,948 from 2,000 individuals)**

Potential confounder		OR	Adjusted OR[1]	95%CI	P-value parameter	P-value unadjusted	P-value adjusted[1]
Gender	Male	1.00	1.00			<0.001	<0.001
	Female	0.20	0.21	[0.17,0.25]	<0.001		
Ethnicity	White: UK	1.00	1.00			0.022	0.258
	White: Mixed	1.21	1.20	[0.81,1.79]	0.359		
	Asian: Indian	1.22	1.12	[0.67,1.89]	0.666		
	Asian: Pakistani	2.25	1.87	[1.09,3.23]	0.024		
	Asian: Bangladeshi	1.23	1.08	[0.78,1.48]	0.649		
	Black: Caribbean	0.67	0.74	[0.45,1.22]	0.234		
	Black: African	1.26	1.23	[0.84,1.80]	0.287		
	Other	1.14	1.11	[0.84,1.46]	0.475		
Health	no condition	1.00	1.00			0.396	0.821
	1+ conditions(s)	0.93	0.98	[0.81,1.18]	0.821		
FAS Categories	Low	1.00	1.00			0.043	0.027
	Moderate	1.03	1.19	[0.83,1.71]	0.349		
	High	1.28	1.50	[1.02,2.20]	0.041		
Take FSM	No	1.00	1.00			0.028	0.132
	Yes	1.23	1.17	[0.95,1.44]	0.132		
Time lived in neighbourhood	>6 years	1.00	1.00			0.173	0.101
	<= 5 years	1.13	1.18	[0.97,1.43]	0.101		
Household composition	Both Parents	1.00	1.00			0.689	0.681
	Other	0.96	1.05	[0.84,1.30]	0.681		
time		0.79	0.76	[0.66,0.88]	<0.001	0.001	<0.001

Results are from Generalised Estimating Equations to account for the dependency across repeated measurements (unstructured working correlation matrix).[1] Adjusted for all other variables of the table

Table G.37 Odds ratios (OR) of outdoor PA vs. not by neighbourhood trust and social support, adjusting for potential confounders **(waves 2 and 3 of the ORiEL Study, n=2,948 from 2,000 individuals)**

Exposure		Unadjusted OR	Adjusted OR[1]	95%CI	P-value parameter	P-value unadjusted	P-value adjusted[1]	Gender interaction (p-value) [2]
Neighbourhood Trust	Not at all	1.00	1.00			<0.001	0.083	0.296
	A little	1.04	1.00	[0.74,1.36]	0.982			
	Some	1.16	1.07	[0.80,1.45]	0.643			
	A lot	1.78	1.42	[1.00,2.01]	0.051			
	Trend*	1.20	1.12	[1.01,1.23]	0.027	<0.001	0.027	0.193
Social support - friend	low	1.00	1.00			0.225	0.124	0.024
	medium	1.03	1.24	[1.01,1.54]	0.043			
	high	0.87	1.15	[0.93,1.41]	0.197			
Social support – family	low	1.00	1.00			0.697	0.453	0.229
	medium	1.09	1.15	[0.92,1.43]	0.214			
	high	1.07	1.10	[0.89,1.35]	0.384			
Social support - sig. other	low	1.00	1.00			0.684	0.446	0.082
	medium	0.93	1.09	[0.87,1.36]	0.471			
	high	0.92	1.15	[0.93,1.41]	0.204			

Results are from Generalised Estimating Equations to account for the dependency across repeated measurements (unstructured working correlation matrix).[1] Adjusted for gender, ethnicity, health condition, FSM, family affluence, time lived in the neighbourhood, household composition and time. [2] The adjusted model was replicated for each outcome with an additional interaction term between gender and the exposure.*Exposure modelled as a continuous variable when evidence of improved fit compared to the categorical option.

Table G.38 Odds ratios (OR) of outdoor PA vs. not by neighbourhood trust and social support stratified by gender, adjusting for potential confounders (waves 2 and 3 of the ORiEL Study, n=2,948 from 2,000 individuals)

Exposure		Unadjusted OR	Adjusted OR[1]	95%CI	P-value unadjusted	P-value adjusted[1]	Unadjusted OR	Adjusted OR[1]	95%CI	P-value unadjusted	P-value adjusted[1]
			Boys					**Girls**			
Neighbourhood Trust	Not at all	1.00	1.00		0.052	0.063	1.00	1.00		0.494	0.472
	A little	1.37	1.37	[0.81,2.33]			0.93	0.87	[0.61,1.26]		
	Some	1.28	1.28	[0.78,2.11]			1.03	0.99	[0.69,1.41]		
	A lot	2.12	2.12	[1.17,3.81]			1.21	1.14	[0.74,1.76]		
	Trend*	1.21	1.21	[1.03,1.43]	0.016	0.021					
Social support - friend	low	1.00	1.00		0.006	0.005	1.00	1.00		0.555	0.442
	medium	1.45	1.47	[1.04,2.08]			1.08	1.09	[0.83,1.42]		
	high	1.76	1.80	[1.22,2.66]			0.94	0.92	[0.71,1.20]		
	Trend*	1.35	1.36	[1.13,1.65]	0.002	0.001					
Social support – family	low	1.00	1.00		0.111	0.116	1.00	1.00		0.912	0.777
	medium	1.33	1.34	[0.92,1.96]			1.05	1.05	[0.80,1.37]		
	high	1.40	1.41	[1.00,2.00]			1.00	0.96	[0.74,1.24]		
	Trend*	1.18	1.19	[1.00,1.42]	0.053	0.055					
Social support - sig. other	low	1.00	1.00		0.042	0.023	1.00	1.00		0.957	0.918
	medium	1.29	1.33	[0.91,1.93]			0.96	0.95	[0.72,1.26]		
	high	1.61	1.68	[1.15,2.45]			1.00	0.95	[0.73,1.23]		
	Trend*	1.27	1.30	[1.08,1.57]	0.012	0.006					

Results are from Generalised Estimating Equations to account for the dependency across repeated measurements (unstructured working correlation matrix).[1] Adjusted for gender, ethnicity, health condition, FSM, family affluence, time lived in the neighbourhood, household composition and time. [2] The adjusted model was replicated for each outcome with an additional interaction term between gender and the exposure.*Exposure modelled as a continuous variable when evidence of improved fit compared to the categorical option.

Table G.39 Odds ratios (OR) of outdoor PA predicted by change in neighbourhood trust and social support, adjusting for potential confounders at baseline (*n=1,083*)

Exposure	Unadjusted OR	Adjusted OR[1]	95% CI	P-value adjusted[1]	Gender interaction (p-value) [2]
Neighbourhood Trust	0.99	1.00	[0.88 , 1.13]	0.941	0.869
Social support - friend	1.04	1.04	[0.94 , 1.15]	0.462	0.823
Social support – family	0.99	0.99	[0.86 , 1.14]	0.865	0.366
Social support - sig. other	1.04	1.03	[0.88 , 1.20]	0.741	0.749

Results are from proportional odds model estimated with Generalised Estimating Equations to account for the clustering of individuals within schools (independent working correlation matrix). The proportional odds assumptions were not violated for the parameters of interest. Results are displayed as ORs of improvement in outdoor PA status (being either constant vs. decrease or increase vs. constant) per unit increase in the original scale of neighbourhood trust and tertile change in social support. OR > 1 indicate an improvement in the outcome as a response to an improvement in the exposure. [1] Adjusted for gender, ethnicity, health condition, FSM, family affluence, time lived in the neighbourhood and household composition at wave 2.

[2] The adjusted model was replicated for each outcome with an additional interaction term between gender and the exposure.

Table G.40 **Odds ratios (OR) of Pay and Play PA vs. not by potential socio-demographic and health confounders (*waves 2 and 3 of the ORiEL Study, n=2,963 from 2,002 individuals)***

Potential confounder		OR	Adjusted OR[1]	95%CI	P-value parameter	P-value unadjusted	P-value adjusted[1]
Gender	Male	1.00	1.00			0.854	0.892
	Female	0.99	0.99	[0.84,1.16]	0.892		
Ethnicity	White: UK	1.00	1.00			0.105	0.153
	White: Mixed	1.10	1.17	[0.84,1.65]	0.352		
	Asian: Indian	1.39	1.38	[0.87,2.19]	0.175		
	Asian: Pakistani	1.04	1.03	[0.69,1.55]	0.890		
	Asian: Bangladeshi	0.76	0.79	[0.60,1.04]	0.094		
	Black: Caribbean	0.99	1.05	[0.68,1.62]	0.830		
	Black: African	0.97	1.05	[0.76,1.46]	0.757		
	Other	1.08	1.11	[0.88,1.41]	0.366		
Health	no condition	1.00	1.00			0.009	0.008
	1+ conditions(s)	1.23	1.24	[1.06,1.45]	0.008		
FAS Categories	Low	1.00	1.00			<0.001	<0.001
	Moderate	1.42	1.50	[1.09,2.08]	0.014		
	High	2.07	2.15	[1.53,3.03]	<0.001		
Take FSM	No	1.00	1.00			0.139	0.797
	Yes	0.88	0.98	[0.82,1.16]	0.797		
Time lived in neighbourhood	>6 years	1.00	1.00			0.907	0.660
	<= 5 years	1.01	1.04	[0.88,1.22]	0.660		
Household composition	Both Parents	1.00	1.00			0.028	0.068
	Other	0.83	0.85	[0.71,1.01]	0.068		
time		0.60	0.57	[0.50,0.66]	<0.001	<0.001	<0.001

Results are from Generalised Estimating Equations to account for the dependency across repeated measurements (unstructured working correlation matrix).[1] Adjusted for all other variables of the table

Table G.41 Odds ratios (OR) of Pay and Play PA vs. not by neighbourhood trust and social support, adjusting for potential confounders **(waves 2 and 3 of the ORiEL Study, n=3,007 from 2,022 individuals)**

Exposure		Unadjusted OR	Adjusted OR[1]	95%CI	P-value parameter	P-value unadjusted	P-value adjusted[1]	Gender interaction (p-value) [2]
Neighbourhood Trust	Not at all	1.00	1.00			0.007	0.026	0.773
	A little	1.04	1.01	[0.77,1.32]	0.940			
	Some	1.22	1.18	[0.91,1.53]	0.221			
	A lot	1.48	1.39	[1.05,1.86]	0.024			
	Trend*	1.15	1.13	[1.04,1.23]	0.004	0.001	0.004	0.496
Social support - friend	low	1.00	1.00			0.881	0.561	0.113
	medium	0.99	0.99	[0.82,1.19]	0.919			
	high	0.96	0.91	[0.76,1.10]	0.324			
Social support – family	low	1.00	1.00			0.841	0.822	0.901
	medium	1.04	1.03	[0.84,1.25]	0.796			
	high	1.05	0.97	[0.81,1.16]	0.749			
Social support - sig. other	low	1.00	1.00			0.867	0.854	0.701
	medium	0.99	0.95	[0.79,1.14]	0.576			
	high	1.04	0.97	[0.81,1.16]	0.763			

Results are from Generalised Estimating Equations to account for the dependency across repeated measurements (unstructured working correlation matrix).
[1] Adjusted for gender, ethnicity, health condition, FSM, family affluence, household composition and time. [2] The adjusted model was replicated for each outcome with an additional interaction term between gender and the exposure.*Exposure modelled as a continuous variable (dose-response relationship) when evidence of improved fit compared to the categorical option (using GLMM).

Table G.42 Odds ratios (OR) of Pay and Play PA predicted by change in neighbourhood trust and social support, adjusting for potential confounders at baseline* (n=1,096*)

Exposure	Unadjusted OR	Adjusted OR[1]	95% CI	P-value adjusted[1]	Gender interaction (p-value) [2]
Neighbourhood Trust	1.02	1.01	[0.87 , 1.17]	0.932	0.087
Social support - friend	1.03	1.02	[0.92 , 1.14]	0.690	0.363
Social support – family	1.06	1.05	[0.91 , 1.22]	0.504	0.173
Social support - sig. other	1.02	1.02	[0.91 , 1.14]	0.703	0.793

Results are from proportional odds model estimated with Generalised Estimating Equations to account for the clustering of individuals within schools (independent working correlation matrix). The proportional odds assumptions were not violated for the parameters of interest. Results are displayed as ORs of improvement in Pay and Play PA status (being either constant vs. decrease or increase vs. constant) per unit increase in the original scale of neighbourhood trust and tertile change in social support. OR > 1 indicate an improvement in the outcome as a response to an improvement in the exposure. [1] Adjusted for gender, ethnicity, health condition, FSM, family affluence, time lived in the neighbourhood and household composition at wave 2. [2] The adjusted model was replicated for each outcome with an additional interaction term between gender and the exposure.