Assessing framing assumptions in quantitative health impact assessments: A housing intervention example

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Abstract

Health impact assessment (HIA) is often used to determine *ex ante* the health impact of an environmental policy or an environmental intervention. Underpinning any HIA are the framing assumptions, which define the causal pathways mapping environmental exposures to health outcomes. The sensitivity of the HIA to the framing assumptions is often ignored. A novel method based on fuzzy cognitive map (FCM) is developed to quantify the framing assumptions in the assessment stage of a HIA, and is then applied to a housing intervention (tightening insulation) as a case-study. Framing assumptions of the case-study were identified through a literature search of Ovid Medline (1948-2011). The FCM approach was used to identify the key variables that have the most influence in a HIA. Changes in air-tightness, ventilation, indoor air quality and mould/humidity have been identified as having the most influence on health. The FCM approach is widely applicable and can be used to inform the formulation of the framing assumptions in any quantitative HIA of environmental interventions. We argue that it is necessary to explore and quantify framing assumptions prior to conducting a detailed quantitative HIA during the assessment stage.

Keywords: Environmental Health, Risk Assessment, Modelling, Health Impact Assessment, Housing

Introduction

The extent to which an environmental policy intervention causes health-related changes is a key question in research. Health Impact Assessment (HIA) identifies possible health consequences of new policy interventions (de Blasio et al., 2012; Kemm, 2004; Mindell et al., 2004). HIA is an area of increasing interest to policymakers in environmental health (de Nazelle et al., 2011; Dhondt et al., 2013; Maire et al., 2012), and there is considerable scope for innovation in the application of quantitative methodologies (Fehr et al., 2012; Mindell and Joffe, 2005). Underpinning any HIA are the framing assumptions, which define the causal pathways mapping environmental exposures to health outcomes. However, the sensitivity of the HIA to the framing assumptions is often ignored in many assessments. Framing assumptions are inevitable when quantifying the health effect of an environmental intervention.

Housing interventions such as improving housing insulation to reduce heat loss are examples of environmental policy interventions. Improving housing insulation, as an energy efficiency measure, is encouraged as part of the UK housing regulations to reduce carbon emission and energy cost (DCLG, 2003). Insulating homes is not only justified on energy efficiency grounds alone, but can also be justified on health grounds. Energy efficiency measures can benefit health through increasing indoor temperature in winter (Barton et al., 2007; Wilkinson et al., 2007). However, changes in the indoor environment as a result of reducing permeability can also affect health adversely. If improving insulation is not accompanied by adequate ventilation, there is the risk of increasing indoor pollutant concentrations (Bone et al., 2010).

Housing interventions are examples of complex (environmental) interventions (Craig et al., 2008). There is no unique definition of a complex intervention. In general, a complex intervention has multiple direct and indirect pathways in which it can affect health (Campbell et al., 2000). The pathways associating a complex environmental intervention with health can also be ill-defined and there are often multiple health outcomes.

HIA has been used to determine the health impacts of housing policy and interventions (Wilkinson et al., 2009a). However, large uncertainties can arise in HIA models from the lack of understanding of the complex associations between the indoor environment and health. Sources of uncertainty can include the framing assumptions associated with the formulation of the HIA, in addition to the more known sources of analytical uncertainty associated with the parameters and the structure of the models (Mesa-Frias et al., 2013).

Framing assumptions arise at the "conceptualisation" of the HIA model formulation (Briggs et al., 2009), and define the causal assumptions underpinning the assessment. The framing assumptions are typically ignored when appraising the uncertainty in many assessments by discarding factors that one considers unimportant (Briggs et al., 2009; Ramsey, 2009). Since the outcome of a HIA can be highly sensitive to the choice of the framing assumptions made initially in the assessment stage, it is important to characterise and quantify these framing assumptions.

Mathematical methods can be used to quantify the framing assumptions when defining the context of the assessment in evaluating the health impact of environmental interventions, *ex* *ante*. The use of complex system mathematical models has been proposed in public health (Galea et al., 2010; Joffe et al., 2012; Shiell et al., 2008). This paper demonstrates the use of another type of complex system modelling approach, known as fuzzy cognitive mapping (FCM). In this study, we use FCM to quantify the framing assumptions in the assessment stage of a HIA model of housing insulation, as a case-study example. The approach however is widely applicable to others examples of complex environmental interventions.

Overview of FCM method

A cognitive map is a conceptual graphical model used to represent causal assumptions (Kitchin, 1994; Wood et al., 2012). Cognitive maps have been used for conceptual modelling in many areas in the social sciences, such as in assessing the social implications of nanotechnologies and in describing social knowledge in the political sciences (Axelrod, 1976; Nakagawa et al., 2010). Cognitive maps can be extended to incorporate imprecise qualitative knowledge into quantitative variables, known as fuzzy cognitive maps. Fuzzy cognitive maps (FCM) have been used as a modelling tool to represent conventional and Aboriginal perspectives on the determinants of diabetes (Giles et al., 2007).

In this study, FCM is used to model framing assumptions quantitatively. Framing assumptions can be first explored with the use of causal diagrams. A causal FCM diagram shows the connections between variables in the "system of interest" and can be used to define the context of the assessment in which the environmental intervention is applied. The main emphasis of using causal FCM diagrams is on identifying causal pathways as they relate to health outcomes.

In general, FCM diagrams are directed graphs, which indicate directional interactions in the causal pathways. Fuzzy cognitive maps diagrams are described by a set of nodes and their causal relationships (links). In the context of this study, each node represents a key indoor factor, a health or a non-health outcome. The relationships between the nodes are described through directional links or connections. Positive (+) and negative (–) signs imply positive and negative causal relationships, respectively. A positive causal link between a pair of nodes means that when the amplitude (level) of one node increases, the amplitude of the other increases. A negative causal link, on the other hand, means that when the amplitude of one node increases, the amplitude of the other node decreases. A value zero (0) between a pair of nodes implies there is no causal link between the nodes.

A FCM was developed here to model the framing assumptions in the assessment stage of a HIA model of housing insulation. Fuzzy cognitive maps were then used to investigate the causal interactions and explain semi-quantitatively how intervention-related changes in the indoor environmental exposures can potentially affect health. Our methodological approach developed in this study is described in five main steps below.

Five steps in assessing framing assumptions

The five main steps in assessing framing assumptions are: (1) synthesising the evidence on causal pathways from the literature; (2) constructing the causal diagrams from individual studies identified from the literature; (3) representing mathematically the combined causal diagram as a system matrix; (4) measuring the structural properties of the system matrix; and

(5) simulating causal processes. Details of the steps are described below. Refer to Appendix A for detailed mathematical description of the steps and Appendix B for a walk-through example.

Synthesising the evidence on causal pathways from the literature

Health-relevant factors and outcomes were identified in the literature to construct causal diagrams that define nodes and inter-nodal relationships. A literature search of Ovid Medline (1948-2011) was conducted using the search terms: “housing” combined with “insulation” and “health” to identify studies investigating factors and outcomes (nodes) influencing the relationship (links) between housing insulation and health. Causal pathways associating housing insulation and health were identified qualitatively. An additional hand search of the literature was conducted in Ovid Medline using the identified key factors and outcomes as search terms to determine quantitative information on the associations.

Constructing the causal diagrams from individual studies identified from the literature

Based on each published study retrieved from the literature - nodes were identified. An individual casual diagram was constructed and positive or negative associations between the nodes of the diagram were determined. Measures of effects, such as odds ratio, were subsequently used to quantify the strength of the causal association between the nodes. The measures of effects (“causal weights”) were noted with each connection between a pair of nodes to represent the strength of the effects, using either the natural logarithm of an odds ratio for a health outcome, or the percentage change in indoor factors or outcomes obtained from retrieved studies in the literature (Appendix A.1).

Representing mathematically the combined causal diagram into a system matrix

Each causal diagram was then mathematically translated into a “connection matrix.” The elements of each connection matrix correspond to the measure of effects between each pair of nodes (causal weights). Each element is an algebraic number, which can be positive or negative. The value zero (0) means that there is no causal link between the nodes. The matrices from each published study were combined through summation and their values were then normalised (by dividing each element by the absolute maximum across all elements) to create a “system matrix” in which each element was in the range -1 to +1 (Appendix A.2).

Measuring the structural properties of the system matrix

The structural properties of the system matrix represent the causal structure mapping the causal pathways in the diagram. Indices are numerical measures, calculated using graph theory (West, 2000), which characterise quantitatively the structural properties of the system. A “centrality index” shows how well connected a node (indoor factor or an outcome) is in relation to other nodes, i.e. how many links join with this specific node. The centrality index measures the centrality of the framing assumptions defined in the assessment. A high centrality index indicates high importance, whereas a low centrality index means less relevance in the system. Nodes are classified according to their input and output values (which are signed causal weights entering or leaving a node, respectively). Those nodes with only input values (i.e. arrows directed to them) can be viewed as the “outcomes” while nodes with only outputs values (i.e. arrows directed from them) may be viewed as the “drivers” or “stressors”. Nodes with both input and output values can be viewed as “mediating factors” playing both roles. The centrality index is calculated by summing the magnitude of the total input and output values in the system (Appendix A.3).

Simulating causal processes

This step is concerned with assessing the sensitivity of the assessment to the framing assumptions. It explores how the intervention "works" based on the framing assumptions made initially in the assessment. Causal processes are evaluated in the system matrix by means of a dynamic simulation between the nodes in the diagram. A "causal process" describes the mechanisms of the causal interactions in the nodes. Each node can have a "causal activity level" which measures their interactions. This causal activity is represented by values between 0 and 1 in the nodes. A node with value 0 denotes the node is fully "inactive" while a node showing a value 1 means that the node is fully "active" in terms of causal interactions. The nodes are propagated through the causal pathways in a dynamic simulation until the system reaches equilibrium. The state of the system at equilibrium depicts the key causal processes (or sources of variations) in the nodes once the interactions are taken into account (Appendix A.4).

Summary of procedures

For easy of illustration, Figure 4 shows the methodological approach and procedures in diagrammatic form and in mathematical matrix representation. The data are hypothetical. The initial phase of the FCM development consisted of developing individual causal diagrams for each study based on associations derived from the literature review (Fig 4.A). The natural logs of risk ratios (or percentage changes) were calculated to define the causal weights in each of the causal diagrams. Each causal diagram was then represented mathematically in a matrix (Fig 4.B). Matrices were combined into one augmented matrix (Fig4.C). The elements of the augmented matrix were then normalised between -1 and 1 to give the system matrix (Fig 4.E).The combined causal system is represented graphically (Fig 4.D) and in matrix form (Fig 4.E).

Results

The literature search generated 40 articles from which 12 articles had sufficient qualitative information to establish association between indoor environmental factors and health outcomes (Barton et al., 2007; Brugge et al., 2003; Chapman et al., 2009; Engvall et al., 2003; Gilbertson et al., 2006; Howden-Chapman et al., 2005a; Howden-Chapman et al., 2007; Howden-Chapman et al., 2005b; Jackson et al., 2011; Levy et al., 2003; Rudge, 1996; Vandentorren et al., 2006). Indoor factors linked to housing insulation that have been shown to have an effect on health, were grouped into two broad themes: indoor environmental exposures and built indoor environment.

Based on the retrieved literature, Table 3 gives a list of potential health-relevant factors associated with housing insulation for inclusion in the causal diagrams. Factors identified in connection with the indoor environmental exposures were indoor temperature (cold), air-tightness, indoor particles, dampness and mould. Factors identified in relation to the physical aspects of the built indoor environment were insulation fabric material, and mechanical ventilation systems. Among the health outcomes identified were winter mortality, mental health, depression, and respiratory conditions such as asthma and wheezing.

In general, the identified studies had different epidemiological designs and each study focused on various associations between different indoor factors and health. This required the assignment of a more generic classification of the indoor factors and health outcomes in the causal diagram. For example, health outcomes such as wheezing, throat irritation, bronchopneumonia, winter mortality and asthma were classified as: *Cardio-respiratory morbidity/mortality*. Health outcomes related to mental health and wellbeing (depression, thermal comfort, psychosocial wellbeing) were classified as: *Impaired mental wellbeing*.

Indoor factors representing several pollutants affecting indoor air quality such as PM2.5, nitrogen dioxide, carbon monoxide, volatile organic compounds (VOCs), radon and environmental tobacco smoke (ETS) were classified as: *Indoor air quality*. In addition, two indoor factors corresponding to the built indoor environment were considered: *Thermal insulation and mechanical ventilation* because they are important energy efficiency measures (Wilkinson et al., 2009b).

A total of 9 studies were identified to have quantitative information that could be used to assign measures of effects for the causal associations between indoor factors and outcomes (Braubach, 2007; Engvall et al., 2003; Fisk et al., 2007; Fisk et al., 2009; Hirsch et al., 2000; Howden-Chapman et al., 2007; Mendell, 2007; Smith et al., 2011; Wilkinson et al., 2009b). Table 4 gives the key health-relevant factors and their reported quantitative associations. Studies judged to represent the same (or equivalent) associations between an indoor factor and an outcome, were combined by summing the measures of effects. For example, effect sizes from factors that represented different types of pollutants such as: carbon monoxide, formaldehyde (VOCs), radon and environmental tobacco smoke (ETS) where combined by summing their effect sizes and the total effect assigned to the node *Indoor air quality*. This level of resolution was deemed appropriate to test the plausibility of the causal structure (framing assumptions). The overall measures of effects were determined as described in the procedure above (Appendix A.2).

Representation of the causal system

The review of the literature identified 10 key indoor factors or outcomes and 12 associations. Figure 5 shows the causal system displaying the causal pathways associating housing insulation and health, based on the evidence available from the literature review conducted. Table 5 gives a representation of the system matrix used to calculate the centrality index and to simulate causal processes.

Structural assumptions

The main indoor factors and health outcomes as identified by the centrality index were indoor *cold, cardio-respiratory morbidity / mortality* and *mould / humidity*, as shown in Table 6. High centrality values reflect high connectivity of the nodes in the system. A high centrality index can be interpreted as key structural assumptions made in the assessment. Centrality overall was low among most nodes, with 7 nodes having centrality index less than unity 1.0. Figure 6 shows graphically the centrality values.

Main causal processes and sources of variations

As described above, the purpose of the simulation is to determine the steady-state (equilibrium) level of the causal activity of the nodes (indoor factors and outcomes). The level of causal activity of the nodes denotes the sensitivity of the assessment to the framing assumptions. Main causal processes and sources of variations can be identified via the level of causal activity in the nodes at equilibrium. Based on the causal diagram shown in Figure 5, a casual simulation was carried out (Appendix A.4). Figure 7 shows the level of causal activity at equilibrium for each node.

Discussion

In this study, we presented a novel methodology to quantify the framing assumptions in a HIA conceptual model example of housing insulation. Framing assumptions represent a set of causal interpretations made about the system based on the evidence available in the literature. This study focused on the causal pathways associating housing insulation and health.

Indoor cold, mould, humidity and cardio-respiratory morbidity/mortality were found to be central to the framing assumptions. In addition by taking a threshold value of 0.5 (midpoint between the lowest and highest value of "causal activity"), the simulation recorded "high level of causal activity" (i.e. higher than 0.5) in the following nodes: cardio-respiratory morbidity / mortality, impaired mental wellbeing, mould / humidity, indoor air quality, ventilation and air-tightness. The threshold value of 0.5 was considered appropriate to test the sensitivity of the framing assumptions on the basis of how each factor ranked in relation to each other. Changes in the health outcome nodes (e.g. respiratory morbidity / mortality, impaired mental wellbeing) are naturally expected to be high because most pathways lead to them. What is more relevant, however, is the finding of the high level of causal activity in the nodes air-tightness, ventilation, indoor air quality, and mould/humidity. Given their high level of causal activity, these indoor factors were identified as being highly sensitive to the framing assumptions. This means that changes in these factors are particularly important because they influence health outcomes and, therefore, can cause health-related changes in relation to the intervention.

Any framing assumptions are likely to be incomplete because they are based on factors or outcomes obtained from a relatively restricted search of the published literature. In the case study example, social factors such as housing composition, socio-economic status, the behaviour of residents were not considered due to lack of quantitative information to assume causal relationships. A more comprehensive representation of the framing assumptions would require a broader range of studies to incorporate housing and social factors, health outcomes and their associations. In addition, we assumed that the included studies provided the same level of evidence and where comparable in terms of population intervention, study type and study quality since our emphasis was at the system level (Campbell et al., 2007; Joffe et al., 2012). For an extensive analysis on housing insulation and health, a systematic literature review will be required with quality assessment criteria prior to selecting the studies to be included in the FCM. Weights can be assigned based on the strength of evidence obtained from a systematic review. Causal weights can be specified in the FCM without affecting the mechanics of the method. Once quality criteria of each study are assessed, and weights are assigned, the result of a FCM can be used to inform the selection of the framing assumptions prior to conduction a comprehensive quantitative HIA.

It is worth noting that most HIAs seek to assess the health impacts of an intervention before a particular policy proposal is implemented. HIA comprises various stages such as: “screening”, “scoping” , “impact assessment” “policy modification and evaluation” (Parry and Stevens, 2001). Of particular interest is the “impact assessment” stage, where the health impacts of a proposal are identified, and causal pathways are constructed. Assessing the sensitivity of the framing assumptions in this stage of the assessment is important. The FCM approach can be applied to supplement this stage of the assessment.

Our approach can be applied to compare and identify differences between stakeholders. Explicit framing assumptions can be shared and compared by making a graphical representation which can be used for representing beliefs. Simulations can be used to determine the sensitivity of the framing assumptions and to test perceptions about how the intervention “works”(ÖZesmi and ÖZesmi, 2003). The FCM approach has some advantages over other methods used for conceptual or causal modelling, particularly in situations where input data is limited, and the elicitation of probabilities has proven to be difficult (Özesmi and Özesmi, 2004). Studies have been conducted in the past (in some participatory settings) by constructing Bayesian networks (BN) in a stakeholder workshop consultation. One of the major limitations for stakeholders of using BN is the elicitation of probabilities (Zorrilla et al., 2009). Bayesian networks also require specific software and cannot deal with feedbacks mechanism contrary to FCM. One potential limitation of FCM, however, over other methods is that it cannot deal with time delays explicitly when exploring the sensitivity of the framing assumptions. Time is implicitly addressed in the causal structure of the FCM.

We argue that it is necessary to quantify framing assumptions prior to conducting a comprehensive HIA. This study has highlighted the use of appropriate methods using FCM to with the framing assumptions. Decision makers should be aware that framing assumptions can have a significant impact in the outcome of the assessment. Our methodology depicts an objective method for quantifying causal assumptions at the system level. We believe that this method can handle many more complex causal pathways than that shown here.

Conclusion

This paper proposed a new method to quantify the framing assumptions in the initial stage of a health impact assessment of an environmental intervention. The method was illustrated using a housing intervention (insulation), as a case-study. The substantive findings of the approach hold promise in terms of applying it to other examples of environmental interventions. We argue that it is necessary to deal explicitly with the framing assumptions prior to conducting a full assessment of the health impacts of an environmental intervention.

Appendix - Supplementary Material

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