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SUPPLEMENT ARTICLE

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Understanding the dynamics emerging from the interplay among poor mental wellbeing, energy balance-related behaviors, and obesity prevalence in adolescents: A simulation-based study

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Summary

Both obesity and poor mental wellbeing have a high prevalence in European youth. Adolescents in six countries identified mental wellbeing factors as main drivers of youth obesity through systems mapping. This study sought to (1) explore the dynamics of the interplay between poor mental wellbeing, energy balance-related behaviors, and adolescent overweight and obesity prevalence and (2) test the effect of intervention point scenarios to reduce adolescent obesity. Drawing on the youth-generated systems maps and a literature synthesis, we built a simulation model that represents the links from major feedback pathways for poor mental wellbeing to changes in dietary, physical activity, and sleep behaviors. The model was calibrated using survey data from Norway, expert input, and literature and shows a good fit between simulated behavior and available statistical data. The simulations indicate that adolescent mental wellbeing is harmed by socio-cultural pressures and stressors, which trigger reinforcing feedback mechanisms related to emotional/binge eating, lack of motivation to engage in physical activity, and sleep difficulty. Targeting a combination of intervention points that support a 25% reduction of pressure on body image and psychosocial stress showed potentially favorable effects on mental wellbeing—doubling on average for boys and girls and decreasing obesity prevalence by over 4%.

KEYWORDS
adolescents, mental wellbeing, obesity prevention, system dynamics

Abbreviations: AdOWOB, Adolescent Overweight and Obesity; CLD, causal loop diagram; CO-CREATE, Confronting obesity: Co-creating policy with youth; EBRB, energy balance-related behaviors; HBSC, Health Behavior in School-Aged Children; MSE, mean squared error; PA, physical activity; PPOBI, perceived pressure on body image; PSS, psychosocial stress; SD, system dynamics; WHO, World Health Organization.

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1 | INTRODUCTION

Obesity is a complex public health problem with a high prevalence among adolescents in Europe.[1,2] One in seven adolescents aged 15 years lives with overweight or obesity,[3] and this number is anticipated to increase to one in five by 2025.[4] Previous studies have found that adolescents with excess weight are at a higher risk of developing depression and anxiety, as compared to adolescents with a normal weight.[5–10] Poor mental wellbeing, in turn, affects energy-balance-related behaviors (EBRB) that increase the risk of obesity such as disordered eating, lack of physical activity (PA), and sleep difficulty.[11,12] Mental wellbeing is a non-clinical measure of positive mental health that includes happiness, self-esteem, contentment, positive relationships, feeling competent as well as resilient in coping with life stressors, working productively, and contributing to the community.[13] It is also a fundamental component of the World Health Organization (WHO)'s definition of both health in general and mental health.[14–16] Determinants of mental wellbeing include not only individual attributes such as the ability to manage one's thoughts, emotions, behaviors, and interactions with others but also social, cultural, economic, political, and environmental factors such as national policies to ensure social protection, living standards, and community social support.[17,18]

This study is part of the project entitled "Confronting obesity: Co-creating policy with youth" (CO-CREATE), a European Commission funded research project that uses a complex systems perspective to identify, in collaboration with adolescents, factors that contribute to adolescent obesity, as well as potential solutions.[19] An initial CO-CREATE study engaged with young people in participatory qualitative systems mapping exercises in six countries (the Netherlands, Norway, Poland, Portugal, South Africa, and the United Kingdom) to identify the adolescents' views on the drivers of obesity.[20,21] An unanticipated result that emerged from this process was the much greater emphasis adolescents placed on the role of poor mental wellbeing as a driver of adolescent overweight and obesity (AdOWOB) compared to the priority it is normally given by academic experts. For example, mental wellbeing factors such as poor self-perceived body image, stress, and loneliness were identified as determinants of excessive dietary intake and reduced motivation to engage in PA. These mechanisms have been investigated further in two CO-CREATE systematic reviews that focus on adolescents and are presented as part of this journal supplement. Nwosu et al.[22] summarized the findings of longitudinal studies investigating the relationship between mental health and changes in body weight status in addition to the role of EBRB. The results provide additional evidence that poor mental wellbeing is related to both EBRB and obesity. Blanchard et al.[23] focused on the role of social media—another factor highlighted by the adolescents in the CO-CREATE systems mapping workshops—and its associations with mental health/wellbeing and diet. This review highlights the presence of relationships between social media use and body dissatisfaction, depressive symptoms, anxiety, and disordered eating symptoms as well as between body dissatisfaction and disordered eating.

Existing research on adolescent obesity, thus far, has mainly focused on the associations between individual mental wellbeing indicators and obesity prevalence in isolation.[8,24,25] There is a paucity of evidence about interconnecting pathways between mental wellbeing and obesity. Poor mental wellbeing and obesity present a complex set of challenges that are resistant to change.[26] While they are essential, most association-based statistical analyses do not consider dynamic changes[27] (i.e., factors that change over time) or represent delays and nonlinearities, which are crucial in understanding complex interactions such as those between poor mental wellbeing, AdOWOB prevalence, and potential intervention options. In addition, intangible variables such as happiness, motivation, and satisfaction are hard to quantify since they are often subject to multiple influences[28–30] and are not amenable to unambiguous objective measurement, yet they often yield important insight into the dynamics of a system. All complex adaptive systems have intangible components, and these will often play important roles in the dynamics emerging from the system, so they should not be ignored simply because they are more difficult to formalize. These variables and their relationships have been conceptualized and analyzed with different tools and methods.[9,31–33] However, the mechanistic relationships between variables, particularly intangible ones, have not been often translated into mathematical equations and tested under a variety of scenarios using simulation.

According to prior systems science research in obesity prevention and public health, the complex feedback mechanisms among the drivers of poor mental wellbeing call for methods that can both represent multiple interactions and synthesize existing evidence in a systems perspective.[34–37] System dynamics (SD) modeling is an approach that is well suited for studying poor mental wellbeing and obesity among adolescents, as it can explicitly capture multiple feedback mechanisms, latent variables, and accumulations that are relevant for understanding trajectories of complex problems.[38,39] Furthermore, SD models can provide useful insights for intervention points, a set of key coordinated strategies that shift the system to generate long-term improvement.[40] Therefore, this study seeks to further investigate the pathways identified by adolescents in the CO-CREATE project and across the empirical evidence applying SD diagramming and simulation techniques. For this purpose, we developed a SD simulation model[41] to address the following research questions:

1. What are the effects of poor mental wellbeing on dietary, PA, and sleep behaviors that contribute to AdOWOB prevalence?

2. What are the effects of potential mental wellbeing intervention points in the system on the prevention and mitigation of current obesity trends?

2 | METHODS

2.1 | The SD modeling approach

SD modeling has been increasingly employed in public health[42] and specifically in obesity prevention research, policy, and practice.[43–47] The development of a SD model is an iterative process that typically involves the following steps.[41,48] First, a problem is defined in terms of behavior over time of main performance indicators (e.g., obesity prevalence). Second, a conceptual model representing the dynamic hypothesis about the causes of the problem is developed. This step involves multiple data collection methods such as literature review, expert consultation, and systems mapping. Third, the conceptual model is formalized by specifying equations and estimating parameter values. Fourth, the model is tested and validated until it is considered robust and reliable against the purpose of the model. Finally, the model is used to identify intervention points and assess their impact through scenarios and policies. Figure 1 shows the process we followed to build the SD model and the diverse data sources used to formalize it.

2.2 | Model structure

The starting point in building the conceptual model was the mechanisms represented in the systems map generated by young people in the CO-CREATE project.[20,21] This system map includes concepts identified by the participants and represented as variables and relationships.[20] For instance, pressure to maintain a specific body image was identified by participants to be related negatively to self-esteem so that the higher the pressure on body image, the lower the self-esteem. These and other various factors and relationships formed feedback loops. The conceptual model represents the dynamic hypothesis about the drivers of rising obesity and declining mental wellbeing in the form of a hybrid causal loop diagram (CLD)[49] that explicitly shows variables that represent states (also called stock or level), a variable that accumulates or depletes over time, and rates (also called flow) of change in a stock, in addition to feedback loops, circular paths of causal influences, and action.[41,50] There are two types of feedback loops: reinforcing, which cause growth or decline to occur at an ever-increasing rate when an action produces a result that affects more of the same action, and balancing, which creates resistance, eventually limits growth, and achieves equilibrium.[51]

We then examined the evidence in peer-reviewed literature that supported or refuted the hypothesized factors and links suggested by adolescents, following a similar procedure as in a previous studies.[52,53] The next iteration of the model resulted in a refined diagram using terminology found in the scientific literature and corresponding articles that supported each link. For instance, the factor "stress" proposed by adolescents was specified as "psychosocial stress" as the literature suggests.[54–56] Then, the hypothesized causal mechanisms were prioritized to align their inclusion or exclusion and level of detail with the breadth and scope of the model.

2.3 | Model formalization

The model was constructed in Stella Architect software version 3.3.0[57] using Euler Integration with a time-step of 1/8 of a year. The model simulates over a time horizon from 2002–2050 with parameters and equations calibrated to historical data (2002–2019).[58] The

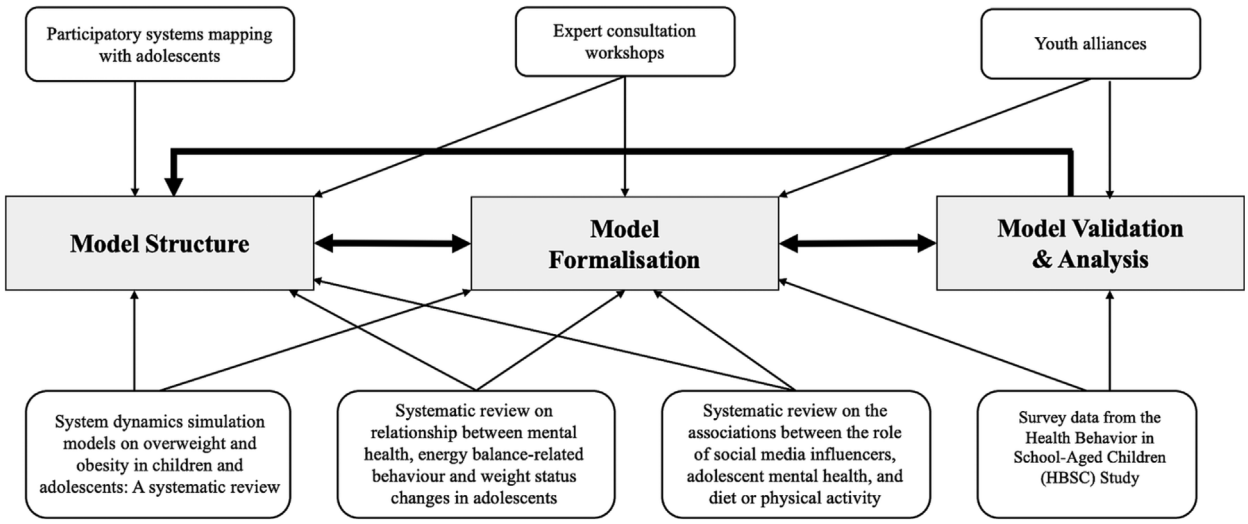

FIGURE 1 Steps and data sources used during the system dynamics model-building process to develop the simulation model on mental wellbeing and youth obesity.

model is disaggregated by two dimensions for gender (male and female) and three dimensions for age groups (11-, 13-, and 15-year-olds adolescents). This model is a sub-model of a larger SD model within the CO-CREATE project, which contains four sub-models: *Population Weight Change Dynamics*, *Food Environment*, *Physical Activity Environment*, and *Mental Wellbeing*. These sub-models capture the complex interdependencies between the population's weight change dynamics and the other sub-models and their variables. The description of the integrated simulation model is presented elsewhere.

The formalization step translates the conceptual model into a simulation model by specifying equations and estimating parameter values. For quantification of the mental wellbeing variables, we used the Norwegian datasets from the Health Behavior in School-aged Children (HBSC) study. HBSC is conducted every 4 years in over 40 countries on 11-, 13-, and 15-year-olds' health behaviors, social environment, perceived health, and mental wellbeing and includes self-reported height and weight.[59] The HBSC variables used in the model were feel nervous, feel low, school pressure, feel fat, computer overuse, bullying, sleep difficulty, and exercise (Norwegian HBSC datasets from 2001/2002; 2005/2006; 2009/2010; 2013/2014; and 2017/2018). Detailed information on data sources of the model's parameters and initial values is shown in Table S6.

Wherever available, model parameters and nonlinear functions were formulated based on evidence available in the literature, and/or we used proxies from the HBSC study. For example, "psychosocial stress" was formulated by normalizing the average value of the responses to the questions "In the last six months, how often have you had the following … feeling nervous?" and "How pressured do you feel by the schoolwork you have to do?" from the survey.[59] Average values from the HBSC study variables related to mental wellbeing were used as scaling factors to formulate the nonlinear relationships between variables in the model. Another formulation example was "motivation to do PA"; a study found that motivation is positively associated with the PA level,[60] while another study found that depression is associated with lower levels of PA and body image dissatisfaction.[61] After discussing these associations with experts, the effect of motivation to do PA function was captured by a nonlinear function determined by mental wellbeing, which positively influences the PA level.

2.4 | Model validation and sensitivity analysis

A series of consultation workshops with experts were held during the Spring of 2021 to obtain expert input on both the conceptual and formalized models. The workshops were co-facilitated by SD modeling experts (AA and ER) applying guidelines and frameworks for conducting group model building workshops using SD.[62–65] The conceptual model for the mental wellbeing sub-model was validated in the first workshop by adolescent obesity researchers. They verified the model structure and identified data sources for its subsequent formalization. Afterwards, another workshop was dedicated to validating the formalized mental wellbeing sub-model, during which a group of diverse subject-matter researchers with expertise in mental health and obesity research, critiqued the assumptions and structures of the model, provided input to estimate parameter values in instances when no data were available, and suggested additional literature. This workshop was beneficial in guiding further model iterations and refinement.

To build confidence in the simulation results, we followed the SD model validation procedures.[41,66,67] The structural validity of the model was established by the systems mapping workshops, the three rounds of expert consultation workshops, and literature reviews. To ensure the robustness of model structure and individual equations, we performed direct- and indirect-extreme conditions tests. To explore the uncertainty space and further validate model behavior associated with poor mental wellbeing and AdOWOB prevalence, we conducted sensitivity analyses for all uncertain parameters in the model. We systematically changed the main model assumptions and assessed their impact on model behavior and long-term patterns of the simulated outcomes (i.e., mental wellbeing and AdOWOB prevalence). Tailored parameter variation experiments were carried out, in which the key parameters governing the main outcome indicators were varied. We changed the value of the parameters by ±25% ranges and established a minimum and maximum values, with the medium value as the baseline. We ran the model 1,000 times for each parameter.

2.5 | Model analysis and calibration

The simulations included a baseline scenario that provided the business-as-usual performance of the main outcome indicators: AdOWOB prevalence, stated as a percentage, and mental wellbeing, given as a scale from 0 to 1, with 0 being the lowest and 1 the highest mental wellbeing. All the simulations in the baseline scenario assumed that the exogenous factors (i.e., external factors influencing the system) remained constant after 2019 at their 2019 values. Then, we provided an endogenous explanation of the simulation runs in terms of the feedback loops guiding the observed behavior. Finally, we tested two intervention points in the model that were identified as intervention entries after conducting sensitivity analyses, namely, perceived pressure on body image and psychosocial stress. These selected intervention points are consistent with the youth's input during the systems mapping sessions.[20,21] We then reported on the simulation results and further explanations of the observed changes over time. We explored three hypothetical scenarios: (1) reducing perceived pressure on body image, (2) reducing psychosocial stress, and (3) the combination of Scenarios 1 and 2. Intervention point scenarios were simulated starting from the year 2023 in increments of 15% and 25% of the intervention point strength.

In line with the purpose of the study and acknowledging the limitations of the quantitative data that inform our model, our focus was on understanding the qualitative changes in the model's behavior rather than obtaining precise numerical values from the simulations. However, we used the mean squared error (MSE) measurement and inequality statistics to evaluate the historical fit of the model[68] and conducted partial model calibration/testing for estimation of

parameters, in which we simulated the behavior of a functional model component, in response to empirical input data for comparison with empirical output data.[69,70]

3 | RESULTS

3.1 | Model structure

Figure 2 presents the simplified representation of the final model structure. It contains four key components involved in the poor mental wellbeing pathways leading to body weight changes: mental wellbeing, perceived pressure on body image, psychosocial stress, and sleep quality. The core model structures are shown in Table 1; it describes multiple interacting reinforcing feedback loops that involve emotional/binge eating (R1ab), lack of motivation to do PA (R2), and sleep difficulty (R3), as well as two balancing feedback loops associated with dietary restraint (B1) and loss of appetite (B2). As an example, R1a can be read as follows: gaining weight adds to the feeling of dissatisfaction with one's body image and the perceived pressure to meet societal ideals of body shape. This pressure further contributes to a decreased self-esteem, ultimately impacting mental wellbeing in a negative way. Consequently, individuals may engage in emotional or binge eating as a response of a poor mental wellbeing, leading to further increases in calorie intake and subsequent weight gain (see Figure 3 for this example feedback loop). The letter R denotes a reinforcing feedback loop, and B denotes a balancing feedback loop. Positive signs on arrows denote a positive link where a change in the influencing element is in the same direction as the influenced element (i.e., they increase or decrease together). Negative signs on arrows denote a negative link where a change in the influencing element is in the opposite direction as the influence element (i.e., one goes up, the other goes down, and vice versa).

3.1.1 | Feedback loops

Table 1 presents the full description of all the feedback loops illustrated in the diagram shown in Figure 2. All loops explained in Table 1 start with the discrepancy between actual and ideal body weight, which is influenced by societal norms on the ideal body weight and may lead to self-stigmatization about one's body image.

3.2 | Model analysis

The baseline run was initialized such that there is a gap between actual body weight and the social norm for an ideal body weight.

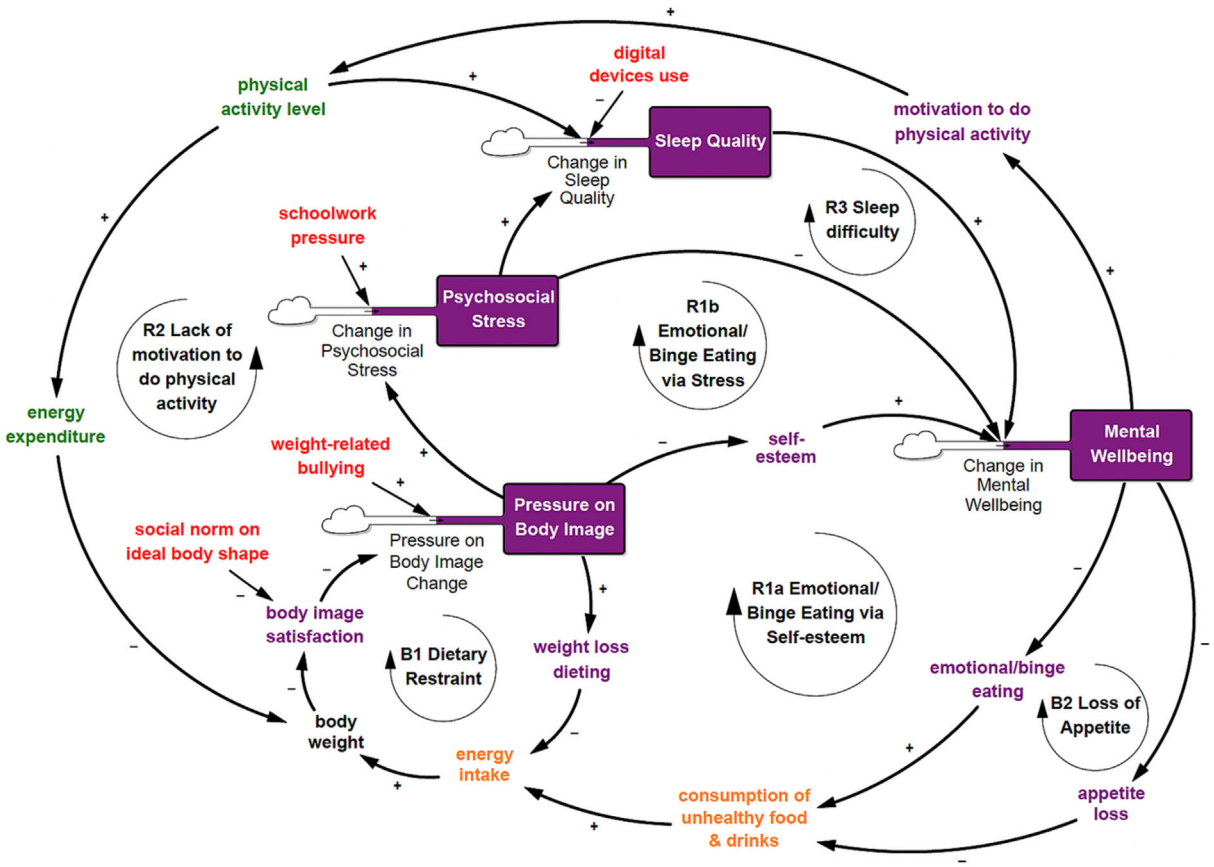

FIGURE 2 Model structure diagram showing the mental wellbeing pathways leading to Adolescent Overweight and Obesity (AdOWOB) prevalence. Red, change levers; green, physical activity; orange, energy intake; purple, mental wellbeing.

TABLE 1 Feedback loops description of the model structure diagram.

Feedback loop	Pathway	Description	Sources
Emotional/Binge eating loop via Self-Esteem (R1a)	Body weight → Body image satisfaction → Pressure on body image → Self-esteem → Mental wellbeing → Emotional/Binge eating → Consumption of unhealthy food & drinks → Energy intake → Body weight	Body weight gain adds to body image dissatisfaction and perceived pressure on body image which can be intensified by social norms on ideal body shape and weight-related bullying respectively. This pressure then contributes to a lower self-esteem resulting in poor mental wellbeing, which could lead to emotional/binge eating behavior. This behavior increases energy intake and subsequent weight gain.	Refs[61,71–88]
Emotional/Binge eating loop via Psychosocial stress (R1b)	Body weight → Body image satisfaction → Pressure on body image → Psychosocial stress → Mental wellbeing → Emotional/Binge eating → Consumption of unhealthy food & drinks → Energy intake → Body weight	Body weight gain contributes to body image dissatisfaction and perceived pressure on body image which can be exacerbated by social norms on ideal body shape and weight-related bullying respectively. This pressure then contributes to an increment in psychosocial stress, which is composed of external stressors such as schoolwork contributing to poorer mental wellbeing. In turn, this can encourage emotional/binge eating behavior, which lead to increased energy intake and body weight.	Refs[9,61,71–74,76,78–90]
Dietary restraint loop (B1):	Body weight → Body image satisfaction → Pressure on body image → Weight loss dieting → Energy intake → Body weight	The pressure on body image can be triggered by celebrities and influencers on social media. This can decrease body image satisfaction and encourage adolescents to follow weight loss diets, which leads to a decrease in calorie intake and a weight loss in a short-term basis.	Refs[61,72–74,77,80,81,83,84,86,88,90]
Loss of appetite loop (B2):	Body weight → Body image satisfaction → Pressure on body image → Psychosocial stress/Self-esteem → Mental wellbeing → Losing appetite → Consumption of unhealthy food & drinks → Energy intake → Body weight	Similar to R1, the pressure on body image increases psychosocial stress and lowers self-esteem impacting mental wellbeing negatively. However, contrary to R1, in some adolescents, this leads to a lack of appetite and decreased calorie intake, and thus a lower body weight.	Refs[61,72–74,76,77,79–90]
Lack of motivation to do physical activity (PA) loop (R2):	Body weight → Body image satisfaction → Pressure on body image → Psychosocial stress → Mental wellbeing → Motivation to do PA → PA level → Energy expenditure → Body weight	As pressure on body image increases, psychosocial stress increases as well, which reduces motivation to do physical activity. The lower the motivation, the lower the physical activity engagement and level are. Lower physical activity implies that less energy will be expended, therefore, producing a positive energy balance and higher body weight.	Refs[54,60,61,72–74,79,81,85–88,90–99]
Sleep difficulty loop (R3):	Body weight → Body image satisfaction → Pressure on body image → Psychosocial stress →	As the perceived pressure on body image increases, psychosocial stress increases as well, which	Refs[31,54,61,72–74,77–81,87–89,94,96,98,100,101]

TABLE 1 (Continued)

Feedback loop	Pathway	Description	Sources
	Sleep quality → Mental wellbeing → Emotional eating/Loss of appetite → Consumption of unhealthy food & drinks → Energy intake → Body weight	reduces sleep quality. The lower the quality of sleep, the lower the mental wellbeing. Poor mental wellbeing leads to unhealthy eating behaviors, either stress eating or loss of appetite, which intensifies body image dissatisfaction and increases pressure on body image further.	

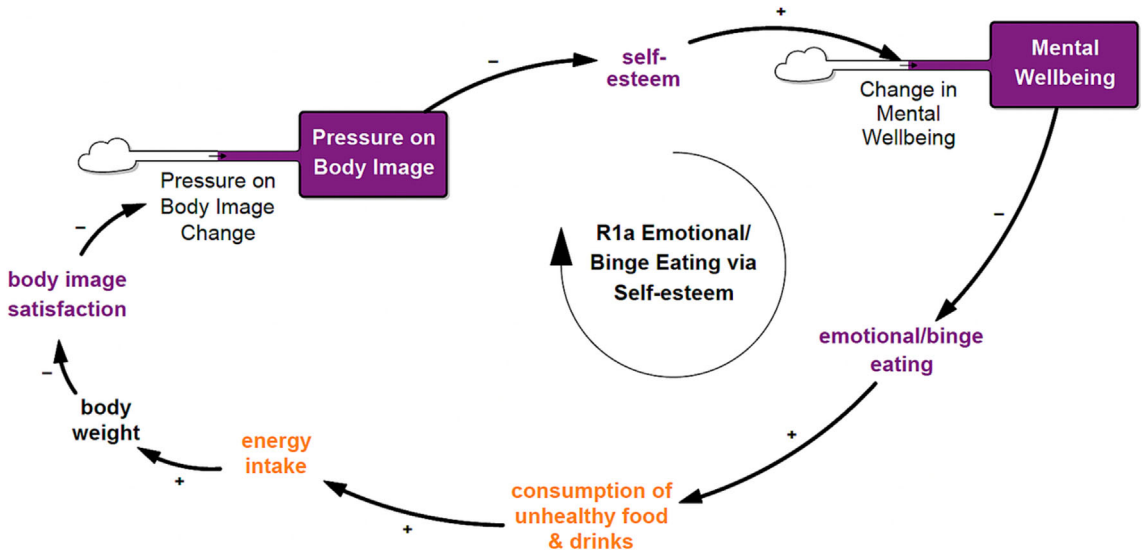

FIGURE 3 "Emotional/binge eating via self-esteem" feedback loop (R1a).

Figure 4A,B shows the main outcome indicator graphs with the trend over time for mental wellbeing and AdOWOB prevalence with its initial values and without testing intervention points. Details on sensitivity procedures and results and extreme conditions tests can be found in Tables S2–S5 and Figures S2 and S3. We present here the simulation results for 15-year-old boys and girls. The complete model documentation is provided in the supporting information (Table S1 and Figure S1: details on calibration results; Table S6: sources of parameter values; Table S7: model equations and documentation).

The simulations in Figure 4 panel graphs show the core dynamics of the model resulting from the baseline parameter values for poor mental wellbeing for both genders and AdOWOB prevalence trajectories. Although mental wellbeing for boys is higher at the start of the simulation, it then decreases over time; meanwhile, girls start with lower mental wellbeing than boys, as they are more sensitive to social norms influence related to body image. Both girls' and boys' mental wellbeing continues to decrease to the end of the simulation, which is roughly consistent with the adolescents' views and the quantitative evidence in HBSC.[59] In terms of AdOWOB prevalence, the combined AdOWOB prevalence for both genders shows a steady increase throughout the time horizon, consistent with historical trends[58,102] and future projections through other modeling methods[103] for Norway.

The simulated behavior for mental wellbeing and AdOWOB prevalence is a result of interactions of major feedback loops involving not only the elements affecting mental wellbeing variables and pathways shown in Figure 2 but also elements operating on the broader social environment involving broader elements of food, built, and social environments. Low-nutritional value foods have a large share of the market and are readily available, palatable, and accessible.[104] In addition, supply of and exposure to built environments for PA are not sufficient to make up for this imbalance in the food environment. These feedback loops interact with mental wellbeing mechanisms. For example, when mental wellbeing is low, emotional eating increases food intake, particularly, of the more accessible low-nutritional value food, leading to further weight gain, whereas, as mental wellbeing declines, motivation to engage in physical exercise also does so, thus contributing to lower demand for PA infrastructure at the social level resulting in weight gain at the individual level. Importantly, weight gain caused by reinforcing feedback loops and constraining elements in the social environment has a negative influence on mental

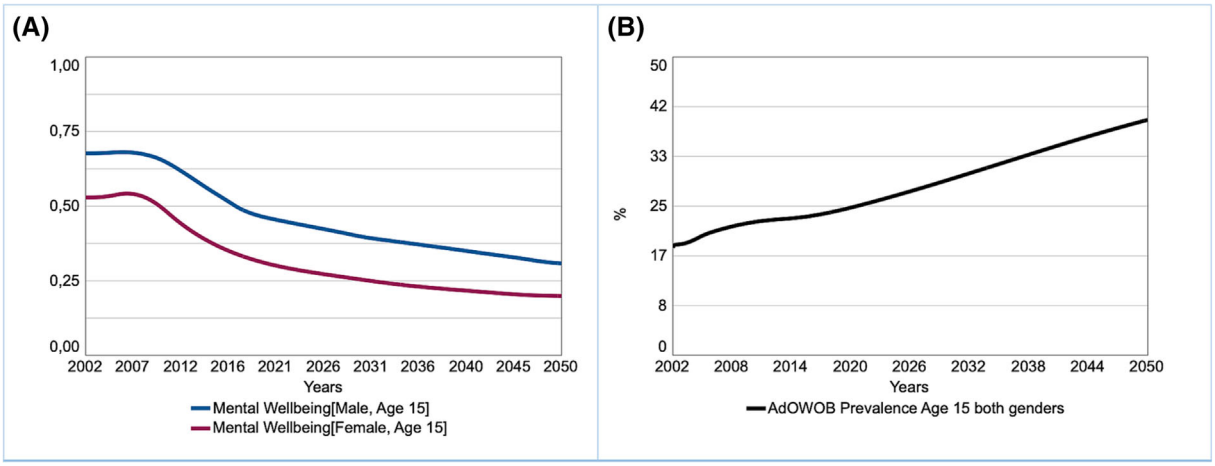

FIGURE 4 Baseline trajectories of outcome variables: mental wellbeing and Adolescent Overweight and Obesity (AdOWOB) prevalence.

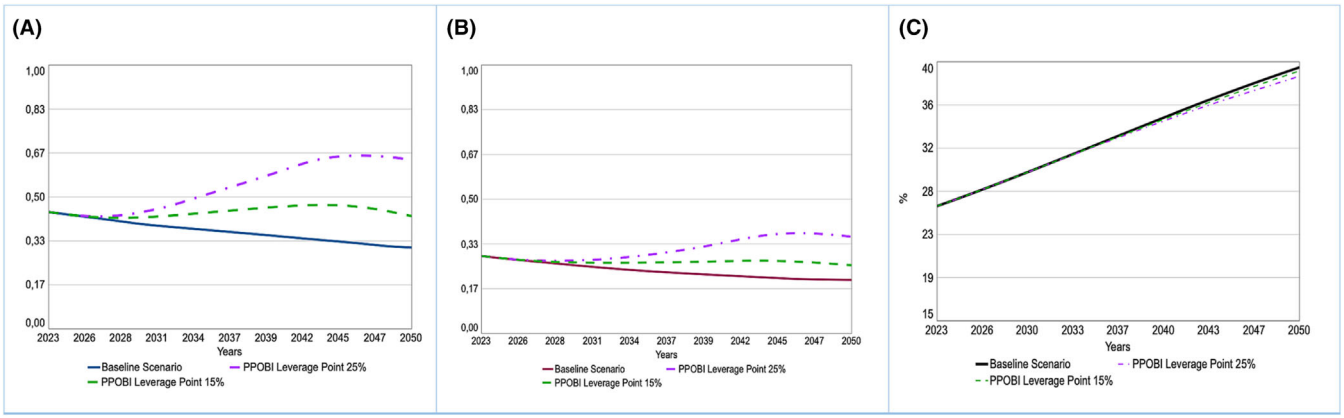

FIGURE 5 Scenario 1: effect of reducing pressure on body image on mental wellbeing and Adolescent Overweight and Obesity (AdOWOB) prevalence.

wellbeing. This creates a vicious cycle that traps individuals in a pattern of worsening mental wellbeing and increasing AdOWOB prevalence.

3.3 | Scenario analysis of intervention points

3.3.1 | Scenario 1: Reducing perceived pressure on body image

In this scenario, both boys' and girls' trajectories of mental wellbeing increase as the strength of the intervention point multiplier increments of 15% and 25% (see Figure 5A,B) and keeps constant until the end of the simulation. Girls' mental wellbeing starts from a lower level than boys in the beginning of the simulation, which is consistent with prior research related to the higher influence of a weight-related social norm on weight perception in girls more than in boys.[105] The intervention point multiplier reduces the perceived pressure on body image (PPOBI) that is influenced by a social norm of supposedly "ideal" body weight and by weight-related bullying. This effect propagates throughout the reinforcing feedback loops related to emotional/binge eating, dietary restraint, appetite loss, sleep difficulty, and lack of motivation to do PA. As observed in Table 2, all factors influencing mental wellbeing improve for both genders when PPOBI is reduced in 15% and 25%. Additionally, there is an overall decrease of 0.85% and 2.16% in AdOWOB prevalence at the end of the simulation with 15% and 25% increments in the intervention point multiplier, although AdOWOB prevalence is still increasing throughout the time horizon as shown in Figure 5C. This indicates that interventions that only reducing PPOBI, for example, by changing social norms on ideal weight or managing bullying, are promising but not sufficient to change the direction of the trend of AdOWOB.

3.3.2 | Scenario 2: Reducing psychosocial stress

Similar to Scenario 1, the trajectories of mental wellbeing for boys and girls increase as the strength of the intervention point multiplier increases in 15% and 25% (see Figure 6A,B). As illustrated in Table 2, changes in the intervention point multiplier reduce psychosocial stress

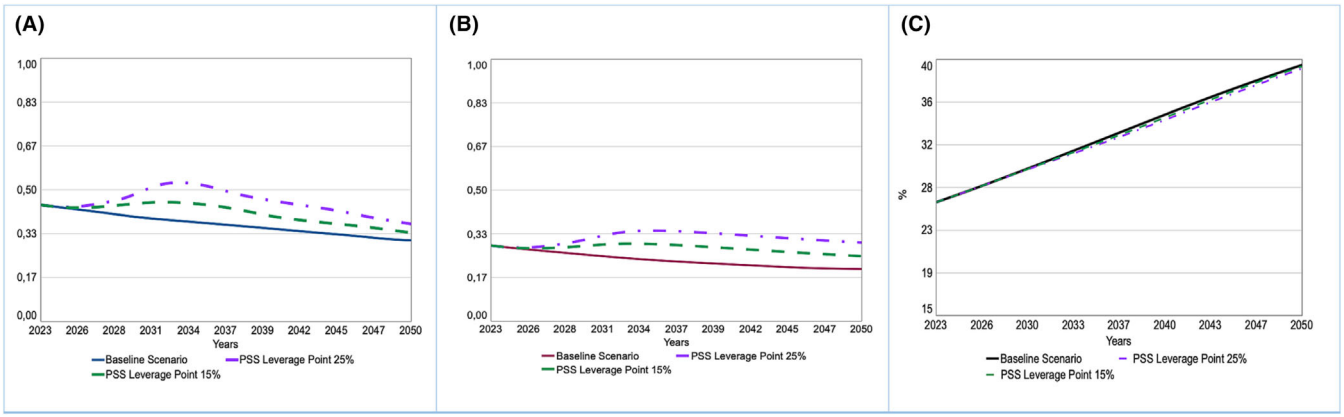

FIGURE 6 Scenario 2: effect of reducing psychosocial stress on mental wellbeing and Adolescent Overweight and Obesity (AdOWOB) prevalence.

TABLE 2 Summary of the changes in the simulation results of the outcome variables under three different scenario.

		Outcome variables		
		AdOWOB prevalence	Mental wellbeing, male	Mental wellbeing, female
Intervention point scenarios	Baseline scenario	39.46	0.31	0.2
	PPOBI—15%	39.12	0.43	0.25
	Change (%)	0.85%	38.71%	25%
	PPOBI—25%	38.61	0.64	0.36
	Change (%)	2.16%	106.45%	80%
	PSS—15%	39.32	0.34	0.25
	Change (%)	0.36%	9.68%	25%
	PSS—25%	39.11	0.37	0.3
	Change (%)	0.89%	19.35%	50%
	PPOBI & PSS—15%	38.78	0.56	0.32
	Change (%)	1.73%	80.65%	60%
	PPOBI & PSS—25%	37.83	0.85	0.65
	Change (%)	4.14%	174.19%	225%

(PSS), and even though mental wellbeing trajectories improve for both genders, we observe that they decrease again after some time. This intervention point is affecting the reinforcing feedback loops related to emotional/binge eating, appetite loss, sleep difficulty, and lack of motivation to do PA. The AdOWOB prevalence is reduced in 0.36% and 0.89% at the end of the simulation as the PSS intervention point multiplier strength changes in 15% and 25% increments, but it is still increasing over time as shown in Figure 6C.

3.3.3 | Scenario 3: Reducing perceived pressure on body image and psychosocial stress

This scenario simulates both intervention points per increment in the multiplier strength. As shown in Figure 7A,B, mental wellbeing improves by about double for both genders, while AdOWOB prevalence continues to increase at the end of the simulation although lower than the baseline as illustrated in Figure 7C and Table 2. Girls' response to a decrease in PPOBI and PSS generates a lesser increase in mental wellbeing than boys, illustrating how difficult it is for girls to improve their mental wellbeing based on the model's initial conditions (see Figure 7B). Also, in Figure 7C, we observe that with 25% for both intervention point strength, there is a visible reduction in AdOWOB prevalence of over 4% although not enough to curb the trend or lower it substantially. Table 2 presents a summary of the changes in the simulation results in this scenario.

4 | DISCUSSION

In this study, we developed an exploratory simulation model of the effects of mental wellbeing factors and feedback pathways

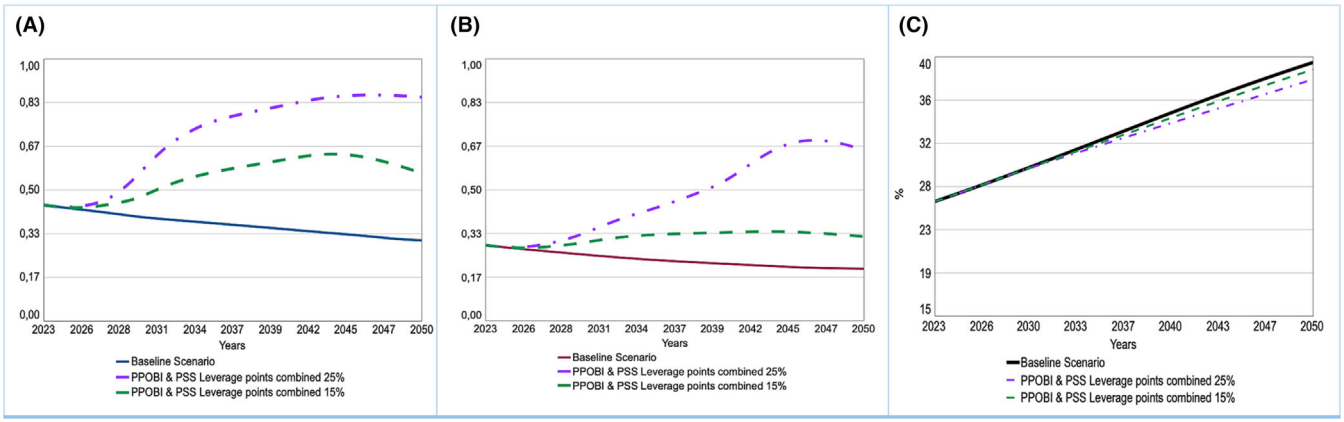

FIGURE 7 Scenario 3: effect of reducing psychosocial stress and perceived pressure on body image on mental wellbeing and Adolescent Overweight and Obesity (AdOWOB) prevalence.

contributing to AdOWOB—as initially identified by adolescents in the CO-CREATE system mapping workshops—and tested potential intervention points for their mitigation.

The results indicate that the pathways related to poor mental wellbeing factors and relationships identified by adolescents in the CO-CREATE project could play an important role in increasing obesity. Our modeling efforts have been focused on endogenous reinforcing loops that potentially explain the impact of poor mental wellbeing on consequent AdOWOB. Those formalized feedback loops represent mostly vicious cycles that worsen mental wellbeing and generate behaviors that increase the risk of obesity. Also, our findings show that a drastic contribution to unhealthy dietary and PA behaviors can be exacerbated by social norms related to body image.[106] The latter are influenced by cultural norms,[107] for example, unhealthy influencers in social media, which lead to dissatisfaction and self-stigmatization about one's body shape. These findings are echoed in the systematic review by Blanchard et al.,[23] which highlights positive associations between the use of social media and body image dissatisfaction or distortion, depressive symptoms, anxiety, and disordered eating behaviors, including weight-loss/control and binge eating, as well as the potential influence of social beauty standards on body image. In turn, body image dissatisfaction was positively correlated with disordered eating behaviors. Other significant contributions triggering poor mental wellbeing loops include weight-related bullying, schoolwork pressure, and digital device use. The model simulations showed high sensitivity to uncertain parameters related to social norms on body image and ideal body weight. This indicates that there is uncertainty in the model, and there is a need of future research to improve the model assumptions and formulations. Nonetheless, this research can be utilized to prioritize future modeling efforts.

The scenario simulations showed promising results in terms of improving mental wellbeing and reducing AdOWOB. However, even in the third scenario, which combines both intervention points with 25% intervention point strength, there is no visible reduction in AdOWOB prevalence. A possible reason for this is that we are only testing intervention points in the mental wellbeing sub-model within the larger simulation model while keeping the food and PA environment sub-models unchanged and without intervention points in them. Also, the intervention points identified and tested in this study, namely, reducing perceived pressure on body image and reducing psychosocial stress, imply changing socio-cultural factors such as social norms on body image. Even if potentially more impactful, these might be more difficult to achieve since they call for a societal-level paradigm shift. According to Meadows,[108] changing paradigms is the hardest but most effective intervention level to target, requiring long-term action, sufficient resources, and political engagement to accomplish. While efforts should include achieving such systems changes, they should be complemented with strategies producing more immediate outcomes, for example, supporting psychosocial therapy or community-led activities to cope with stress and deal with negative body image.

This study contributes to the literature in several ways. First, our major contribution lies in capturing untested complex pathways in a dynamic model and their interactions and combined impact on mental wellbeing and AdOWOB. Prior studies have not modeled the endogenous relationship between mental wellbeing and AdOWOB prevalence and do not often elucidate causal drivers, their intersections, or numerical cues to formalize them. Instead, they largely remain limited to investigating bidirectional relationship between drivers separately rather than investigating pathways more deeply.[22] Second, this modeling work reflects the interrelationships between the individual level factors and behaviors and the societal impacts,[109] which is consistent with research on socioecological models.[110,111] Lastly, our findings support previous research showing that focusing on single interventions and disregarding other parts of the system do not offer a meaningful reduction of AdOWOB.[27] Instead, to be substantially effective, preventive strategies must engage multiple intervention points in combination, taking into account the impact in other areas of the system in order to prevent and reduce AdOWOB.[35,112,113] In this work, we focused our modeling efforts on representing and quantifying intangible variables that are mostly present in the mental wellbeing model such as stress, perception of body weight, self-esteem, and mental wellbeing. Our model's causal structure is parameterized to be qualitatively consistent

with the magnitudes of variables and patterns that were hypothesized by adolescents, expert input, and supported by the literature. Intangible variables were quantified and incorporated into the simulation model allowing to observe the effect of the main feedback mechanisms acting in the system. Little prior research captures this level of aggregation and complexity that simulate feedback pathways linking poor mental wellbeing to AdOWOB, particularly in relation to intangible variables[114–116] in obesity research; therefore, our study may serve as a step towards future work on developing population-level models that tackle this issue.

5 | STUDY LIMITATIONS AND FUTURE WORK

Interpreting the results of this work requires consideration of some methodological aspects. Even though this model considers the behavioral and population dynamics that influence AdOWOB, system models with this level of aggregation cannot fully incorporate all complex mechanisms and trajectories that influence people's individual decisions about their diet and PA. The complex nature of the model, the paucity of information on the relationships between mental wellbeing and AdOWOB, and limited quantifiable data in the form of time series prevent us from producing precise numerical estimates. Yet the model shows the complexity of population-level AdOWOB prevalence incorporating mental wellbeing factors and feedback processes. Moreover, our approach broadly examined those areas within the system where interventions could be introduced to alleviate the problem, rather than focusing on specific interventions or considering their economic impacts. The model thus provides strategic guidance about high-leverage intervention points, while implementation of specific interventions and policies requires more detailed actions.

Our model was informed by existing literature about the relevance of mental wellbeing for AdOWOB and pathways that the youth had suggested earlier in the project. It therefore partially absorbs deficits in the current knowledge of mental wellbeing processes in adolescents, which could have compromised the model's ability to accurately reproduce the system behavior against data. Nevertheless, we ensured that the patterns of behavior produced by the model coincided with existing trajectories of the main outcome indicators. In other words, the model can produce qualitatively indicative results. A particular challenge of this study consisted in the quantification of the many variables including to mental wellbeing and related factors, which pose significant demands on their quantification. Despite the relatively limited availability of data on psychological variables, we attempted to mitigate this issue by supplementing the formulations of those variables with adolescents' perspectives, relevant literature, and experts' knowledge to validate the structure of the model. In order to quantify many of the model's intangible variables, we used proxies and relied on self-reported questionnaires, which may be susceptible to bias. However, self-report methods have remained the most common psychological measures and research using secondary data often rely on them. Our sensitivity analysis and model testing, which involved comparing AdOWOB rates to a simulated baseline scenario and intervention point scenarios, helped us confirm that many of these intangible variables are realistic representations of real-world conditions.

Although applicable to AdOWOB in general, this model is calibrated using expert knowledge and Norwegian data, as data about Norway were readily accessible during the model construction process. The results might vary in other national contexts. Likewise, social inequalities, geographical variations between countries, and cultural differences were not modeled, as this was beyond the scope of the current work. Furthermore, the questions that were available in the HBSC dataset linked to mental wellbeing and obesity constrained our research. We were restricted solely to using the variables that were addressed throughout all five survey periods. More data points would have helped with our model's parameter estimation and validation, improved the robustness of relationships among different factors, and allowed testing of the model's trajectories using historical time-series data. Further enhancement of the model, subject to available data, would allow for such more fine-grained analyses. Yet the model already provides a robust basis from which testing intervention points is possible.

Future research should focus on using simulation modeling to assist with the development of interventions in country-specific settings and for specific population groups. Based on our findings, these interventions should aim to (1) improve body image and reduce the associated pressures—such as weight-related bullying—by normalizing different body types and challenging unrealistic norms around appearance and weight status in adolescents.[117–119] This could, for example, include work with industry bodies to change the imagery used in advertising and marketing campaigns.[120] Poor body image is known to affect self-esteem, mental health, and overall wellbeing. Therefore, interventions should also aim to (2) offer psychosocial support to young people relating to body image, stress, and self-esteem, for instance in educational, healthcare, and community settings,[121] as well as addressing stigmatizing behaviors of those who interact with young people and provide them services, such as in healthcare settings.[122] Lastly, the impact of social media on body image and mental health deserves further research attention,[123] and policies should be implemented to regulate harmful content.

6 | CONCLUSIONS

This study highlights the key role of mental wellbeing in obesity prevalence that was suggested by in the systems map developed by youth from the CO-CREATE project. Our SD model represents the adolescent population's response to both endogenous and exogenous psychosocial stressors impacting mental wellbeing and consequently adolescent obesity. Our simulation results reveal that reinforcing loops involving perceived pressure on body image and psychosocial stress aggravate the negative energy-balance related behaviors that contribute to obesity prevalence such as emotional/binge eating, lack of motivation to do PA, and sleep difficulty. Likewise, our findings

suggest two priorities to act on, namely, reducing pressure on body image and reducing psychosocial stress and take into account their effects on other parts of the system.

This work shows that SD modeling is a useful methodology to support better understanding of the feedback effects of mental well-being mechanisms on the prevalence of AdOWOB and for exploring the most highly influential points for intervention for sustained system change. Our simulation model can also be used for stakeholder engagement and enable important discussions among decision-makers for understanding obesity as a complex problem and for developing effective strategies for its prevention.

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CONFLICT OF INTEREST STATEMENT

All authors declare no conflict of interest.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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