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Evaluating the Impact of Community Interventions on Childhood Obesity in Populations living in Low-income Households in Los Angeles: A Simulation Study

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Contributors: RAN contributed to the problem definition, conducted the data analysis and wrote the first draft. MM wrote the introduction, searched for the parameters and contributed to the analysis and interpretation of the results. BK and KK implemented the simulation model in the AnyLogic Software and NO supervised the implementation of the simulation model. CC provided statistical expertise, analysis and interpretation of the results and LN helped with data gathering and analysis. TN provided support for accessing the WIC database and interpreting the results. TK gave input and provided community contexts for the interventions used in the model. MCW and MP obtained funding for this study, led the problem definition, conceptualized and supervised the implementation of the analysis plan, reviewed and revised the manuscript. All authors provided critical input and insights into the development and writing of the article and approved the final manuscript as submitted.

CONFLICT OF INTEREST
The authors declare no conflicts of interest.

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Abstract

Background.—The complex multifactorial nature of childhood obesity makes community interventions difficult to evaluate using traditional approaches; innovative methods are needed.

Objective: To evaluate the impact of various interventions targeting childhood obesity-related behaviors, and classified as using a micro-level (e.g., home visitation programs) or macro-level (e.g., business practices) strategy, on obesity among children enrolled in the Special Supplemental Nutrition Program for Women, Infants, and Children (WIC).

Methods.—We simulated a population of 1500 children enrolled in WIC, with specific diet, physical activity, breastfeeding behaviors and BMI z-scores (BMIz), following them from age 2 to 5 years.

Results.—Combined interventions targeting breastfeeding appeared to be moderately effective, reducing BMIz by 0.03 (95%CI −005, −0.01). Two strategy-specific interventions, home visitation programs and business practices targeting obesity-related behaviors, appeared to be moderately effective at reducing BMIz by 0.04 (95% CI −0.06, −0.02) and 0.02 (95% CI −0.04, 0.00), respectively. Contrary to expectation, combining all micro and macro interventions appeared to have no impact or moderately increased the proportion of obesity/overweight among children.

Conclusion.—Interventions targeting breastfeeding behavior were most effective when both micro and macro strategies were implemented. Interventions targeting obesity-related behaviors in general were effective for two strategies, home visitation and business practices.

Keywords

childhood obesity; adiposity; interventions; simulation; community

INTRODUCTION

Childhood obesity is a significant public health problem in the US and worldwide.[1] In the U.S., one in three children are overweight or with obesity and over 10% of 2–5 year-olds are with obesity or severe obesity.[2] Childhood obesity disproportionately affects racial/ethnic minority and socio-economically disadvantaged groups.[3]

Los Angeles County (LAC) in California is one of the most socioeconomically, racially and ethnically diverse counties in the U.S. and has some of the highest rates of early childhood obesity, marked by socio-economic and racial/ethnic disparities. Reaching a peak of nearly 22% in 2009, the obesity prevalence among LAC’s preschool-aged children enrolled in the Special Supplemental Nutrition Program for Women, Infants and Children (WIC) has been especially high among those from the lowest income households.[4,5] In 2005, in an effort to arrest the rapid climb in childhood obesity rates in LAC, the California Endowment established the Healthy Eating and Active Communities Initiative, providing funding for six communities in California to find innovative ways to address childhood obesity.[4] Other private organizations and governmental agencies such as First 5 LA, Kaiser Permanente and the Centers for Disease Control and Prevention (CDC) also began to provide funding to address childhood obesity in LAC.[6–8]

Through these initiatives, efforts were made to promote healthy eating and physical activity in various environmental settings (e.g., childcare, school, worksite, neighborhood) in different parts of LAC, presenting a unique opportunity to evaluate the effectiveness of various combinations of community interventions and policies in a socio-culturally, economically, and environmentally diverse region of the country – a task undertaken by the Early Childhood Obesity Systems Science Study (ECOSyS) (NIH R01HD072296).[9]

In places like LAC, the influx of funding, the multiple co-occurring intervention efforts, and the complex and multifactorial nature of obesity make intervention impacts difficult to evaluate. To facilitate the evaluation of such interventions and initiatives, ECOSyS developed a system for classifying intervention strategies.[9] This system recognized that micro-level strategies, defined as those that directly target children and their families (e.g., counseling or group education)[9], may be more intense in their activities but have less reach, while macro-level intervention strategies, defined as those that address social and/or physical environmental access to food and physical activity (such as grocery stores and parks), change business practices (such as menu labelling or product placement) or involve policies that influence feeding, eating and physical activity [9,10,11] (such as child-care food policies or baby friendly hospital policies) may have greater reach but be less intense.

Public health researchers are increasingly using computer simulation models to understand the mechanisms shaping observed patterns or to compare potential impacts of intervention alternatives and inform actions before they are implemented. In particular, dynamic modeling methods have allowed researchers to evaluate the cost- or comparative-effectiveness of public health interventions.[12] Simulation models can incorporate available evidence concerning individual behaviors and health outcomes and can be thought of as virtual laboratories where virtual experiments can be conducted to evaluate the effectiveness of potential interventions by simulating counterfactual (“what if”) scenarios.[13–15] This method has been used to evaluate the potential mechanisms underlying how social norms may impact obesity rates,[16] how food choice decisions are made among low income adults,[17] and other questions that involve dynamic interactions between factors at multiple levels of influence (e.g., individuals, families, schools, worksites, disposable income, social norms, government policies, etc.).

The objective of this study was to evaluate the impact of various community health interventions on early childhood obesity in populations living in low-income households and residing in LAC. Specifically, we sought to project the individual and combined impact of various interventions, employing micro- or macro-level strategies, on obesity prevalence in preschool-aged children enrolled in WIC.

METHODS

Model overview

To achieve our objective, we developed a stochastic, dynamic, discrete time, simulation model. We simulated a population of 1500 children living in low-income households and enrolled in WIC, following them from 2 to 5 years of age for a total time horizon of three years. The size of the population was chosen to reflect the size of the analytical sample from the WIC database used to obtain the model input parameters. The model was developed and calibrated using AnyLogic software (version 8.3.2)[18] and the statistical analyses were conducted using R software.[19] Six steps undertaken to develop our simulation model (Fig S1) are described in detail below. Data were collected from 2017–2019 and analyzed in 2019–2020.

1. Model scope and conceptual design—The model scope represented by a causal diagram was developed through an iterative process and incorporated critical inputs from community stakeholders (i.e. including funders and grantees) and medical and public health obesity experts (e.g., Los Angeles County Department of Public Health). This process, sometimes referred to as a community-based modeling approach, is an important first step to ensure that factors incorporated and interventions evaluated in the model are relevant to the population of interest.[20] We also elicited feedback from community partners through structured interviews and surveys and meetings. The process for gathering input from our partners, which resulted in the development of a community dose index, are described elsewhere.[9] Community partner input, the socio-ecological model, and a review of published literature guided the establishment of the framework underlying the simulation model described herein (Figure 1).

2. Model specification

- **Simulated individuals (socio-demographics, behaviors and outcomes):** Each simulated individual had three domains of attributes that have been shown to be important correlates of childhood obesity risk.[21] The first domain was the individual's socio-demographic characteristics [age, sex, socio-economic status (SES) as indicated by poverty status, race/ethnicity], representing the child's individual susceptibility to obesity. The second domain was dynamic (i.e. changed over time) and pertained to the individual's behaviors, specifically whether the individual met the established recommendations for engaging in obesity prevention-related behaviors – including whether the child was exclusively breastfed for six months or longer (EBF), was physically active on any given day (PA), ate 5 or more servings of fresh fruits and vegetables per day (FFV), consumed less than one fast-food meal per week (FFD), and did not drink any sugar-sweetened beverages (SSB). The last domain, also dynamic, was the outcome of interest, the individual's BMIz and obesity and overweight status. Obesity status was determined based on the WHO growth charts.[22]

- **Decision rules and equations:** Changes in individual behaviors over time in the model were defined using decision rules based on mathematical equations and conditional statements. A detailed description of the equation structure is presented in Fig S2. In the model, socio-demographic variables were considered exogenous to the model, while meeting the recommended level of a behavior was considered endogenous. All behavior equations (i.e., EBF, SSB, FFV, FFD, PA) had a common form whereby the current behavior (i.e., meeting the recommended level of a behavior) was a function of the following: past behavior, socio-demographics and any intervention exposure. The probability of meeting any of the recommended behavior levels was calculated using the inverse logit function. Current BMIz was a function of past BMIz and past behavioral risk factors described above (Fig S2). The prediction of BMIz was heterogenous across weight status, that is, we had a separate prediction equation for children that are underweight, normal-weight, overweight, and with obesity to reflect the potential heterogeneity of various factors across weight categories. Individual children were then classified in corresponding weight categories according to their predicted BMIz using cut-offs based on the WHO growth charts for BMIz.[22] (Table S1) The time step was a one-year increment and the BMIz of each child was updated every year as the child aged.

3. Parametrization

- **Information on baseline attributes:** To parametrize the model, data maintained by Los Angeles-based PHFE-WIC, a program of Heluna Health, and the largest local agency WIC program in the nation (phfewic.org)[23], was utilized. A cohort of children was created from this dataset and followed virtually for 3 years. To assign attributes to simulated individuals, we randomly sampled from the joint probability distributions of the attributes so as to preserve the correlation and heterogeneity between individual attributes at baseline.[24] (Table S2) Examples of attributes included age, sex and whether the child was exclusively breastfed for 6 months.

- **Information on intervention efficacy or strength:** To inform the model, information on the "efficacy" of selected public health intervention strategies (e.g., group education, business practices) targeting breastfeeding, fresh fruit and vegetable consumption, fast-food and SSB consumption and physical activity were obtained from a search of the literature. A summary of the values and data sources of key parameters are presented in Table S3 and S4. A detailed description of the search methodology and information on additional parameters can be found in the appendix (Text S1). Briefly, to identify parameter estimates for the simulation model, we conducted a comprehensive literature search in PubMed. To be included, studies had to be quantitative, written in English, published in peer reviewed journals. We first prioritized pulling parameter estimates from those papers that were evaluating: WIC populations, infants/preschoolers living in low-income households, early childhood populations, African American/Hispanic populations, and that were US-based. If we were unable to find papers focused on the above, we expanded the search to include non-US based studies, studies targeting young children across SES groups, and studies targeting older children. When estimates at the population level were not available, we included studies evaluating intermediary outcomes (for example, whether government policies affect the availability of healthier offerings in food stores or whether healthy menu changes in restaurants influence sales of healthier items). Studies using the following study designs were also prioritized in this order 1) peer-reviewed articles using systematic reviews, meta analyses, randomized control trials, and cohort studies and 2) peer-reviewed articles using cross-sectional study designs.

4. Initial specification, calibration, and validation of the model—We performed a model calibration[25] wherein the calibration objective function was defined as the square root of the mean squared error divided by the average of the predicted and actual parameter. We compared the predicted mean BMIz at 5 years to that of children living in LAC and enrolled in WIC in 2014. Parameter values that minimized the objective function were selected to parametrize the model. Two categories of parameters for each equation were calibrated, the intercept parameters and the "feedback" parameters. These feedback parameters reflect the relationship between current behavior (or BMIz) and previous behavior (or BMIz), all else equal (Table S1). In other words, our model captured how interventions that change obesity-related behavior early on in childhood can also affect obesity/obesity-related behaviors later in childhood.

5. Evaluating the main experiments and interventions in the model

a) Implementing interventions: Interventions were implemented yearly throughout the child's life at 2, 3,4 and 5 years and were implemented singly and in combination with one another. For instance, to evaluate the impact of the fruit and vegetable intervention, only the fruit and vegetable intervention was "turned on" while the other interventions were "turned off". To evaluate the impact of the several interventions, such interventions were "turned on" while the others were "turned off". We used regression-based decision rule as outlined in Figure S2. Briefly, the child's future behavior was determined by the child's susceptibility (e.g., age, sex, race/ethnicity, SES), past behaviors and the potential effect of the intervention. For instance, when a hypothetical intervention is implemented, such intervention will affect the probability of meeting the desired health behavior (e.g., eating at least 5 fruits and vegetables) which in turn would affect the child's weight. The child's weight was determined as a function of the child's susceptibility, past weight and past behaviors. When the behavior changes as a result of the intervention, the weight also may change as a result of the change in the behavior.

b) Evaluating interventions: First, we simulated a natural course scenario (i.e., with no intervention or status quo) and then ran several experiments to assess the 3-year impact of several interventions on children's BMIz score. A total of fifty-two interventions implemented at the micro- and macro-levels were evaluated across our experimental runs. These intervention strategies could influence five different behaviors evaluated in the model: meeting breastfeeding, physical activity, fresh fruit and vegetable consumption, fast-food consumption and sugar-sweetened beverage consumption recommendations (see Fig S3). For our experiments we tested a combination of intervention strategies together/alone, targeting all obesity-related behaviors/targeting specific obesity-related behaviors, and interventions at the micro-level/macro-level (discussed in more detail below). We calculated and reported mean differences (MD) in BMIz and prevalence differences (PD) in obesity or overweight at age 5 years for the entire cohort and within subgroups defined by sex (male/female), SES (extremely low-SES [below federal poverty level], low-SES [above federal poverty level] and race/ethnicity (Whites, Non-Whites), comparing outcomes under various interventions, singly and in combinations with other interventions, to that of the natural course.

6. Uncertainty and Sensitivity analysis—The model was simulated 1000 times to evaluate the uncertainty around estimates and generate standard errors. Confidence intervals were calculated using a normal approximation. In addition, a two-way sensitivity analysis was conducted by testing how varying the calibrated values (intercept and feedback terms) for BMIz and the behaviors by +/− 10% would affect the simulation results in the natural course.

RESULTS

Model calibration and validation

We compared our simulation results to observed data to calibrate and validate our model. The simulation model-generated values (using the input parameters from WIC, the literature and the optimization process) broadly matched the observed means and proportions from the WIC database (Table S5).

Main experiment

We virtually implemented interventions singly and in combination with one another. For instance, we implemented interventions using the same strategy (strategy-specific intervention; e.g., group education), interventions targeting a single behavior (behavior-specific intervention; e.g., group education, government policies, screening and referral programs, etc. all targeting breastfeeding behavior), interventions using micro-level interventions only or macro-level interventions only, and interventions employing both micro-level and macro-level intervention strategies. Results are presented in Figure 2, 3 and 4.

- **BMIz—**Among the strategies that targeted specific behaviors, only those that targeted breastfeeding showed a beneficial impact on obesity. In particular, combined interventions targeting breastfeeding moderately reduced BMIz by 0.03 (95%CI −0.05, −0.01). In addition, among strategies that did not target any one specific behavior, home visitation and business practices appeared to be moderately effective; population MD = −0.04 (95%CI −0.06, −0.02) and −0.02 (95%CI −0.04, 0), respectively.

There was some heterogeneity regarding which intervention was effective and how effective the intervention was in reducing BMIz by race/ethnicity, sex and income level. For instance, group education intervention targeting fast-food consumption behavior was effective at reducing BMIz only among minority populations (MD = −0.03 (95%CI −0.05, 0)) and group education targeting SSBs was effective at reducing BMIz only among extremely low-SES populations (MD = −0.02 (95%CI −0.04, 0)) (Fig S4, S5 and S6).

- **Proportion of children who are overweight or with obesity—**Combined and single interventions evaluated did not appear to reduce the proportion of children who are overweight or with obesity in the entire population. Combining all micro and macro interventions increased the proportion of obesity and overweight among children overall by 2.5% (95%CI, 1.9%, 3.2%) and 0.7% (95%CI, 0.2%, 1.3%), respectively. (Figure 3 and 4)

As with BMIz, there was some heterogeneity regarding which intervention was effective and how effective the intervention was in reducing obesity and overweight prevalence by race/ethnicity, sex, SES. For instance, the group education intervention targeting physical activity was effective in reducing obesity only among Whites (marginal prevalence difference, PD = −0.8% (95%CI, −1.6%, −0.1%)) and combined interventions targeting breastfeeding were effective in reducing the prevalence of overweight only among the extremely low-SES group, by 0.6% (95%CI, −1.1%, −0.1%). (See Fig S7–S12)

Sensitivity analysis

Fig S13 summarizes the results of the two-way sensitivity analysis with varying calibrated values (intercept and feedback terms) for BMIz and the behaviors (ranging from −10% to +10% of the parameter). As can be seen from the results, the mean BMIz at 5 years as well as the prevalence of obesity at 5 years were moderately to largely influenced by a simultaneous altering of both the intercept and calibrated values. In other words, our results were sensitive to the calibrated values of the intercept and feedback terms, highlighting the importance of our calibration endeavor.

DISCUSSION

Our study found that, among the different types of obesity-related interventions implemented in LAC since 2005, combined interventions targeting breastfeeding appeared to be moderately effective at reducing BMIz; however, the effect was not large enough to reduce the prevalence of obesity and overweight in the simulated cohort. In addition, certain strategy-specific interventions (i.e., interventions that used a specific intervention strategy regardless of the behaviors targeted), namely, home visitation interventions and interventions related to business practices targeting obesity-related behaviors, appeared to be moderately effective at reducing BMIz. Contrary to expectation, we also found that combining all micro and macro interventions appeared to have no impact or moderately increase the proportion of obesity and overweight among children. There was also some notable degree of heterogeneity regarding which intervention was effective and how effective the intervention was in reducing BMIz and obesity and overweight prevalence by race/ethnicity, sex and SES.

These results are consistent with other studies evaluating interventions targeting eating and physical activity interventions in preschoolers living in low-income households. Nianogo et al.[21], using a causal inference approach to evaluate a similar portfolio of interventions, found that interventions that promoted exclusive breastfeeding for six months or longer were the most effective at reducing population-level weight-for-height z scores in the same population of children enrolled in WIC. This work adds to the growing body of literature highlighting the importance of breastfeeding and early life exposures to later obesity risk.[21,26] Similarly, an earlier simulation study evaluating specific types of interventions on breastfeeding found that postpartum breastfeeding counseling and a supportive workplace environment promoted the maintenance of breastfeeding at 6 months; breastfeeding for at least 6 months has been found to be associated with reductions in obesity rates in early childhood.[21,26]

As found in this study, certain strategy-specific interventions, such as home visitation and business practices targeting health behaviors (engaged by the food industry and other private industry), were moderately effective in reducing BMIz. For instance, previous research has shown reductions in orders of SSBs and increases in orders of FFV after healthier children's menu were adopted.[27,28] Home visitation programs have also been shown to be especially effective for increasing the continuation of breastfeeding among mothers living in low-income households,[29] which can similarly impact obesity risk. Recent studies have highlighted the importance of another strategy-specific intervention, the change in the WIC food package to better align with the dietary guidelines.[30,31] This policy change, which occurred in 2009, led to a reduction in obesity risk among children enrolled in WIC.[30,31]

In our study, contrary to our expectation, we found that combining all micro- and macro-level interventions did not appear to be effective at reducing BMIz or the prevalence of overweight or obesity at 5 years. This could be due to several potential explanations. First, interventions can have heterogeneous effects in opposite directions such that the sum of their effects at the population level appears to be either null or in an unanticipated direction. Second, competing “counter interventions” such as the aggressive marketing of large quantities of nutrient poor foods as well as the excessive portions served by retail food outlets could potentially undermine the effects of prevention efforts. Third, our findings may be highlighting the fact that interventions focused on individual-level behaviors may have limited long-term population-level effects. Fourth, it is possible that the efficacy estimates obtained from the literature were either biased or incorrectly applied. Finally, factors such as social determinants of health (e.g., extreme poverty, housing instability, food insecurity, trouble paying utilities, employment conditions, crime, and psychosocial stress) could potentially make it difficult for populations living in low-income households to engage in health-promoting behaviors even when implementing intervention strategies that may be successful in other social or environmental contexts.[32]

Other studies, most of which targeted preschool-aged children living in low-income households, evaluating multicomponent interventions have also reported null findings, highlighting the difficulty of changing health behaviors and of preventing obesity, especially in populations living in low-income households[33–35] or of detecting changes using traditional study designs.

These findings highlight the importance of intervening on obesity early in life. Continuing to support WIC mothers so they can meet recommendations for breastfeeding, in particular, may have long-term implications for childhood obesity in this population. These findings also underscore the difficulty in shifting obesity trajectories through diet and physical activity interventions alone, even when both micro- and macro-level strategies are applied, especially in populations living in low-income households that are disproportionately exposed to psychosocial and physical chronic stressors such as neighborhood violence, environmental pollutants and other social determinants of health that may impact their overall obesity risk.[36–38] Furthermore, this study confirms the challenges of designing, implementing and evaluating multi-component and/or multi-level interventions. For example, a recent study found that children enrolled in both WIC and the Supplemental Nutrition Assistance Program (SNAP) increased not only consumption of fruits and vegetables but also sugar-sweetened beverages compared to children enrolled in WIC alone.[39] This, however, is not to say that optimal combinations of interventions could not be established to produce further impact. Future research to understand the reasons and mechanism for these unexpected effects will inform the design, implementation, monitoring and evaluation of future obesity-related interventions.

To our knowledge, this is the first study to use empirical data and a classification of various intervention strategies in the application of simulation to the evaluation of multiple obesity-related interventions implemented simultaneously. The study has several limitations. Findings from our simulation model, as with other simulation modeling endeavors, are bounded by the limitations of the data, the efficacy estimates and the underlying assumed structure of the model. The list of selected interventions is not exhaustive or complete; only about 50 interventions that stakeholders identified as important were evaluated – other interventions could have also impacted obesity risk.

This work raises many policy and funding questions. Communities, private funders, and governmental agencies often set priorities for high-risk and high-need communities, which affect funding decisions that can limit or encourage options for the types of interventions created and delivered in the community. In the past decade, there has been increasing interest in supporting macro-level interventions, often described as policy, system and environmental changes, as well as multi-level interventions which focus beyond individual-level focused efforts and change. In a community setting, which always includes a variety of interventions, risk factors and risk conditions, it is methodologically challenging to evaluate what types of strategies and specific interventions are effective for whom, when, and where. Important contributions of this type of research include 1) the documentation of the plethora of interventions that have been directly or indirectly implemented to prevent obesity, 2) the finding that most of the interventions implemented fell short in achieving substantial reduction in obesity partly because such interventions did not target or were not effective at targeting macro-level interventions such as the food environment and food marketing practices and 3) the insight that interventions targeting only individual behaviors may have limited lasting long-term population-level effects. Finally, this type of research has the potential to add value and provide decision-makers with another tool to inform critical resource-dependent decisions that can improve the conditions and health of communities.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Data availability statement:

All data needed to reproduce this study are provided in the supplemental materials

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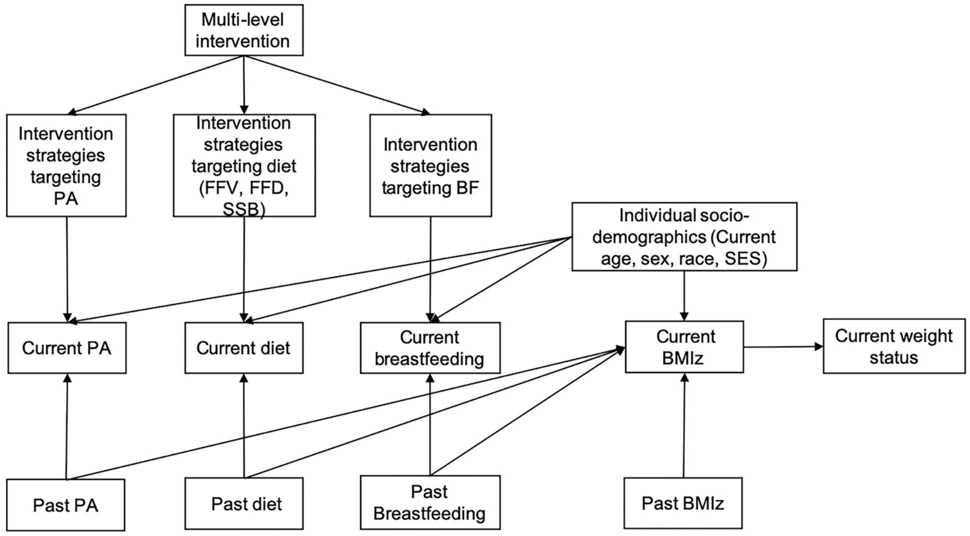

Figure 1: Childhood obesity causal diagram highlighting the assumed relationships between factors

EBF: Exclusive breastfeeding, PA: Physical activity; FFV: Fresh fruit and vegetable consumption, FFD: Fast-food consumption, SSB: Sugar-sweetened beverage consumption; BMIz: body mass index z-score.

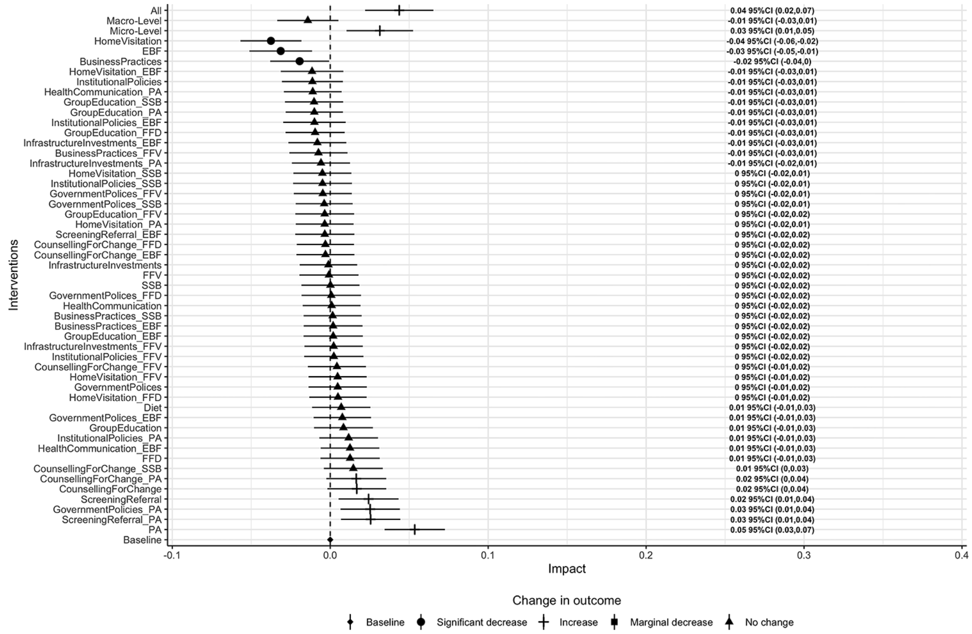

Figure 2. Impact of interventions on BMIz under various intervention using the simulation model

EBF: Exclusive breastfeeding, PA: Physical activity; FFV: Fresh fruit and vegetable consumption, FFD: Fast-food consumption, SSB: Sugar-sweetened beverage consumption; BMIz: body mass index z-score.

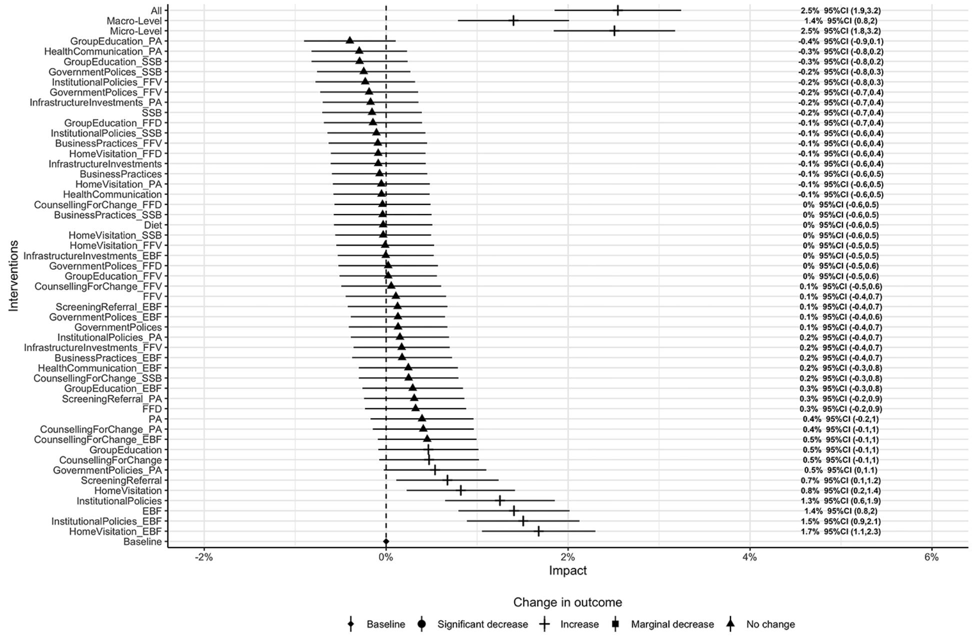

Figure 3. Impact of interventions on obesity prevalence under various intervention using the simulation model

EBF: Exclusive breastfeeding, PA: Physical activity; FFV: Fresh fruit and vegetable consumption, FFD: Fast-food consumption, SSB: Sugar-sweetened beverage consumption; BMIz: body mass index z-score.

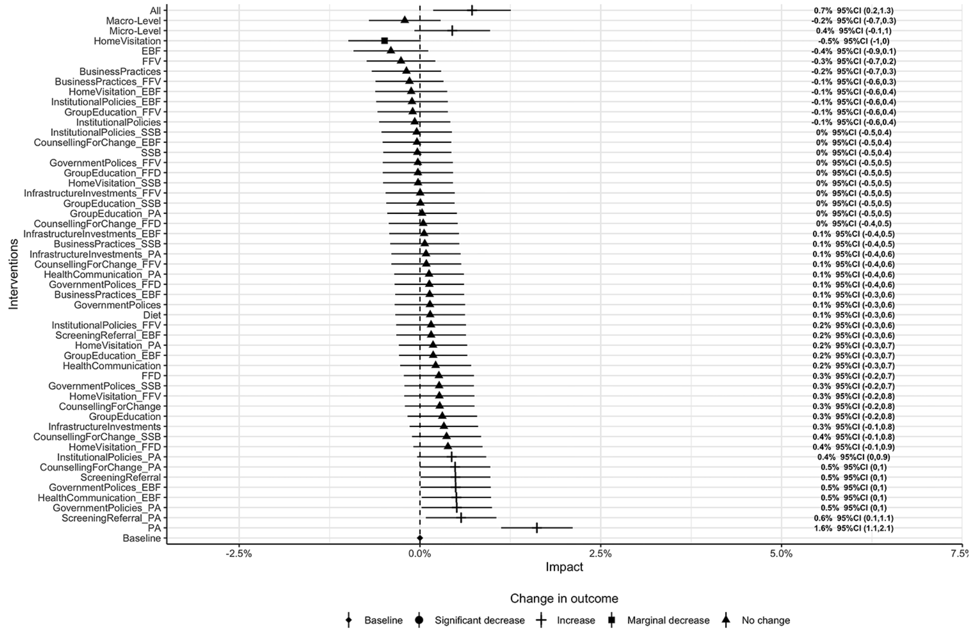

Figure 4. Impact of interventions on overweight prevalence under various intervention the simulation model

EBF: Exclusive breastfeeding, PA: Physical activity; FFV: Fresh fruit and vegetable consumption, FFD: Fast-food consumption, SSB: Sugar-sweetened beverage consumption; BMIz: body mass index z-score.