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Insights from a codesigned dynamic modelling study of child and adolescent obesity in Australia

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ABSTRACT

Introduction Child and adolescent obesity is associated with a range of immediate health issues and influences obesity in adulthood. The complex nature of health determinants that contribute to obesity makes it challenging to deliver effective public health interventions. This research presents insights from a system dynamics model of childhood and adolescent obesity aimed at supporting evidence-based decision-making.

Methods A system dynamics model was developed using the best available evidence and data, with input from research and industry experts to map the hypothetical causal structure of the factors contributing to childhood and adolescent obesity in Australia. The model was calibrated to fit the historical prevalence of obesity (R^2 =0.97, mean squared error (MSE)=4.94E-04). Intervention-based scenarios were simulated to examine how changes in environmental factors and health-related behaviours may affect the prevalence of obesity. The potential economic benefits of the scenarios were estimated from changes in population healthcare spending and quality of life compared with base model projections.

Results A series of interventions were explored in the model, including changes in early childhood behaviours, changes to diet and physical activity in childcare and school settings, financial support for organised sports and sugar-sweetened beverage taxation. The most promising individually implemented intervention scenario for reducing the prevalence of childhood and adolescent obesity was a sugar-sweetened beverage tax (0.57 percentage points and 0.61 percentage points, respectively) and government funding of organised sports (0.42 percentage points and 0.63 percentage points, respectively). When all interventions were implemented in combination, childhood obesity was reduced by 1.43 percentage points and 1.81 percentage points in adolescents.

Conclusions The findings highlight the challenges faced by policy-makers and public health practitioners working to reduce childhood and adolescent obesity. Insights from the model emphasise the value of public health programmes over the life course. Implementing initiatives with broad reach that support healthy choices may reduce obesity, resulting in a healthier Australian population.

WHAT IS ALREADY KNOWN ON THIS TOPIC

⇒ Previous reviews of system dynamics models of obesity have shown that most modelling efforts focus on adult populations and are contextualised for North America. Few models have been developed for the Australian population or used to examine public health strategies for children and adolescents.

WHAT THIS STUDY ADDS

⇒ In this study, we developed a national system dynamics simulation model to explore how various policy interventions impact child and adolescent obesity in Australia. The model provides a platform to examine policy implementation using the same base assumptions to enable direct comparisons. We used multiple population-representative data sources to reflect the known behavioural differences in age, gender and weight status, and we considered a comprehensive uncertainty analysis to assess the likelihood of each scenario's health benefits.

HOW THIS STUDY MIGHT AFFECT RESEARCH, PRACTICE OR POLICY

⇒ The scenarios considered in this model had a small impact on reducing child and adolescent obesity, highlighting the challenging nature of developing public health strategies for obesity prevention. Interventions with higher coverage across the life course had a higher impact on weight status, namely, sugar-sweetened beverage tax and supporting child-organised and adolescent-organised sports. Furthermore, the model suggests that combinations of other settings-focused interventions can provide synergistic support to individuals as they age throughout the system.

INTRODUCTION

Child and adolescent obesity is a major global public health issue. The prevalence of overweight and obesity has stabilised at a high level in many high-income countries but is continuing to increase in many middle-income and low-income countries.[1] In Australia, the prevalence of overweight and obesity for children and adolescents aged 5–17 increased from 20.1% in 1995 to 24.7% in 2007, with relatively little change between 2007 and 2018.[2] However, recent data from the National Health Survey indicate that the prevalence of being overweight or obese rose to 27.7% in 2022.[3] Additionally, differences in wealth,[4] ethnicity[5 6] and location[7] create inequalities in the affordability of and access to healthy foods and facilities for physical activity. High body mass index (BMI) (weight/height^2) in children and adolescents is associated with a range of health problems, including fatty liver disease, hypertension, insulin resistance, type 2 diabetes, sleep apnoea and an increased risk of obesity in later life.[8] High BMI may also affect the mental health of children and adolescents, with depression, anxiety, disordered eating[9] and low self-esteem being most common.[10] Child and adolescent overweight and obesity and their associated health problems also create an increased economic burden from the cost of healthcare.[11 12]

The process of tackling childhood and adolescent obesity has been slow and inconsistent,[13] which is attributed to the complexity of understanding, treating and preventing obesity. Socioecological models highlight the hierarchical organisation of health determinants contributing to obesity; these conceptual frameworks provide an overview of how the various levels of factors create complexity in obesity research.[14 15] Biological processes such as energy homoeostasis and the cognitive and emotional control of dietary intake influence body weight regulation.[16] Interpersonal relationships with peers and family members influence various health-related behaviours,[17] which in turn are contextualised within organisational and community settings, affecting individuals' exposure to foods and physical activity choices.[18 19] Commercial and technological trends can influence changes in consumer behaviours, impacting the normative culture around food and physical activity.[20] These differing levels of influence span multiple societal sectors, making it challenging to coordinate effective strategies for adoption and dissemination.[21]

The complex nature of obesity prevention poses significant challenges in enacting effective prevention policies. Current strategies aim to include a multifaceted whole-of-community strategy[22] and the built environment.[23] These approaches create difficulties for public health decision-makers, where there is an increasing need for evidence to inform action to provide the greatest impact with limited resources.[24] Traditional epidemiological techniques, such as population-attributable fractions, are commonly used to estimate the burden of obesity.[25] However, these methods are static and assume that the relative risk between population factors remains constant, ignoring the dynamic composition of the population.[26] Furthermore, evidence of health benefits can often focus on the internal validity of a particular intervention strategy, leaving potential gaps in policy-makers' understanding of its utility for wide-scale adoption.[27 28] Providing decision support for public health policy requires additional considerations of the complex implementation characteristics of obesity.[29]

One approach to investigating causal relationships and identifying the potential success of interventions in reducing the prevalence of obesity is system dynamics (SD) modelling, a mathematical modelling method that combines disparate sources of evidence to map and quantify hypothetical causal relationships.[30–32] The main goal of an SD model is to understand the endogenous behaviours (eg, feedback loops) and relationships between system components that lead to changes in population trends and identify strategies that can influence behaviours.[33] SD models can be used to assess and compare hypothetical policies and facilitate causal reasoning about the root causes of a complex issue. A model that sufficiently captures a system's behaviour can be used to simulate health and cost benefits from policies to aid in decision-making.[34]

SD models are being increasingly used to model the dynamics of obesity in public health research.[35–38] Reviews of the SD literature have advocated for additional modelling of child age groups to consider the potential impacts of preventative interventions for obesity.[35] Additionally, there are differences in demographics and healthcare systems in different contexts and countries. Therefore, applications of SD modelling need to account for these differences if they are to effectively support policy design.[38] The Australian healthcare system is federated, with different policy responsibilities and intervention options residing at different levels of government. Previous childhood obesity modelling in Australia focused on state-level representation and policy goals.[39] This current study aims to expand this work by incorporating updated data sources, expanding the scope to consider national policy objectives in Australia and examining the economic consequences of implementing public health policy, increasing its utility.

This paper presents insights from an SD model designed to assess the prevention and reduction of childhood and adolescent overweight and obesity in Australia. The purpose of the model is to describe system characteristics to understand how changes in national-level health determinants may lead to changes in population outcomes. The model aims to provide support for policy decision management by informing cost-effective strategies for obesity reduction and prevention. Policy scenario analysis was used to identify the best combination of public health interventions to reduce the prevalence of overweight and obesity among children and adolescents. This study presents the research findings in the context of model uncertainty for health and economic benefits, broadening its application in policy planning. Additional information on the model's core equations and technical considerations can be found in online supplemental material and elsewhere.[40]

METHODS

Model development

The SD model presented in this paper was developed in collaboration with diverse group of expert stakeholders, including child health researchers, clinicians, methodologists, health advocates and policy-makers. Stakeholders contributed to the development of the model in four workshops held between June 2019 and June 2020 following participatory modelling methods described elsewhere.[41 42] In workshop 1, participants were orientated to the project objectives and were asked to map the determinants of obesity in children and adolescents. The resulting conceptual map is presented in online supplemental figure S1. Key components of the conceptual map, which had a known causal structure and available data, were prioritised for inclusion in the model. In workshop 2, participants gave feedback on the model structure and prioritise potential policies and interventions that could be integrated into the model. Workshop 3 provided further opportunities to showcase the model structure and examine evidence that could be used to synthesise intervention effects. Workshop 4 aimed to present participants with the scenario findings, establish a level of face validity for the modelling insights and discuss their implications for policy and planning.

Outcomes

The International Obesity Task Force age-gender BMI cut points were used to define cohort weight status into three BMI categories: underweight and healthy weight, overweight and obesity.[43] The primary aim of the model was to assess changes in the prevalence of BMI categories as a result of interventions being implemented in the modelled population. Aggregate changes in the prevalence of obesity were reported for children (2–12 years) and adolescents (13–18 years). The model time horizon was 50 simulated years from 2007 to 2057, where model equations were updated 12 times per simulated year. Each tested policy scenario commenced in 2025, allowing for a 5-year rollout at lower effectiveness, and was in full effect from 2030 to 2057. The model-generated prevalence was analysed to estimate the health benefit of each scenario. A longer time horizon was deemed necessary for intergenerational effects to manifest.

The model was based on Australian national data to inform data inputs and exogenous relationships; data and methods used in model development are summarised in online supplemental table S1. Model verification was conducted using nationally representative prevalence data for each age-gender group in the model. The model was compared against data from the Australian National Health Survey,[44] the Longitudinal Study of Australian Children[45 46] and the 2007 National Children's Nutrition and Physical Activity Survey[47] for the period 2007–2017. Sensitivity analysis was conducted to examine how changes to the model's initial conditions resulted in logical and anticipated changes in the model and scenario outputs.[40] The model was developed using ISEE Stella (V.1.9.4), and model results were analysed in R (V.3.6.3).

Model structure

Figure 1 presents a schematic of the overarching model structure. The structure of the model, including the core model equations used and technical considerations, has been reported in detail by Chiu *et al*.[40] Furthermore, the accompanying supplementary material for this paper provides detailed images (online supplemental figures S2–S38) and equations for each model component, input values used in the model (online supplemental table S2–S22) and reference data sources. The model comprises six main components, each representing different aspects of the complex system contributing to obesity. The aging-BMI chain was modelled as a series of stocks representing cohorts moving between various age-gender-BMI categories over time. This module captures population dynamics such as ageing, changes in BMI, net migration, mortality and fertility. The flow between BMI categories is a crucial dynamic of the model and is influenced by population-level dietary and physical activity behaviours captured in the energy balance component. Dietary and physical activity changes are propagated through key child-to-child and adult-to-child relationships to reflect the impact of peer and parental role modelling. The subsequent energy imbalance interacts with the BMI distribution component to simulate how people flow between BMI stocks. The intergenerational component enables early childhood factors such as parental BMI status, infant feeding and infant activity behaviours to influence the BMI category of children entering the model. Finally, intervention scenarios are implemented into the model and compared against the baseline outcome. The effects of intervention on the prevalence of overweight and obesity were accounted for in the intervened population component, which tracks changes in population weight status and is used to represent relapsing behaviours after the intervention roll-out. This allows the model to examine how relapse affects the longer-term health benefits arising from each intervention scenario.

The development process was focused on assessing the final model's features, scope and purpose. Existing obesity research highlights differences in opportunities and access to enable health behaviours between broad societal structures such as economic status and location. However, disaggregating the model structure to incorporate these differences requires detailed data to support model inputs and an understanding of how the population moves between subgroups, that is, economic mobility and within-country migration. A parsimonious model with limited subgrouping was prioritised, focusing on the stratifications needed to describe the system behaviours. This limitation has multiple implications, namely that policies designed to deliver equality to marginalised subgroups cannot be tested, and macro trends cannot be incorporated into the analysis.

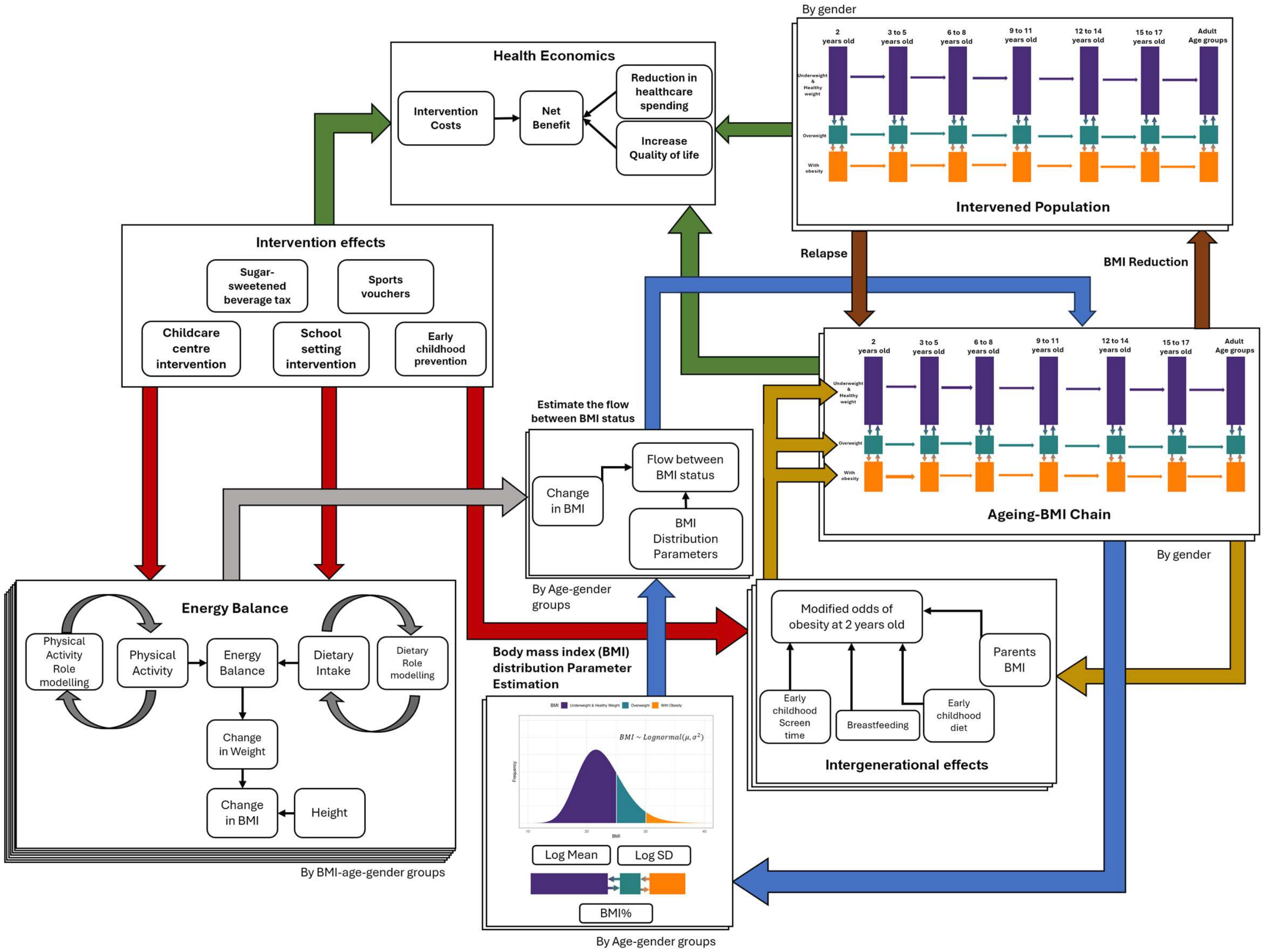

Figure 1 Overview of model structure. BMI, body mass index. Note: Images with greater detailed Stella model structure and explanation are presented in online supplemental material.

Additional information about the model's structure, data sources, parameters and assumptions, along with enlarged images of the model structure, can be found in supplementary material sections 3 to 13 with corresponding online supplemental appendix table A1–G4. The model is available on request.

Analysis of cost effectiveness

The cost-effectiveness of the simulated intervention scenarios was modelled using a health sector perspective and compared against the base model projections. The cumulative cost of each scenario was compared against the changes in healthcare costs (at the national government, state government and household levels) and the monetised change in quality-adjusted life-years (QALYs) based on an estimated willingness to pay of $A50 000 for 1 QALY.[48] All costs and utilities were discounted at 5% annually and valued in 2020 AUD. Additionally, an auxiliary analysis (online supplemental table S23) estimated the effect of interventions on reducing productivity losses incurred by parents or guardians. Parameter uncertainty was assessed using a global model uncertainty analysis. Economic assumptions for each scenario and healthcare cost can be found in Supplementary material.

Calibration

The model input parameter values were drawn from individual-level data and data aggregated from the literature. However, when data were unavailable or had significant limitations (eg, potential self-reporting bias), the model was calibrated to estimate input values. Model-generated estimates of BMI prevalence were compared against published historical values for each age-gender group. Calibration was conducted to allow shifts in dietary intake and energy expenditure values to correct for possible unmeasured bias in the data and allow for societal trends in these behaviours. Calibrated dietary intake and energy expenditure changes propagate through the energy balance and distributional structure, impacting the model-generated BMI prevalence.

Online supplemental material provides additional information on the methods used to summarise data sources for model inputs and specific variables used in calibration.

Policy scenario testing

Expert stakeholder participants were surveyed during the model development to identify and prioritise several interventions. Proposed interventions were assessed for appropriateness with model scope, availability of health evidence and implementation costs. Table 1 presents an overview of the selected interventions targeting different life stages. While these interventions were hypothetical, literature was used to derive the magnitude of intervention effects on model components.

The outcomes for the base case model, in which no policy modification was implemented, were compared with the outcome for each policy scenario. The difference in obesity prevalence is reported as the percentage point reduction stratified by child and adolescent age groups. Interventions were simulated both individually and in combination to assess potential synergistic effects. In this context, synergy denotes the combined effects of multiple interdependent interventions resulting from non-linear system interactions. The results report synergy effects by providing a ratio of combined intervention effects divided by the sum of individually implemented intervention effects. A ratio exceeding one indicates a synergistic cooperative effect among combined interventions, suggesting an increased efficiency compared with the implementation of individual interventions alone.

Uncertainty analysis

Each intervention scenario contains a set of parameters that define an assumed intervention effect and exposure. The initial values of these parameters were derived from published evidence as described in Supplementary material. The input data for the base model interacts with these scenario parameters. Global Monte Carlo sampling was used to select 10 000 variations of both sets of input parameters (base model and scenarios) within reasonable ranges based on their respective 95% CIs, or, when CIs could not be calculated, ±10% of the initial values.[49] The Latin hypercube sampling method was used to effectively explore the parameter state space.[50] The estimated change in the prevalence of childhood and adolescent overweight and obesity was modelled for each set of intervention scenarios.

The reported point estimates presented in the results sections correspond to the median percentage point reduction in the prevalence of obesity from an intervention. The uncertainty intervals were calculated as the 2.5th and 97.5th percentiles of model results from 10 000 sampled variations of input parameters. These quantile intervals describe the distribution of model results and are not conventionally derived 95% CIs from standard errors; instead, 95% of model results fall within this reported range. The reported quantiles show the likelihood of the health outcomes of each intervention after accounting for variations in the base model and scenario implementation assumptions.

Additional information on parameter estimates and uncertainty sampling ranges are included in online supplemental appendix table A1–G4.

RESULTS

Supplementary material includes quantitative measures of model fit with figures comparing model-generated BMI prevalence with historical data. The model was shown to have an overall good fit with a small mean-squared error (R^2=0.97, MSE=4.94E−04) and Theil decomposition statistics which suggest small and unsystematic errors. Supplementary material presents additional model validation results in online supplemental table S24 and figure S39. Figure 2 shows the percentage point reduction in obesity prevalence over time for each scenario. The plots are stratified by age group (children and adolescents), with each panel showing the results for a different scenario or scenario combination. The shaded areas represent the effect of uncertainty on the assumed intervention effects, representing 95% of sampled model results.

The effects of the interventions over time show several characteristics. While some interventions are targeted at children, such as early prevention of obesity and childcare centre interventions, they also have a minor delayed effect on adolescents, and this effect increases over time as the children age. The effects of the childcare centre and school-based interventions reached an equilibrium after several years. Conversely, sports vouchers and sugar-sweetened beverage tax interventions can take up to 10 years to reach equilibrium. Finally, the uncertainty of intervention benefits increases over time and is generally larger in the adolescent age group; these relationships are attributed to the ageing processes in the model and highlight how changes in the underlying assumptions propagate through to the outcome.

Figure 3 shows the percentage point reduction in the prevalence of obesity for each intervention, individually and in combination, at the end of the model. Interventions were shown to have the largest effect on their respective targeted age groups. A simulated implementation of early childhood prevention of obesity and childcare centre interventions reduced childhood obesity by 0.03 (uncertainty interval: −0.38, 0.58) and 0.19 percentage points (uncertainty interval: 0.0, 0.54), respectively. The model shows a residual effect on adolescents as the children exposed to the intervention moved into the older age groups. During adolescence, the cohorts are no longer exposed to the interventions, and their behaviour may relapse, reducing the effect on adolescent obesity. The reduction in adolescent obesity due to early childhood prevention was 0.01 percentage points (uncertainty interval: −0.40, 0.40), while the reduction in adolescent obesity as a result of the childcare centre intervention was 0.05 percentage points (uncertainty interval: −0.08, 0.38). A combined scenario in which both early childhood prevention and childcare centre interventions are jointly

Table 1 Intervention scenario descriptions

Intervention	Age groups	Intervention health effect					Description
Early prevention of obesity in children	Mothers	Breastfeeding up to 6 months		+15%			Support for mothers to continue breastfeeding for up to 6 months. For infants, delayed and reduced consumption of discretionary foods and screen time. Intervention exposure depends on the proportion of mothers engaging in the intervention.[80]
	0–1 years	Television >1 hour/day		−37%			
		Consumption of non-core foods		−23%			
Childcare centre interventions	2–3 years 3–5 years	Dietary change	Vegetables	+10.52%			Increased light physical activity, decreased screen time, increased fruit and vegetable consumption and reduced consumption of discretionary foods and SSBs.[81] Intervention exposure is modified by the percentage of children attending childcare and the adherence and enrolment of participating childcare centres.
			Fruit	+7.25%			
			Juice	−40.55%			
			SSBs	−34.95%			
			Discretionary foods	−8.61%			
		Physical activity change	Screen time	−2.96%			
			Light physical activity	5.13%			
School-based interventions	6–8 years 9–11 years 12–14 years 15–17 years	Reduction in student purchases at school canteens		−14.18%			Increased moderate to vigorous physical activity through quality physical education[82] and reduced consumption of non-core foods purchased at in-school retail food businesses, such as school canteens or cafeterias.[83] The proportion of participating public schools modified intervention exposure.
		Change in moderate physical activity		+13.01%			
Sports vouchers	6–8 years 9–11 years 12–14 years 15–17 years	Average increase in organised sports (hours/week)*	Age	UW/HW	OW	OB	Increased participation in organised sports and physical activities through sports vouchers, a government financial aid programme. Sports vouchers increase participation in sports and participants' physical activity levels by reducing financial barriers.[84]
			6–8 years	+1.78	+1.79	+1.54	
			9–11 years	+2.38	+2.4	+2.13	
			12–14 years	+3.16	+3.17	+2.9	
			15–17 years	+3.42	+3.44	+3.16	
	All age groups	Valoric tax (flat tax)			20%		A 20% SSB flat tax increases the price of soft drinks, fruit drinks and syrup cordials to reduce consumption. The overall reduction is calculated using a price elasticity assumption.[85]
		Changes in consumption*	Regular soft drink		−11.40%		
			Cordial/syrup concentrate		−33.20%		
SSB tax			Fruit drink		−25.20%		

*Interim calculations to describe intervention effect.
OB, obesity; OW, overweight; SSB, sugar-sweetened beverage; UW/HW, underweight/healthy weight.

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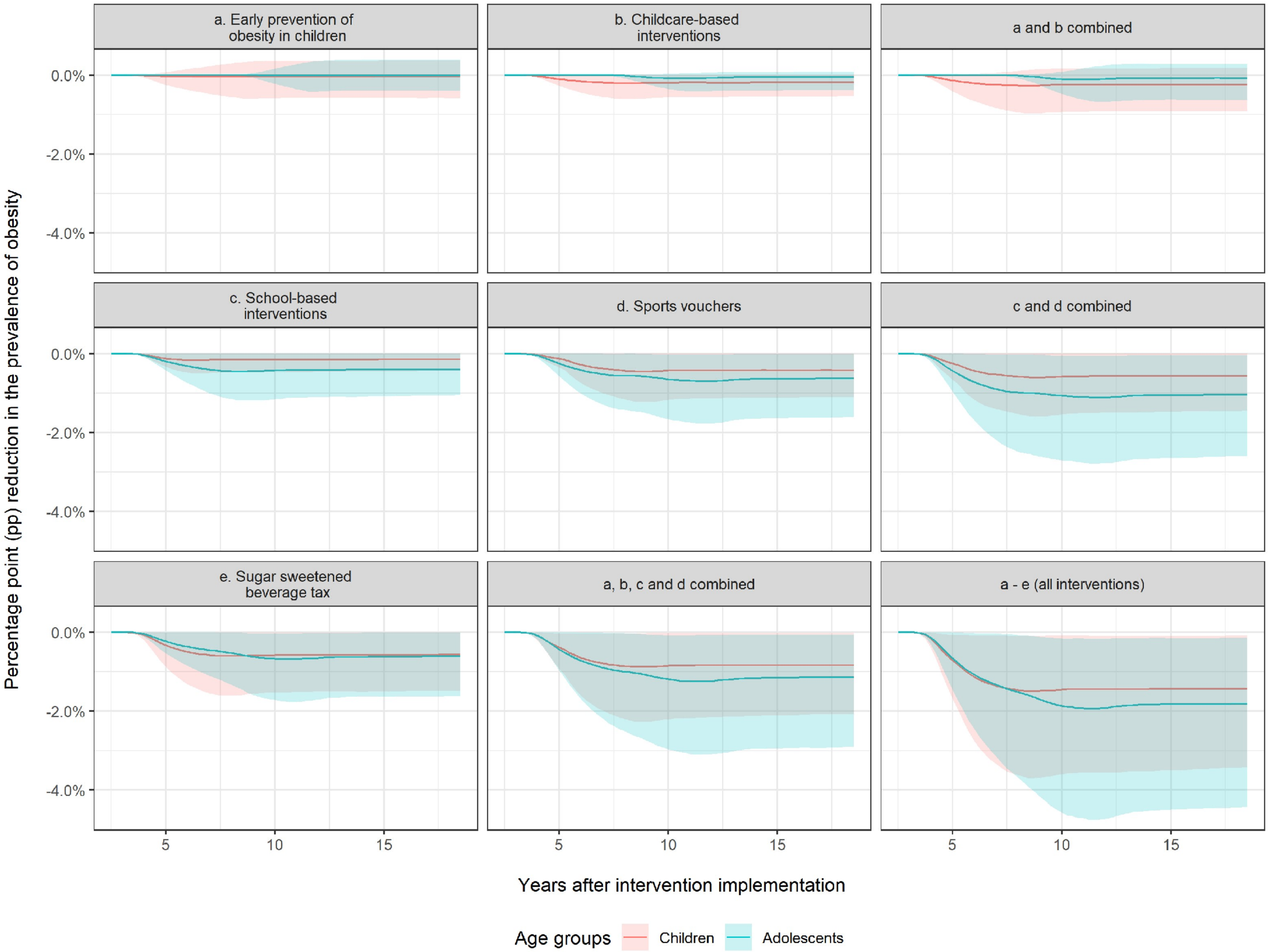

Figure 2 Percentage point reduction in the prevalence of obesity after implementing interventions. Note: Model results reflect the modelled years between intervention rollout and the end of the model (2025-2057). The shaded regions represent the 2.5th to 97.5th quantiles for the modelled results.

implemented shows a reduction in the prevalence of childhood obesity of 0.24 percentage points (uncertainty interval: −0.18, 0.92) and a reduction in the prevalence of adolescent obesity of 0.08 percentage points (uncertainty interval: −0.28, 0.63).

School-based interventions and increased sports participation through vouchers focus on delivering healthy environments for older children (6–12 years) and adolescents. The results show that school-based intervention reduces adolescent obesity by 0.40 percentage points (uncertainty interval: 0.00, 1.05) and childhood obesity by 0.15 percentage points (uncertainty interval: 0.00, 0.44), while sports vouchers reduce adolescent obesity by 0.63 percentage points (uncertainty interval: 0.01, 1.60) and childhood obesity by 0.42 percentage points (uncertainty interval: 0.00, 1.10). When both interventions were implemented together, there was a reduction in adolescent obesity of 1.04 percentage points (uncertainty interval: 0.04, 2.60) and a reduction in childhood obesity of 0.56 percentage points (uncertainty interval: 0.00, 1.10) by the end of the modelled time horizon.

All age groups in the model were exposed to the sugar-sweetened beverage tax intervention. The results show that reducing sugar-sweetened beverage consumption through taxation reduced childhood obesity by 0.57 percentage points (uncertainty interval: 0.02, 1.49) and adolescent obesity by 0.61 percentage points (uncertainty interval: 0.02, 1.62).

When all childhood and adolescent interventions were delivered together, there was a reduction in childhood obesity of 0.83 percentage points (uncertainty interval: 0.02, 2.08) and adolescent obesity of 1.14 percentage points (uncertainty interval: 0.06, 2.90). When the sugar-sweetened beverage tax was combined with the remaining interventions, childhood obesity was reduced by 1.43 percentage points (uncertainty interval: 0.09, 3.43) and adolescent obesity was reduced by 1.81 percentage points (uncertainty interval: 0.15, 4.43). The median effect when all interventions were implemented in the model was 7% higher in children and 5% higher in adolescents compared with when they were implemented individually.

			Median pp (2.5th and 97.5th quantiles)	Synergy ratio
Children interventions	a. Early prevention of obesity in children	Children	0.03 (-0.38,0.58)	
		Adolescents	0.01 (-0.40,0.40)	
	b. Childcare-based interventions	Children	0.19 (-0.00,0.54)	
		Adolescents	0.05 (-0.08,0.38)	
	a and b combined	Children	0.24 (-0.18,0.92)	1.09
		Adolescents	0.08 (-0.28,0.63)	1.26
Children and adolescent interventions	c. School-based interventions	Children	0.15 (-0.00,0.44)	
		Adolescents	0.40 (0.00,1.05)	
	d. Sports vouchers	Children	0.42 (-0.00,1.10)	
		Adolescents	0.63 (0.01,1.60)	
	c and d combined	Children	0.56 (-0.00,1.45)	1.00
		Adolescents	1.04 (0.04,2.60)	1.01
Population wide interventions	e. Sugar sweetened beverage tax	Children	0.57 (0.02,1.49)	
		Adolescents	0.61 (0.02,1.62)	
Combined	a, b, c and d combined	Children	0.83 (0.02,2.08)	1.06
		Adolescents	1.14 (0.06,2.90)	1.05
	a - e (all interventions)	Children	1.43 (0.09,3.43)	1.05
		Adolescents	1.81 (0.15,4.43)	1.07

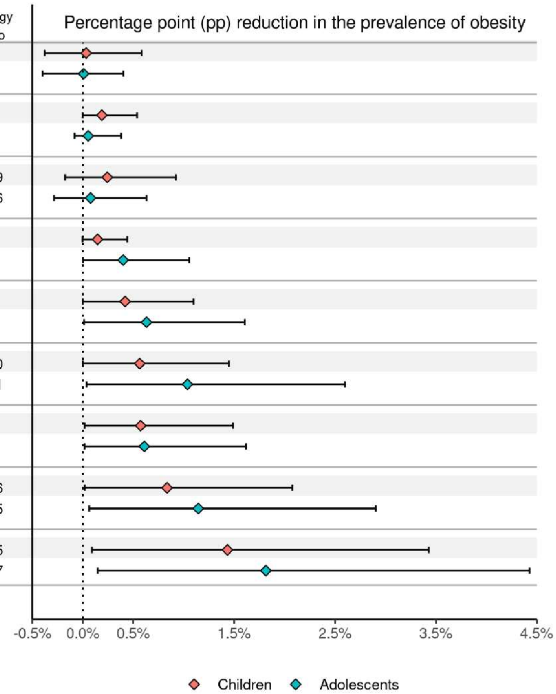

Figure 3 Estimated median reduction in obesity between interventions by 2057. Note: Uncertainty is estimated over 10,000 model simulations. The 2.5th to 97.5th quantile range represents the region that captures 95% of modelled results. The synergy ratio is the effect of the combined scenario divided by the sum of the separate individual scenario effects.

The scenario results for reducing overweight in children and adolescents are presented in online supplemental figure S40. It should be noted that increases in the prevalence of overweight are possible because of the obesity cohort moving to a healthier weight status without subsequent reductions in the overweight BMI category. Comparatively, the qualitative insights between interventions observed in the obesity results are mirrored in the overweight results.

Modelled cost-effectiveness

Table 2 presents the hypothetical cost of implementing each scenario and the resulting change in public healthcare spending and QALYs. The hypothetical cost of each intervention was subtracted from the sum of these benefits to estimate the net monetary benefit. Each age-targeted intervention and their combinations had a net negative benefit, indicating that the implementation cost was higher than the value of the benefits obtained. The cumulative implementation costs ranged from \$A650 million (\$A20 million annually) for the childcare centre interventions to \$A19.8 billion (\$A650 million annually) for school-based interventions; all interventions combined were estimated to cost \$A30 billion (\$A930 million annually). The sugar-sweetened beverage tax resulted in a substantial net benefit, although the wide quantile intervals suggest that the estimated values are relatively uncertain. When the potential benefits from interventions were widened to include the reduction in parents' and guardians' productivity losses, the effects remained modest and net benefit inferences were unchanged (see online supplemental table S23).

DISCUSSION

Our SD model of Australian children and adolescents was used to examine the effects of a series of prioritised, evidence-based interventions on the prevalence of overweight and obesity. The model allows interventions to be compared in a hypothetical environment under identical assumptions. Each intervention led to relatively modest reductions in the prevalence of child and adolescent obesity. However, the most notable reductions in obesity from an individually implemented intervention were observed when the sugar-sweetened beverage tax and sports vouchers were implemented separately. Furthermore, the sugar-sweetened beverages tax was the only tested intervention where the healthcare savings and changes in the health-adjusted life-years were expected to outweigh the cost of implementation and provide a net benefit, aligning with existing literature.[51] Scenarios that combined all tested interventions provided exposure across the population's life course from early childhood to adolescence, leading to sustained health improvements and were the most successful at reducing overweight and obesity. This tested portfolio of interventions was also observed to have a synergistic effect compared with single intervention implementations. Reductions in obesity, when all interventions were implemented together, were 5% more effective in children and 7% more effective in adolescents.

Our findings support prevention theory, which advocates for sustained interventions over the life course.[52] The model suggests that the coordinated implementation of a suite of interventions over the entire life course

Table 2 Cumulative economic results for each tested scenario

Intervention		Total intervention cost	Reduction in healthcare costs	Increase in cumulative utilities		Net benefit
		(Million $A)		(QALY)	(Million $A)	(Million $A)
		Median (2.5th, 97.5th percentiles)				
Childhood interventions	Early prevention of obesity in children	3081 (2854, 3307)	19 (–77, 96)	1604 (–8161, 15 622)	79 (–418, 775)	–2969 (–3584, –2211)
	Childcare centre interventions	650 (469, 848)	36 (–5, 83)	4060 (–2821, 15 932)	199 (–142, 795)	–408 (–822, 177)
	a+b	3732 (3446, 4028)	56 (–43 149)	5781 (–5054, 27 532)	284 (–247, 1346)	–3379 (–4069, –2246)
Childhood and adolescent interventions	School-based interventions	19 884 (17 084, 23 089)	143 (29 255)	12 473 (1093, 23 887)	613 (53, 1217)	–19 137 (–22 285, –16 262)
	Sports vouchers	6319 (5421, 7294)	197 (27 373)	18 556 (1649, 36 827)	907 (77, 1891)	–5203 (–6586, –3825)
	c+d	26 229 (23 209, 29 550)	336 (65 609)	31 190 (4264, 56 511)	1525 (202, 2891)	–24 378 (–27 989, –20 970)
Population-wide intervention	Sugar-sweetened beverage tax	57 (41, 72)	1031 (252, 1904)	90 530 (–25 005, 213 281)	4438 (–1207, 11 091)	5418 (–599, 12 445)
Combined	a+b+c+d	29 954 (26 928, 33 264)	395 (85 699)	37 275 (5246, 71 195)	1830 (253, 3667)	–27 723 (–31 491, –24 089)
	a+b+c+d+e (all interventions)	30 015 (26 987, 33 347)	1439 (452, 2405)	128 778 (–1977, 260 147)	6339 (–103, 13 570)	–22 236 (–29 999, –14 216)

Results are cumulative, with estimates calculated over a 32-year study period (2025–2057). Results are reported as medians and 2.5th and 97.5th percentiles to summarise the distribution of model results. All dollar estimates are presented as 2020 AUD. The net benefit is the sum of the reduction in healthcare costs and increase in utility, minus total intervention cost.
QALY, quality-adjusted life-year.

has a greater effect on health outcomes compared with individual interventions alone.[53] This concurs with previous literature, which has estimated only modest effects on obesity prevention with single policies,[54–56] and more meaningful impacts are achieved through a range of prevention and reduction strategies.[39 57] Further, we found that high-exposure interventions that support healthy food choices by changing the environment, such as taxing sugar-sweetened beverages, were more effective when coupled with targeted settings-based interventions. Policy-makers may consider how revenue generated through taxation can be used to support other prevention programmes.[58]

The modest reductions in obesity observed in our findings are reflected in existing literature highlighting the challenging nature of obesity prevention. Other countries have observed an underwhelming daily-per-capita caloric reduction from a sugar-sweetened beverages tax, resulting in calls for increased taxation to provide greater health benefits.[59] Marginal decreases in overweight and obesity attributed to sports vouchers stem from a high uptake in children who are already active,[60–62] reducing the population-level impact on obesity. These modest estimated changes in obesity and relapsing behaviours have flow-on implications for the economic outcomes of the model. Further, the differences in healthcare costs and utilities between BMI categories are relatively small, especially for younger age groups. The possible cost savings from obesity prevention increase with age, impacting obesity-related chronic diseases.[63] This reinforces the need for interventions that can produce sustained health benefits and minimise behavioural relapse. Implementation characteristics that aim to increase sustainable intervention delivery may assist policy planning in a resource-constrained decision environment.[64]

Limitations

SD modelling focuses on aggregate-level effects contributing to system behaviour.[65] However, many factors contribute to overweight and obesity, some of which (eg, energy intake and expenditure) differ between individuals. The aggregate nature of the model means that individuals cannot be tracked over time, making it challenging to represent individual characteristics such as personal behaviour relapse, adherence and population heterogeneity.[30] Furthermore, model disaggregation is challenging for subgroup analysis where individuals are transient, such as in remote locale or economic status. This means that targeted policies that aim to provide equity to these subgroups were beyond the scope of this study.

The model's primary insight relates to changes in weight following an intervention. However, the model did not consider well-known associations between behavioural change, weight status and other health concerns.[66] For example, increased participation in organised physical activities may improve the mental health of young people through increased social engagement[67]; increased rates of breastfeeding can improve infant immunity[68] and dietary changes can improve dental health[69] and sleep quality.[70] Further, interventions can also indirectly affect other sectors, such as the built environment; access to sports facilities can encourage participation, which warrants additional facilities to accommodate increased demand, creating a reinforcing loop.[71] The model does not consider these cobenefits and may influence a resulting cost–benefit analysis.

The scenario analysis aimed to illuminate how settings, behaviours and implementation characteristics contribute to interventions' effects on young people's weight status. However, the insights are not conclusive; they are hypothesised effects derived from data-driven calibration of energy intake and expenditure so that the model reflects known trends in obesity over time and as cohorts age. Therefore, the real-world effects of model-informed interventions should be evaluated to understand the extent to which differences between the model findings and real-world effects indicate a need for refinement of the model or intervention strategies.

The economic analysis adopted a health sector perspective, as the health sector is anticipated to be the primary funding source for potential interventions and beneficiary of cost savings (apart from the sugar-sweetened beverage tax). This approach is valid and consistent with previous economic evaluations.[72–74] A societal perspective would capture a broader range of potential benefits, such as the effects of interventions on productivity loss through obesity-related morbidity.[75] Further, childhood obesity interventions may have broader macroeconomic effects, such as taxation revenue[58 76]; however, this was beyond the model's scope.

Broadening the system perspective of future modelling research in child and adolescent obesity may provide greater utility to decision support. Subgroup analysis considering broader societal domains, such as economic status and location differences, may allow for tailored policy design. The wider implication of obesity reduction on the incidence of obesity-related comorbidities will further highlight the importance of prevention and reduction. Broader-scoped SD modelling with integrated economics may also help provide insights into budget constraint decision support, where revenue spent and generated is contextualised in a limited annual budget.

The model findings provide important considerations for public health practitioners and decision-makers working to prevent overweight and obesity. The model results, for instance, support the ongoing narrative for broader initiatives across the life course for obesity prevention and reduction. The modest reductions in obesity prevalence also demonstrate the difficulties in influencing population-level outcomes, as the highly internally valid effects derived from randomised trial effects can be washed out when a protocol is generalised to a population outside the original recruited sample.[77 78] Furthermore, simulation modelling can be used to consider the resilience of population measures and help design government population targets to balance achievable and ambitious goals.[79]

CONCLUSION

Childhood and adolescent obesity is a complex public health issue. SD modelling enables the use of multiple data sources with a defined, testable causal structure of systemic relationships to determine which combination of interventions will deliver the greatest population-level outcomes for child and adolescent obesity. The scenario analyses show that interventions with high exposure (reach) and high adherence (fidelity), such as a sugar-sweetened beverage tax, can potentially reduce obesity in childhood and adolescence. The modelled scenarios provide policy and programme decision-makers with a support tool to mix and match interventions and investigate the likely effect of each simulated combination. In the scenarios analysed, combining multiple interventions targeting different age groups across the life course had a larger influence on reducing the prevalence of obesity in children and adolescents compared with interventions targeted at a single age group.

The SD model focused on well-known concepts of overweight and obesity in children and adolescent populations. Future modelling of population-level factors associated with childhood and adolescent overweight and obesity may improve our understanding of the risk factors and how they interact. Ongoing research is needed to understand scaled up implementation characteristics and dynamics and generate innovations in obesity prevention programmes focusing on supporting children throughout life. Finally, broadening the health benefits considered and the perspective of health economics could help identify the unrealised benefits of each intervention. SD modelling is uniquely placed to support existing evidence-based public health strategies to inform and guide policy development and implementation.

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