Obesity Research/Methods

Applications of systems modelling in obesity research

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Summary

Obesity is a complex system problem involving a broad spectrum of policy, social, economic, cultural, environmental, behavioural, and biological factors and the complex interrelated, cross-sector, non-linear, dynamic relationships among them. Systems modelling is an innovative approach with the potential for advancing obesity research. This study examined the applications of systems modelling in obesity research published between 2000 and 2017, examined how the systems models were developed and used in obesity studies and discussed related gaps in current research. We focused on the applications of two main systems modelling approaches: system dynamics modelling and agent-based modelling. The past two decades have seen a growing body of systems modelling in obesity research. The research topics ranged from micro-level to macro-level energy-balance-related behaviours and policies (19 studies), population dynamics (five studies), policy effect simulations (eight studies), environmental (10 studies) and social influences (15 studies) and their effects on obesity rates. Overall, systems analysis in public health research is still in its early stages, with limitations linked to model validity, mixed findings and its actual use in guiding interventions. Challenges in theory and modelling practices need to be addressed to realize the full potential of systems modelling in future obesity research and interventions.

Keywords: Agent-based modelling, obesity, system dynamics modelling, systems modelling.

Abbreviations: ABM, Agent-based modelling; BMI, Body mass index; BRFSS, Behavioral Risk Factor Surveillance System; CHS, Community Health Survey; ECLS-K, Early Childhood Longitudinal Study – Kindergarten; FAB, Food Attitudes and Behaviors; FF, Fast food; FV, Fruits and vegetables; NCD, Non-communicable chronic disease; NHANES, National Health and Nutrition Examination Survey; NLSY79, National Longitudinal Survey of Youth 1979; PA, Physical activity; PE, Physical education; SDM, System dynamics modelling; SM, Systems modelling; SSB, Sugar-sweetened beverage.

Introduction

Obesity has become a public health crisis in the USA and worldwide, while at present more than 40% of adults worldwide are overweight or have obesity (1,2). Obesity and overweight have many serious health and financial consequences. For example, they account for a significant proportion of US total healthcare costs, e.g., 17% by 2030 based on our studies (2), and if the obesity trend continues, the life expectancy of the US population will decline (3). Approaches to halt the epidemic, therefore, are an imperative public health challenge (4).

The drivers of the growing obesity epidemic are complex, involving the multilayered interactions of policy, social, economic, cultural, environmental, behavioural and biological factors. As illustrated by the UK Foresight Project obesity map about a decade ago, the obesity system involves a broad range of subsystems and factors, including energy homeostatic control, physiology, physical activity (PA), PA environment, food consumption, food production/industry, individual psychology, social psychology, appetite control in the brain, force of dietary habits and psychological ambivalence (5).

Systems modelling (SM) methods have gained increasing interest and support during recent years, because of their potential in helping understand the complex interrelationships among factors related to the obesity epidemic (6–9). As an example, a Global Center of Excellence was established in 2011 based on a $16m U54 Center grant our international multidisciplinary team received from the National Institutes of Health (NIH, Systems-oriented Pediatric Obesity Research and Training [SPORT] Center of Excellence [U54]), aiming to promote the applications and training of SM as well as international interdisciplinary collaboration in obesity and non-communicable chronic disease (NCD) research at a worldwide scale (10).

Systems science is a broad term referring to a family of modelling approaches that aim to elucidate the behaviour of complex systems (e.g. policy, social, economic, cultural, environmental, behavioural and biological systems) and to inform policy and intervention efforts that address one or more problems manifested in a system or system of systems (6). SM is a systems-science-based simulation modelling approach for quantitative analysis of a research problem using computational and mathematical modelling, including methods like agent-based modelling (ABM) and system dynamics modelling (SDM) (11,12).

The application of SM in the public health field including obesity research is in its early stages. There are still many unanswered questions. Despite the increasing interest, studies systematically examining the applications of SM in obesity research remain scarce. In 2011, Levy *et al.* reviewed the simulations models of obesity published during 2006–2010 (13). Only four studies that used SM methods were reviewed along with other types of simulation models such as discrete-time Markov models, Monte Carlo models and statistics-based models (14–17). They found that simulation models addressing policy interventions are at an early stage of development (13). Skinner and Foster reviewed 21 studies published through March 2012, about the causes and/or consequences of obesity from a systems science perspective (18). While this review found that a true, integrated systems science perspective was not adopted in these studies, applications of SM were not included in this review. A 2015 review examined ABM of NCD (19), covering studies published during 2003 through mid-2014. They found that ABM was underutilized in NCD research, and environmental effects were not adequately modelled to study their impact on health outcomes (19). Among the 22 studies reviewed, only 13 studies were obesity related. In addition, the review did not examine the modelling details of each study, such as model structure, parameterization, calibration and validation.

The present study aims to fill in these gaps in the field by providing an overview of the applications of SM in obesity research over the past two decades, with details on advances in modelling techniques. Using this information on the state of the art, the present study also provides insights for overcoming technical challenges and enabling SM to advance future obesity research. The section on Systems Modelling and Obesity Research: Background and Related Key Concepts presents related background information and related key concepts; the Applications of Systems Modelling in Obesity Research section examines specific applications of SM in obesity research and reports findings; the fourth section discusses the challenges of SM applications in current research and provides recommendations for future research; and the last section presents the conclusions.

Systems modelling and obesity research: background and related key concepts

Obesity – a complex system problem

At the individual level, obesity is a result of behavioural patterns associated with excess energy intake. Human behaviours mediate the entry of pathogenic agents such as added sugars and saturated fats in the environment into the human body, thereby bridging the above-the-skin factors (e.g. food environment, built environment and social norms) with under-the-skin factors (e.g. genes, metabolism and neuroendocrine factors) (20). The two key behaviours that determine energy balance and thus affect obesity risks, eating and PA (including physical inactivity), are affected by many factors at various levels. When these and other behaviours are learned and spread among people (21–24), the net effect is to enable susceptibility to the environment to be transmitted in human populations.

Limitations of traditional research approaches in obesity research

A reductionist paradigm (e.g. in obesity research, linking obesity to a single cause or a set of causes by studying the relationships separately) has dominated the public health field for decades. This approach has made impressive achievements and has gained enormous support (25–27). It has identified causes and risk factors for both infectious diseases and NCDs (28–32). Research findings based on this approach have been translated into public health policies and campaigns (33,34). For instance, the impact of tobacco smoking on the risks for cancer and cardiovascular diseases has brought public attention to the need for tobacco control, leading to significant decreases in smoking by the US population (35–37).

Nevertheless, the limitations of the reductionist approach have become more apparent, particularly because of the unresolved questions about the aetiology of the obesity epidemic. Most notably, the reductionist approach does not consider the complex, multi-level nature of the system that supports obesity. There is a diversity of actors (e.g. consumers, food industry, families, schools, retailers, government agencies, policymakers, trade associations, public health agencies, the media and healthcare providers) and factors (e.g. socio-environmental determinants that affect the accessibility, availability, and affordability of healthy food and built environments) that affect energy-balance-related behaviour and obesity risk. Policies that do not take into account the full set of relevant actors and their coupled responses can result in unexpected, undesirable outcomes. For example, when the National School Lunch Program added new rules in 2012 that required children to select a fruit or a vegetable at each meal, decreased consumption of fruits and vegetables (FV) and increased food waste were observed.(38)

Another example is the built environment, in which the underlying assumption is that its influence on human behaviours and public health is unidirectional in the aetiology of obesity, i.e. the environment affects individuals. The evidence shows otherwise: the environment provides opportunities for individuals to make choices through space and time via the process of utility maximization (39). Conversely, individuals influence the environment they reside in through their presence and activities (40): peoples' travel patterns influence land use and transportation development, the landscape of local food markets changes and evolves in response to the local population's health choices and interactions between individuals change the social aspects of the local environment. Nevertheless, there has been no appropriate reductionist approach to study how the shifts in built environments that characterize the macro-level emerge from individual behaviours at the micro level. SM can simulate this bottom-up process of environmental dynamics (41).

Why use systems modelling in obesity research?

Compared with traditional approaches, SM can deconstruct the underlying mechanisms, modelling non-linear and circular causality and studying the whole obesogenic environment and individual-level factors instead of focusing on an isolated study of selected factors. It recognizes that in complex systems, interacting components can generate cascading effects; therefore, small events can catalyse large changes in the system. SM acknowledges that a change in one area of a system can adversely affect another area of the system; thus, it explicitly incorporates interactions at all levels to avoid narrow interpretations that characterize siloed analyses (6,7).

Two main types of systems modelling

Although several SM approaches exist, thus far, SDM and ABM are most widely used in the public health research field.

Systems dynamics modelling

Systems dynamics modelling is a modelling and simulation tool to investigate complex dynamic problems by incorporating non-linear relationships and interdependence of multilevel subsystems (e.g. policy, environmental, behavioural and biological), dynamics of information flows such as the transitions of normal-weight, overweight and populations with obesity, and correlated factors that affect the dynamic relationships and system outcomes at different levels. The mechanisms, outputs of the system, and related factors are of interest at the system level, so SDM usually uses variable-based equations to capture relationships among factors.

Agent-based modelling

Different from SDM, ABM takes a bottom-up view of studying systems. ABM recreates and predicts the complex phenomena of a group/system by simulating the individuals' actions and interactions, which are the building blocks of the group/system. The process is one of emergence from the lower (micro) level of systems to a higher (macro) level. The individual agents are presumed to be acting in what they perceive as their own interests (e.g. health, economic benefit or social status). The individuals may experience learning, adaptation and reproduction. In an ABM, every individual's behaviours are determined by decision rules formulated as computer codes.

An essential distinction between ABM and SDM is that the former can include space in the computation model: physical space (distance), social space (social networks) or information space (i.e. Internet networks). Agents are placed in a spatial context with specified starting conditions and interact with each other and with their environment given a set of behaviour rules. In the case of obesity, agents can be heterogeneous and different from one another in numerous ways, e.g. gender, age, race, socio-economic status, environment and social network. In this way, the computer simulation 'grows' macro-level patterns and trends from the micro level (11).

Applications of systems modelling in obesity research

This study is not intended to be an exhaustive review, but to highlight the notable key applications of SM, namely ABM and SDM, in obesity research. Based on our searches in PubMed, Google Scholar and the Web of Science of studies published from 2000 to 2017, we included 35 original obesity studies that used systems models (Table 1).

Systems modelling has been applied in various ways and arenas in obesity-related research, on various topics such as diet behaviour, PA, food environment, built environment and metabolism as well as population dynamics, policy effect simulations and social influence. Published studies of social influence analysis dominate the applications of SM; about 50% were related to social influence and social networks, particularly ABM applications (Table 2) (15–17,22,54,56–58,60–62,65).

Trend in publications using systems modelling in obesity research

Systems modelling publications in the obesity field during 2000–2010 were scarce (Fig. 1). Since 2010, an increasing number of SM studies have been published, with an unequal rate of increase between ABM and SDM. The number of ABM publications was about two times higher compared with that of SDM publications.

Scientific impact of published systems modelling obesity studies

As an important indicator of scientific impact, we examined the citations and related temporal trends of the published SM studies (Fig. 2). Citations of ABM and SDM studies had been increasing, with a sharp increase occurring during 2009–2015, reaching a peak in 2015 and 2016. However, the absolute numbers of the citations of SM studies remained low, with maximum annual citations of 92 for ABM in 2015 and 60 for SDM studies in 2016.

Specific applications of system dynamics modelling in obesity research on various related topics

Metabolism simulation

The early application of SDM in obesity research was to simulate energy metabolism. An important study by Abdel-Hamid demonstrated the biological mechanisms involved in the systems that affect energy metabolism and obesity (42). The model consisted of four subsystems: body composition, energy intake, energy expenditure and energy metabolism. The simulations suggested that exercise protected against the loss of fat-free mass compared with weight loss through dieting; however, exercise at moderate levels produced less weight loss than did dieting. This study demonstrated the potential of using SDM to model under-the-skin mechanisms by synthesizing existing biological knowledge and empirical studies.

Body weight dynamics

Levels and feedback loops are important features of an SDM that provide convenient tools to model the dynamics of weight change. Simulating body weight change dynamics is the most prevalent application of SDM. The dynamics can be modelled at the population level. Homer *et al.* built an SDM to simulate weight status changes as horizontal transitions between four weight status categories, with ages changing vertically in the model from 0 to 99 (14). National Health and Nutrition Examination Survey (NHANES) data for adults and statewide pre-K through 12th-grade assessment data for children in Arkansas were used to calibrate constants of body mass index (BMI) category down-flow rates in the model. Their simulation suggested that being overweight and having obesity at younger ages would lead to the growth of the prevalence of overweight and obesity at older ages, while removing energy imbalance in youth as well as among young adults could significantly eliminate the growth in the numbers of adults with obesity.

Weight changes can also be modelled at the individual level using SDM. Such a study simulated weight gain and obesity in reproductive age women (48). Pre-pregnancy weight, pregnancy weight and postpartum weight were the key state variables in the model, all of which formed a feedback loop. This study used a representative woman, for example, a 34-year-old White person, with other relevant attributes. Two studies provided elements and parameters for the simulation (71,72). Their findings suggested that women with obesity would become more obese during pregnancy, while pre-pregnancy weight loss could be beneficial but might affect fertility.

Population-level weight changes can be modelled through individual-level weight change dynamics. Rahmandad and Sabounchi explicitly modelled energy imbalance at the individual level using an SDM and aggregated the changes at this level to model the trends of obesity at the population level (43). In their model, energy demand included energy for maintenance of the body and energy for growth. They used NHANES 2000 data to initialize the model and compared the moments generated by the model and from the NHANES 2002–2008 data to calibrate the model. This method provided a possible approach to estimate dynamic models based on cross-sectional individual-level data to model population-level weight dynamics. In one study, our team used a similar method to include micro-level model dynamics with population-level obesity distribution in SDM (45). By using an average person in sub-population groups based on adult age and gender, individual-level metabolism was

Table 1 Summary of key characteristics of systems modelling studies in obesity research published during 2000–2017

Study ID	Reference	Year	Study aims and analysis	Empirical data used	Main results and conclusions
				SDM	
1.	Abdel-Hamid(42)	2003	Examined impacts of PA and diet on weight gain/loss	Parameters from existing literature	Exercise can contribute to energy expenditure and protect against fat-free mass loss compared with dieting alone; moderate to high exercise intensity may be counterproductive for a sedentary subject with obesity to lose weight; dynamic interactions between diet composition and PA should be taken into account when designing weight loss strategies.
2.	Homer *et al.*(14)	2006	Simulated US obesity trends; examined interventions options targeting school-aged youth to curb obesity trends; explored the subpopulations and time frame for effective interventions.	NHANES (1971–1974,1976–1980, 1988–1994,1999–2002); NHES (1960–1962, 1963–1965,1966–1970)	Overweight or obesity in children leads to the same conditions in adults; targeting youth alone is not effective in reducing obesity; removing energy imbalance in youth could greatly reduce risk of having adults with obesity; comprehensive weight loss programme interventions are best.
3.	Rahmandad and Sabounchi(43)	2012	Modelled individual-level weight change dynamics and built aggregate individual-level models to simulate population-level weight changes	NHANES (2000–2009)	The study shows a possible approach to estimate dynamic models based on cross-sectional individual-level data to model population-level weight dynamics.
4.	Frerichs *et al.*(44)	2013	Assessed sensitivity of prevalence of overweight/ obesity in childhood to peer and adult social transmission rates; tested effect of prevention/ treatment interventions on the prevalence of overweight/ obesity in childhood.	NHANES (2009–2010)	Prevalence of overweight/obesity in childhood may be more sensitive to changes in adult-to-child social transmission rate; targeting adults may be more efficient; treatment + prevention gave the best results; social transmission dynamics should be considered when designing prevention and treatment interventions.
5.	Fallah-Fini *et al.* (45)	2013	Explored the method of connecting micro-level dynamics with population-level distribution.	NHANES (1971–2010)	Comparing results with those obtained from an individual-based model, the proposed method delivers accurate results with less computation than the individual-based model.
6.	Abidin *et al.*(46)	2014	Simulated the effects of eating behaviour changes of British children (2–15 years) on weight/ obesity and identified time frame to remove obesity as a public health concern by 2020	Health Survey for England and other published sources	Simulation results indicated that 2020 target will not be achieved until 2026 at the earliest, suggesting a longer period may be needed to reduce obesity.
7.	Basu *et al.*(47)	2014	Estimated changes in calorie intake and PA necessary to achieve the Healthy People 2020 objective	NHANES (1999–2010)	Obesity will shift towards older adults and minority lower-income groups if current energy intake trends continue; >10% daily calorie restriction or increased exercise would in theory achieve the Healthy People 2020 objective.
8.	Sabounchi *et al.* (48)	2014	Examined the dynamics of weight gain/loss in women of reproductive age, to inform policies and interventions targeting women with obesity	Parameters from existing literature	Women with obesity who become pregnant exhibited increasing obesity levels over time, with elevated morbidity and mortality; women with obesity who lost weight pre-pregnancy had improved reproductive outcomes but risk an age-related decline in fertility
9.	Fallah-Fini *et al.* (49)	2014	Based on the method developed in their 2013 study, this study intended to quantify the energy imbalance gap in gender/racial subpopulations related to obesity in the USA	NHANES (1971–2010)	Energy balance gaps across subpopulations and over time were different, suggesting tailored interventions to meet subpopulations' needs.
10	Liu *et al.*(50)	2016	Simulated policy effects of allocating revenue collected by SSB taxation across sustainable	Parameters from existing literature	There could be counter-intuitive behaviours caused by implementation-related factors, including delays and other uncertainties in

(*Continues*)

Table 1 (Continued)

Study ID	Reference	Year	Study aims and analysis	Empirical data used	Main results and conclusions
			implementation strategies to maximize benefits of taxation for prevention of obesity in childhood		dynamic systems; policymakers should design and implement reliable implementation strategies for high-leverage, long-term policies, rather than focusing on short-term fixes.
11.	Powell *et al.*(51)	2017	Simulated the potential impact of a given policy intervention or combination of policy interventions on the future prevalence of obesity in childhood in the USA	Population data from US Census Bureau, BMI data for children in Georgia from K-12	Status quo, the prevalence of obesity among children and adolescents aged ≤18 in Georgia would be 18% from 2014 through 2034; mandat ing daily school PE would reduce prevalence to 12%; integrating moderate to vigorous PA into el ementary classrooms would reduce prevalence to 10%; the prevalence of obesity in childhood would decrease from 18% to 3% if all policies were simultaneously implemented.
				ABM	
12.	Hammond and Epstein(17)	2007	Mathematically demonstrated the difficulties of weight change and influence of social norms on individual weight adjustment and mean social weight changes	Parameters from existing literature	CLR diet and constant temptation level diet were more efficient than CEL diet in reducing BMI; CLR caused higher temptation to cheat; CEL was less effective for male than female participants; follow-the-average social norm produces upward trending BMI in the population.
13.	Burke and Heiland(15)	2007	Assessed impacts of food prices, endogenous social body weight norms and individual metabolism on weight distributions	NHANES (1976–1980, 1988–1994,1999–2000), BRFSS (1990 and 1994–2002), Schofield (1985)	Food price drop causes mean, median, standard deviation, 95th-percentile weight, 99th-percentile weight and obesity rates increase; social norm leads to increased weight; concave metabolic function along with social weight norm generates right-skewed weight distribution.
14.	Bahr *et al.*(16)	2009	Simulated obesity spread/social interactions under the influence of social force and social volatility	Framingham study	People with similar BMI cluster; initially biased distribution of BMI towards a certain class forms a dominant cluster of that BMI class; social forces push the formation of dominant cluster; effective interventions should target well-connected individuals on the edge of the cluster and individuals.
15.	Auchincloss *et al.* (41)	2011	Examined effects of income and geographic food store distributions on inequality of diet quality	Parameters from existing literature	Food price/store locations are determinants of diet quality of low-income households; expensive healthy food stores could not survive in low-income areas because of lack of demand; spatial segregation of food stores increases inequality in diet quality across income groups.
16.	Yang *et al.*(52)	2011	Simulated the effects of community safety in adult daily walking behaviour	National Household Travel Survey 2001	A low safety level associated with low-SES neighbourhoods could lead to less walking in low-SES groups; proximity to destinations encourages more walking but influence could be offset by safety concerns.
17.	Giabbanelli *et al.* (53)	2012	Social influence and environmental influence on weight changes in children	NLSY79	Environment may affect weight changes; network structure may influence the environment influence and micro-level social ties may make populations less influenced by environment influence.
18.	Shoham *et al.*(54)	2012	Examined impact of social influences on adolescent body size and related behaviours independent of friend selection	National Longitudinal Study of Adolescent Health (Add Health)	Simulations suggested homophily and social influence on BMI; no evidence of homophily on screen time; homophily on playing active sports (in one school); evidence of social influence on screen time (in one school) and playing active sports (in both schools).
19.	Widener *et al.*(55)	2013	Examined the impact of various policy interventions on low-income households' FV consumption	Hoover's business directory, 2010 parcel data of the City of Buffalo and data from the Internet	Diets were influenced by habit; increasing the frequency of households' grocery shopping could help increase FV consumption; utilizing convenience stores and mobile market could

(*Continues*)

Table 1 (Continued)

Study ID	Reference	Year	Study aims and analysis	Empirical data used	Main results and conclusions
					increase FV stocking, which would lead to increased FV consumption.
20.	Hammond and Ornstein(56)	2014	Examined social influence (follow the average) on body weight	NLSY97	BMI clustering in networks can be linked with local conformity, in addition to homophily; impact of clustering depends on the agents' BMI satisfaction range; dependencies in the dynamics of social norm change should be well considered in interventions shaping social norms to prevent obesity.
21.	Orr *et al.*(57)	2014	Explored policy efficacy of improving neighbourhood school quality in reducing racial disparities in obesity	Data from Massey, Gross and Shibuya (1994)	Improving school quality can reduce, but not eliminate, racial disparities in obesity-related behaviour; degree depends partly on social network effects.
22.	Trogdon and Allaire(58)	2014	Simulated effect of peer selection on social multipliers for weight loss interventions	NHANES (II, III and 1999)	Social multipliers increased with number of intervention participants' friends; increased weight clustering reduced social multipliers.
23.	Wang *et al.*(22)	2014	Examined the effects of social norms on school children's BMI growth/fruit and vegetable consumption and effects of misperceptions of social norms on US children's BMI growth	The ECLS-K cohort	Social norm influences US children's BMI growth; high obesity prevalence leads to a continuous increase in children's BMI owing to increased socially acceptable mean BMI.
24.	Yang *et al.*(59)	2014	Examined the impact of the WSB on children's active travel to school	Parameters from existing literature	The study illustrated how an ABM can identify location of routes maximizing effects of WSB on active travel; e.g. to maximize active travel to school, children should arrive on time at 'bus stops' to allow faster WSB walking speeds.
25.	Zhang *et al.*(60)	2014	Simulated the effects of different policies on unhealthy eating behaviours (taxes, subsidies, healthy norms and regulation of local food environments)	2007 FAB Survey	Imposing a tax on fast food and improving the visibility of positive social norms could improve the consumption of fruits and vegetables and lower fast food consumption. Zoning policies had no significant impact.
26.	Zhang *et al.*(61)	2015	Tested effectiveness of interventions for increasing PA in children after school	Add Health	Interventions that leverage friendship could increase PA after school; an intervention that leverages influence of the most popular kids may not affect inactive kids socially marginalized; interventions should aim at shifting entire distribution of PA.
27.	Zhang *et al.*(62)	2015	Examined network mechanisms irrelevant to obesity prevention and assessed approaches that may leverage social networks impact on overweight/obesity prevalence in adolescents	Add Health	Increasing the strength of peer influence may prevent overweight in populations with low obesity; underlying distribution of BMI influences the effect; interventions targeting diet of agents highly connected in a given network may not work.
28.	Chen *et al.*(63)	2016	Examined water fountain and SSB vending machine influence on children's choices, energy balance and dehydration after PE class	Parameters from existing literature and estimated from ECLS-K	Interventions to increase water access in schools can successfully increase water consumption; installing more water fountains and increasing SSB prices would reduce use of SSB for rehydration after PE.
29.	Li *et al.*(64)	2016	Examined how a mass media and nutrition education campaign may promote fruit and vegetation consumption in NYC	2010 US Census data of NYC, 2010 ZIP Code Business Patterns data, FAB Survey, NYC CHS	A mass media and nutrition education campaign that improves the influence of positive social norms (e.g. 10% and 5%) would increase the proportion of individuals who consume fruits and vegetables at least two servings per day in NYC; there may be variations across neighbourhoods.
30.	Mooney and El-Sayed(65)	2016	Investigated the mechanism for how body habitus norms and weight-based stigma influences	BRFSS (1991–2011)	Weight-based stigma may increase the risk of depression in population with low obesity; relation between prevalence of resistance to obese

(*Continues*)

Table 1 (Continued)

Study ID	Reference	Year	Study aims and analysis	Empirical data used	Main results and conclusions
			depression in the population with obesity		environment and depression may not be linear (u-shaped), which may generate unintended health consequences in interventions aiming to increase resistance to obesogenic environment.
31.	Orr *et al.*(66)	2016	Examined effects of increasing neighbourhood availability of good food stores, PA infrastructure and school quality on reduction of Black/White disparities in BMI	2007 National Health Interview Survey	Effect of upstream policies in reducing BMI disparities between Blacks and Whites is not immediate, and different policies may have different time windows; the impact of school quality may accelerate over time; multiple policies carried out simultaneously may not interact with each other over time.
32.	Beheshti *et al.*(67)	2017	Compared effectiveness of obesity interventions using network-based targeting methods with interventions using conventional targeting methods including random selection, based on individual obesity risk and vulnerable areas	NLSY79	A network-based targeting method would be more effective and lead to greater impact compared with conventional targeting methods.
33.	Lee *et al.*(68)	2017	Tested the effects of increasing the proportion of youth meeting two different levels of PA recommendations: 25 min of high-calorie-burning PA three times a week (active to healthy level) and 60 min of moderate PA each day (CDC's PA guidelines)	NHANES (2005–2013)	Increasing the proportion of children meeting CDC's guidelines and 'active to a healthy level' to 50% would avert net present values of \$11.4bn and \$8.1bn in direct medical costs and \$25.1bn and \$13.8bn in lost productivity each year; increasing the proportion to 75%, net present values would be \$25bn and \$16.6bn in direct medical costs and \$43.8bn and \$23.6bn in lost productivity each year.
34.	Lee *et al.*(69)	2017	Examined the impact of SSB point-of-purchase warning label policies on mean change in BMI and obesity prevalence in Baltimore, Philadelphia and San Francisco	NHANES (2010–2014); Reference USA	SSB warning labels would reduce the prevalence of overweight, obesity, and mean BMI. Low literacy may reduce effectiveness of warning labels. The impact of warning labels remained after reducing store compliance in the simulations.
35.	Li *et al.*(70)	2017	Simulated the impact of increasing the accessibility to and reducing fruit and vegetable price on fruit and vegetable consumption in adults in NYC	2010 US Census, the 2010 NYC CHS and FAB Survey	Improving the numbers of FV vendors and reducing FV price would lead to increased FV consumption; there was a positive association between education level in a neighbourhood and the intervention impact.

Note: ABM, agent-based modelling; BMI, body mass index; BRFSS, Behavioral Risk Factor Surveillance System; CDC, Centers for Disease Control and Prevention; CEL, constant eating level; CHS, Community Health Survey; CLR, constant loss rate; ECLS-K, Early Childhood Longitudinal Study – Kindergarten; FAB, Food Attitudes and Behavior; FV, fruits and vegetables; NHANES, National Health and Nutrition Examination Survey; NHES, National Health Examination Survey; NLSY79, National Longitudinal Survey of Youth 1979; NYC, New York City; PA, physical activity; PE, physical education; SDM, system dynamics modelling; SSB, sugar-sweetened beverage; SES, socio-economic status; WSB, walking school bus.

connected with population-level weight distributions. Using this method and similar NHANES data, another SDM study estimated the energy imbalance gap involved in the trends in the US adult obesity epidemic among different gender and ethnic groups, finding that the energy balance gaps across sub-populations and over time were different (49).

Health behaviours

Assessing the effects of behaviour interventions is another popular use of SDM. Frerichs *et al*. utilized SDM to simulate social transference of unhealthy behaviours from adult to adult, adult to child and child to child (44). The model made strong assumptions about the relationship between obesity prevalence and the likelihood for a normal population to become overweight or develop obesity; i.e. they are positively and proportionally correlated. The study used data from NHANES 2009–2010, Framingham Heart Study and other existing studies to obtain parameters for the model. Their results showed that the prevalence of children with obesity was slightly more sensitive to adult-to-

Table 2 Specific sub-fields of applications of systems modelling in obesity research

Research topics	Total number of applications of systems models	Number of ABM application (study ID)	Number of SDM application (study ID)	Number of studies linked with empirical data
1. Dietary behaviour	6	4 (12, 25, 29, 30)	2 (6, 7)	5
2. Food environment	7	7 (13, 15, 19, 25, 28, 31, 35)		5
3. Built environment	3	3 (16, 24, 31)		2
4. Human metabolism/weight change dynamics	4	1 (12)	3 (1, 3, 8)	2
5. Physical activity	5	4 (16, 24, 26, 33)	1 (7)	4
6. Population-level dynamics	5		5 (2, 3, 4, 5, 9)	5
7. Policy	8	6 (18, 20, 21, 23, 24, 34)	2 (10,11)	5
8. Social influence	15	14 (12, 13, 14, 17, 18, 20, 22, 23, 25, 27, 28, 30, 31, 32)	1 (4)	13

Note: ABM, agent-based modelling; SDM, system dynamics modelling.

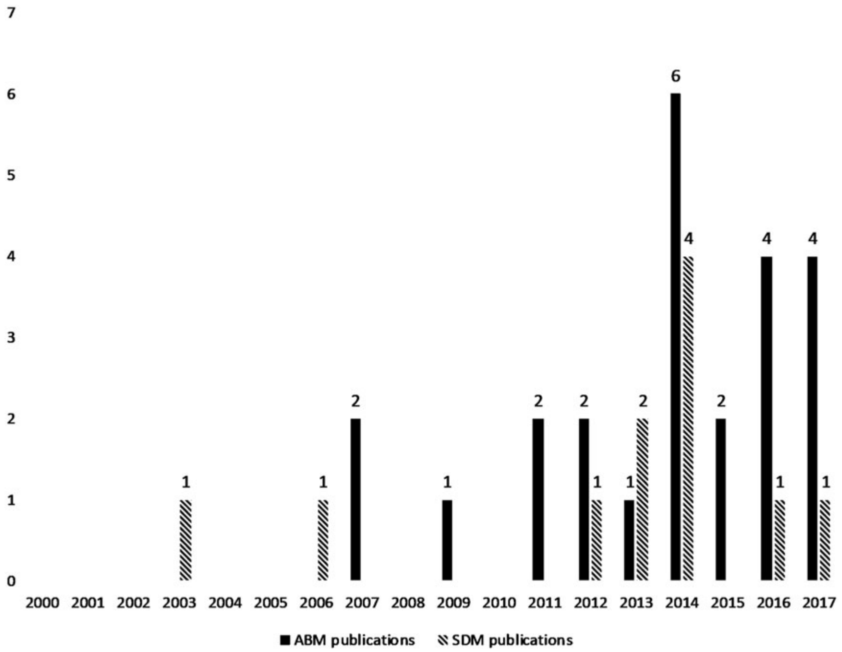

Figure 1 Number of publications in peer-reviewed journals of ABM and SDM applications in obesity research during 2000–2017. Data source: Web of Science, PubMed, Google Scholar, January 1, 2000, to December 31, 2017. ABM: agent-based modelling; SDM: system dynamics modelling

child social transmission relative to child-to-child transmission. The study recommended adding treatment in prevention to maximize reduction in the prevalence of obesity in childhood.

Another study used SDM to simulate the dynamic interactions among several sectors: food intake, energy expenditure, physical measurement and BMI impact (46). The authors modelled food consumption as a function of portion size and number of meals, which determined the consumption of total fat. Average fat portion size in different eating occasions including home, school and outside of meals played an influential role in the model, determining the prevalence of obesity. The study used the data from the Health Survey for England to validate the model. Their findings suggested that the British government would need at least an additional 6 years to achieve its goal to curb obesity among British children.

Policy analysis

The potential of using SDM to explore policy impact as a complementary approach to randomized control trials and natural experiments has not been fully realized. Applications in this area are still rare. Our team built an SDM to examine how allocating revenue collected by sugar-sweetened beverage (SSB) taxation across sustainable implementation strategies may maximize the benefits of such taxation for the prevention of obesity in childhood (50). This model helps researchers and policymakers to understand and

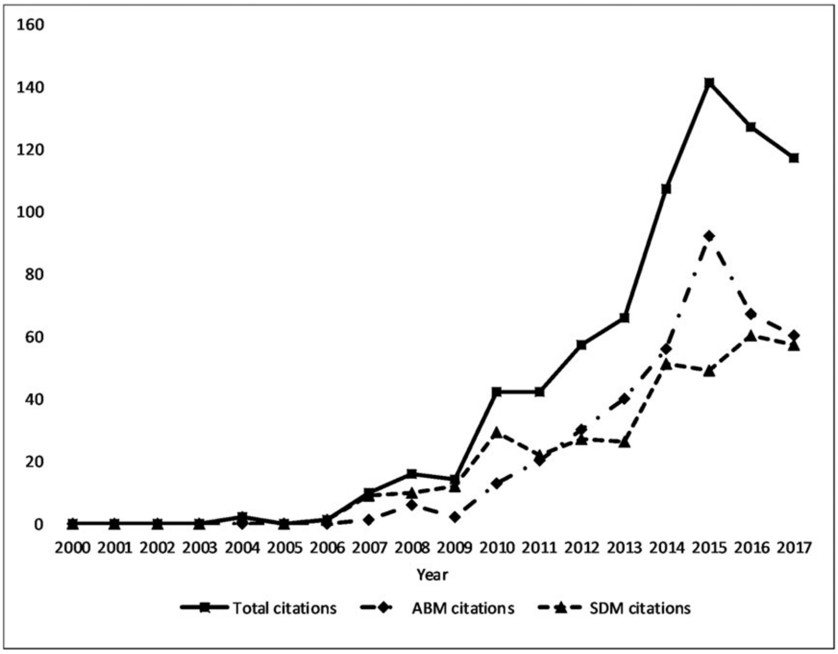

Figure 2 Temporal trend in number of citations of ABM and SDM studies published in peer-reviewed journals during 2000–2017. Data source: Web of Science, Google Scholar, January 1, 2000, to December 31, 2017. ABM: agent-based modelling; SDM: system dynamics modelling.

anticipate the possible counter-intuitive behaviours caused by implementation-related factors, such as delays and other uncertainties, and allows them to design and implement reliable implementation strategies for high-leverage policies, rather than focusing on short-term fixes.

Based on the model developed by Homer and colleagues in 2006, a team comprising state legislators, legislative staff members and experts in nutrition, PA, epidemiology, economics and systems dynamics developed a system dynamics model to predict obesity among children in Georgia, and the team updated the model in 2014 (51). The updated model simulations suggested that, compared with a scenario with no policy change in which the prevalence of obesity among children in Georgia would remain 18% from 2014 to 2034, mandating daily school physical education (PE) would reduce the prevalence of obesity in childhood to 12%, integrating moderate to vigorous PA into elementary classrooms would reduce the prevalence to 10%, and if all policies were implemented simultaneously, the prevalence would be reduced to 3%.

Specific application of agent-based modelling in obesity research on various topics

Social influence on obesity-related outcomes

Exploring social influence is the most widespread use of ABM. In contrast to conventional social network analysis, ABM can model social mechanisms explicitly by introducing specific structures and features of networks and imposing clear governing rules to model the interactions between agents with highly heterogeneous attributes.

The existing applications of ABM have moulded social influence through two primary channels: (1) weight perception channel and (2) behaviour perception channel. Through the weight perception channel, an agent's self-weight perception was influenced by the weight status of other agents in a given social network, which shaped the energy-balance-related behaviours (e.g. diet and PA) and weight outcome of the agent. This type of application includes that of Burke and Heiland (73), Bahr *et al.* (16), Wang *et al.* (22), Zhang *et al.* (62), Mooney and El-Sayed (65) and Trogdon and Allaire (58).

For example, Burke and Heiland modelled the agent's weight as a function of the average weight among all agents in the population (73). This study explicitly derived equilibrium conditions based on the utility maximization problem and thus provided estimates of equilibrium food consumption, nonfood consumption, and equilibrium weight and equilibrium weight norm. The model was calibrated based on data for US women aged 30–60 years in NHANES between 1976–1980 and 2000 with the body weight norm derived from the Behavioral Risk Factor Surveillance System data. Their simulation suggested that a drop of food prices would cause an increased obesity rate. Trogdon and Allaire made an extension of Burke and Heiland's model by setting the reference weight as proportional to a function of the agent's friends' weights (15,58). Empirical data were used to calibrate the model by matching the known features of social networks of the Add Health and Framingham data. Weight distribution was calibrated based on data from NHANES II (1976–1980), III (1988–1994) and 1999. The simulations suggested that the effect of a weight loss programme increased at the aggregate level when the number of the agent's friends increased.

Our team built an ABM based on empirical longitudinal data collected from the Early Childhood Longitudinal Study – Kindergarten (ECLS-K), a US nationally representative study, and tested potential peer influences (social norms) affecting children's BMI growth and food consumption (22). Agents maximize their utility by following the average BMI in a given social network and average FV consumption. The model was parameterized and validated based on the ECLS-K data. Our simulations suggested that the follow-the-average social norm acts as an endogenous stabilizer, which automatically adjusts positive and negative deviance of an individual's BMI from the group mean of a social network (22). Hammond and Ornstein used similar methods to study the impact of social influence on body weight, using longitudinal data from American youth.(56) Their findings confirmed our finding that the social norm does influence children's BMI.

The impact of dynamic social network structure changes could also be incorporated in social influence through the weight perception channel. In Zhang *et al.*'s model (62), agents could choose to add a new tie or drop an existing tie in the social network (called network change) based on the values of objective function before and after network change. With empirical data from wave 1 of the National Longitudinal Study of Adolescent Health (Add Health Study), they simulated models and validated them with data from wave 2 of Add Health. Findings suggested that increasing peer influence could help decrease the prevalence of overweight and that underlying BMI distribution influences such peer effects. Similar methods were used in studies by Shoham *et al.* (54) and Zhang *et al.* (61), which explored social influence on BMI and PA.

Social influence was also modelled through the behaviour perception channel, in which an agent's diet and PA behaviours were affected by his or her perception of other agents' related behaviours in these studies: Li *et al.* (64), Giabbanelli *et al.* (53), Beheshti *et al.* (67).

For example, Li *et al.* used a similar ABM developed by Zhang *et al.* (60) to simulate how a mass media and nutrition education campaign may promote FV consumption by improving positive social norm influence in New York City (NYC). The individuals connected in a given neighbourhood formed a 'small-world' type of network, and individuals influenced each other through a few social ties. ABM simulations indicated that the campaign can promote FV consumption in NYC with geographic variations across neighbourhoods.

Giabbanelli *et al.* simulated the social influence and environmental influences simultaneously on diet and PA (53). Built upon energy homeostasis of energy intake, energy expenditure and energy storage, the ABM simulated how individuals influenced each other on food intake and PA. Social network influence and environment influence (ENV) were modelled together as a fixed value to represent socio-environmental influence. The model parameters were determined in a way that would generate realistic weight changes (e.g. average weight change) from the National Longitudinal Survey of Youth 1979. This study found that ENV is a significant factor that affects weight changes, network structure may influence the ENV effect and micro-level social ties may make populations less influenced by ENV.

Based on the model developed by Giabbanelli *et al.*, Beheshti *et al.* built a modified ABM to examine how social network-based targeting strategies may influence the effects of obesity interventions (53,67). In this modified ABM, two threshold values (low and high) for energy intake and PA were used. Each agent was assigned different threshold values as compared with the same values for the whole population. The model was fit to identify these individual threshold values by matching the model-generated weight change data to the National Longitudinal Survey of Youth 1979 dataset. Moreover, ENV values were set as specific to agents' location instead of using one value for the whole population. The degree of nodes and clustering coefficients was based on information from datasets such as the Framingham Heart Study and the Add Health study. The simulations suggested that network-based approaches would generate greater impact compared with non-network-based strategies.

Eating behaviours and food environment

Agent-based modelling has been used to examine the relationship between obesity and food environment. Simulating the effects of improving accessibility and affordability of healthy foods was the primary application of ABM in this area. For example, Auchincloss *et al.* examined the effects of income and geographic food store distributions on diet quality inequality (65). The agents in the model were households and food stores. Households' decisions of where to shop were determined by four factors: price of food at the store, distance to the store, the household's habitual behaviour and the household's preference for healthy foods. The simulation suggested that location of healthy food stores determined dietary quality.

Widener *et al.* used an ABM to examine the FV consumption of low-income households (55). The model used real household locations in Buffalo, New York, and locations of food vendors including supermarkets, convenience stores, farmers' markets and mobile grocery markets to replicate the real-world food environment. Agents chose to go to a supermarket or a convenience store to purchase food based on the nearest option for each store type. This study found that more frequent grocery shopping was associated with more FV consumption.

In a study published in 2016, our team designed an ABM to test whether and how placement of drinking fountain and SSB vending machines in schools might influence children's beverage choices, energy balance and dehydration after PE classes (63). The ABM represented a hypothetical school environment in which the agents, children, chose to obtain fluids from water fountains and/or vending machines during and after PE class. The agents' goal was to rehydrate as soon as possible by evaluating the time cost associated with different fluid sources. Agents interacted with each other by influencing one another's time cost. The simulation results suggested that installing more water fountains and decreasing the affordability of SSBs by raising their prices would reduce school children's SSB consumption (63).

In another recent study, our team developed an ABM to simulate individual dietary behaviours of adults in NYC under hypothetical interventions: (1) a 10% and 20% increase in the number of FV vendors, (2) a 10% and 20% reduction in the price of FV, (3) a 10% increase in the number of vendors and 10% decrease in price and (4) a 20% increase in the number of vendors and 20% decrease in price (70). In the ABM, agents were individuals with various attributes (geographic and demographic characteristics, taste preferences, health beliefs and price sensitivity). Individuals were connected with each other through social connections that may influence their taste preferences and health beliefs. Data from the 2010 US census, the 2010 NYC Community Health Survey and the Food Attitudes and Behaviors Survey were used to populate the model and to estimate needed parameters for the model. We found that improving the numbers of FV vendors and reducing FV price would lead to an increase in FV consumption, and there was a positive association between education level in a neighbourhood and the intervention impact.

Agent-based modelling was also used to model the reciprocal relationship between food environment and dietary behaviours. Zhang *et al*. built an ABM to explore the interactions between individuals' dietary choices and the adaptation of food outlets (60). In the model, individuals chose to consume FV or fast food (FF), with probabilities calculated from the 2007 Food Attitudes and Behaviors Survey. Food outlets adapted to individuals' consumption in the neighbourhood and decided on that basis to sell FV or FF. Their simulations showed that the effects of taxing unhealthy food and increasing FV store density in increasing FV and lowering FF consumption were small; promoting healthy norms may have greater impact.

Examining policy effect is an important application of ABM. One recent example is a study that tested whether SSB warning labels would influence consumption and the prevalence of obesity in Baltimore, Philadelphia and San Francisco in a 7-year period (69). An ABM was developed to represent adolescent populations with specific characteristics (e.g. gender, race/ethnicity, height, and lean and fat tissue mass) in assigned schools, households, and food and beverage environments. In the simulations, agents chose to consume meals and snacks at different locations (home, school or a retail location) with corresponding probabilities estimated from NHANES 2010–2012. The simulations suggested that warning labels may be effective to reduce overweight and obesity rates in children.

Physical activity and built environment

Agent-based modelling is suitable to examine the influence of built environments on PA at micro and macro levels. Yang *et al*. used ABM to explore adults' walking habits (52). The model included adults, households, local establishments (groceries, nonfood shops, social places and workplaces) to mimic the real setting of the city of Ann Arbor, Michigan. Agents had three types of walking purposes: for work, for basic needs (e.g. shopping) and for leisure. An agent's decision to walk was based on comparisons between the actual distance and his or her maximum walking distance ability. The study used the 2001 National Household Travel Survey data to calibrate its model parameters. Another study by Yang *et al*. developed an ABM to examine the impact of a 'walking school bus' (WSB) on children's active travel to school (59). The ABM was a hypothetical city with four school zones having a grid-shaped road network and children living in these school zones. A WSB is a group of children walking to school with one or more adults. A child's decision to walk from his or her home to join a WSB, to walk to school on his or her own or to be driven to school was determined by factors including parents' traffic safety concerns and the child's attitude towards active travel to school. These studies showed the importance of safety concerns about the environment and the individuals' attitudes in their walking decisions.

Agent-based models have also been used to assess the impacts of increasing children's PA at the national level. Lee *et al*. developed an ABM in which each agent was assigned attributes including age, sex, ethnicity, height and lean and fat mass that matched the representative children in these groups based on the NHANES 2005–2013 data (68). A metabolic model was used to convert energy intake and energy expenditure into weight changes. Energy expenditure from two possible interventions, 'active to healthy level' (25 min of high-calorie-burning PA three times a week) and the Centers for Disease Control and Prevention (CDC) guidelines (60 min of moderate PA each day), was simulated in the model by increasing the proportions of agents meeting these recommendations to 50%, 75% and 100% to predict changes in the prevalence of overweight and obesity in youth and the related savings on medical and economic costs. The model showed significant benefits by increasing the proportions of children who meet the PA recommendations, noting that the CDC's PA guidelines may generate greater impact.

The food environment and the built environment were also examined simultaneously in ABM. For example, with a model set-up similar to one they developed in 2014 (57), Orr *et al*. used an ABM to simulate the effects of good food stores, PA infrastructure and school quality (neighbourhood-level student/teacher ratios) on BMI in Whites and Blacks (66). The 2007 National Health Interview Survey data were used to estimate the association between education level and PA. Agents' BMI is a function of diet and PA. Their results suggested that upstream policy may help reduce BMI disparities between Whites and Blacks, but it takes time.

Discussion

This study examined the applications of SM (ABM and SDM) in obesity research published during 2000–2017. As a new and innovative approach, especially in the public health and obesity research fields, SM provides systems-level thinking and modelling strategies and tools to study obesity as an integrated system, explicitly modelling the dynamic, non-linear and circular causality of this complex system.

Key messages

Our systematic examination of the literature revealed several key findings. First, the past two decades have seen a growing body of SM in obesity research, especially since 2010. The applications of ABM and SDM have covered a variety of domains in obesity research, ranging from under-the-skin metabolism to behaviour, environment, social influences and policies. Applications of ABM in social influence studies accounted for about 50% of SM applications during 2000–2017. ABM provides a suitable platform to model interactions between agents in a simulated world, in which there are ideal and relatively easy-to-implement social behaviours, network structures and mechanisms. However, the effects of social interventions for obesity prevention that have been revealed by these studies have varied across populations and settings and seemed to be sensitive to model assumptions. Thus, the related findings have limitations in terms of guiding future intervention development.

Second, SM is suitable to test intervention and policy effects through simulations. Compared with randomized controlled trials, SM can mimic real-world situations and test interventions and policy effects in simulated settings. Interventions and policies that are time-consuming, costly and sometimes unethical and infeasible to test in controlled trials or experiments in the real world can be carried out and examined in SM easily. For example, Orr *et al*. tested 16 conditions in different 'what-if' scenarios to examine potential policy effects (57). Moreover, SM simulations may generate counter-intuitive and unintended system phenomena that could have significant implications for policy and intervention development. For example, Mooney *et al*. found a u-shaped relationship between the prevalence of resistance to an obesogenic environment and depression, which may lead to unintended health consequences in interventions not taking into account the non-linear nature of the relationship. Our review suggests that SMs have not been widely used for policy and intervention analysis (54,60–62). This is a growing field that warrants more SM-based exploration.

Third, the number of SM obesity studies published in peer-reviewed journals has been rising consistently since the early 2000s. However, the absolute number remains low, with an average of two to three publications each year. There was a sharp increase in 2014, partially due to the influence of the NIH's support of using systems science in public health research. In addition, the impact of the published SM obesity studies remains limited. This is demonstrated by the less than 800 total citations of these published SM studies. It is evident that the application of SM in the obesity field is still in its early stages. Substantial coordinated efforts are needed to promote this paradigm shift; interdisciplinary integration and synergy of SM with traditional public health approaches should be widely and deeply incorporated into future obesity research to more effectively tackle this global epidemic.

Challenges and recommendations for future research

Systems modelling has exhibited good potential to enhance and complement traditional public health and obesity research. However, it is still a young field and faces many challenges, such as the following:

1 *Model calibration*. An intriguing feature of a well-performed systems model is its ability to grow the reality: 'If you didn't grow it, you didn't explain its emergence'.(74) This becomes more important when effectiveness assessment of an intervention through model-simulated counterfactual comparisons is of interest. However, how to calibrate and to what extent to calibrate a systems model to generate observed phenomena remain a major challenge in the field. Among the 35 studies reviewed, 14 studies calibrated the systems models using empirical data by adjusting model parameters to generate simulated data to match the observed real-world data (15,22,43,46,52,53,55,57,58,60,65,67,69,70). The match or 'goodness-of-fit' was assessed by comparing the characteristics of related distributions, e.g. mean weight (15,43,46,53,67), mean height (43), mean

BMI (46), mean healthy diet (57), mean/median distance of trips (52), prevalence of obesity (15,65), proportion of people who consumed at least two servings of FV (64), variance and skewness of weight and height distributions (43) and probabilities of food purchasing and comsuption (55,60,69,70). Macro validation, i.e. comparison between model output and real-world output, dominated the field. Determining how valid the parameters are, especially when the purpose is to generate a new hypothesis, could become very challenging: first, how to prove and ensure the uniqueness of the solution remains under discussion and has not attracted adequate attention in modelling practice; second, being preoccupied with the closeness to observation would limit the researcher's scope of understanding the system, because the modeller's mental model could be limited by a lack of empirical data and thus hinder the capability of the systems model.
- **Recommendations**: Systems models should be developed based on solid theoretical foundations and clearly defined model boundaries integrating all related domain knowledge and content expertise. Assessment of model performance should include a comprehensive list of criteria and reflect soundness of the whole modelling process.

2 *Transparency and replicability*. Systems models are still new and challenging tools to most public health researchers. Our review reveals that the existing SM studies, in general, did not provide detailed model documentation to allow for easy replication. Among the 35 studies reviewed, only four studies provided supplementary documentation with information on model equations or computer programs (16,45,57,70).
- **Recommendations**: Making the SM process transparent to the extent that other researchers can understand, replicate, learn and expand upon it is challenging but is critical to promoting SM applications. Systems studies should be required to provide well-documented model details. Model codes should be deposited and shared with the public. Data used to fit the models should be deposited in a relevant data repository or made available upon request. The systems society and the obesity society should work together to develop related standards and guidelines to instruct model documentation and sharing practice.

3 *Deep interdisciplinary collaboration*. SM for studying public health problems, including obesity, is highly interdisciplinary by nature, because the various related systems in society always involve information and insights from a wide variety of disciplines, such as health science, social sciences, urban planning, environmental sciences, economics, statistics, mathematics, computer science, engineering and other disciplines. Ideally, SM should involve researchers from diverse disciplines and work collectively through the whole modelling process, including model architecture design, model building, calibration, validation and results interpretation. However, our review suggested that the desired level of comprehensive, in-depth, interdisciplinary modelling practice has not really occurred yet. Except for a few studies that explicitly described the interdisciplinary expertise involved in the modelling (14,22,44,45,48,49,51,59,61,62,64), the synergistic effects of interdisciplinary collaboration have not generated new insights and significant progress in obesity research. This dearth exposes the challenge posed by a lack of well-trained interdisciplinary researchers with diverse backgrounds, which will continue to pose major obstacles to applying SM approaches in public health research.
- **Recommendations**: Systems science-oriented interdisciplinary collaborations should be valued and promoted, including by funding agencies. Systems thinking and modelling practices should be incorporated in public health education programmes to train the next generation of public health researchers.

Conclusions

Obesity is a complex system problem. SM provides innovative systems approaches to fight the obesity epidemic. Despite the challenges associated with SM applications, SM brings fresh opportunities to study obesity and related public health issues from a systems perspective in a way that can complement the methodologies and knowledge derived from the traditional reductionist paradigm. Current SM applications in obesity research are still limited. Challenges in theories and practice should be addressed to bring out the full capacity of SM to advance obesity research and intervention.

Conflict of interest statement

The authors declare no conflicts of interest.

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