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SUPPLEMENT ARTICLE

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A systematic review of system dynamics and agent-based obesity models: Evaluating obesity as part of the global syndemic

Alexandra B. Morshed[1] | Matt Kasman[2] | Benjamin Heuberger[2] | Ross A. Hammond[1,2,3] | Peter S. Hovmand[1]

[1] Brown School, Washington University in St. Louis, St. Louis, Missouri
[2] The Brookings Institution, Washington, DC
[3] The Santa Fe Institute, Santa Fe, New Mexico

Correspondence
Alexandra B. Morshed, Washington University in St. Louis, 1 Brookings Drive, Campus Box 1196, St. Louis, MO 63130.
Email: a.b.morshed@wustl.edu

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Summary

The problem of obesity has recently been reframed as part of the *global syndemic*—the co-occurring, interacting pandemics of obesity, undernutrition, and climate change that are driven by common underlying societal drivers. System science modeling approaches may help clarify how these shared drivers operate and the best ways to address them. The objective of this paper was to determine to what extent existing agent-based and system dynamics computational models of obesity provide insights into the shared drivers of the *global syndemic*. Peer-reviewed studies published until July 2018 were identified from Scopus, Web of Science, and PubMed databases. Thirty-eight studies representing 30 computational models were included. They show a growing use of system dynamics and agent-based modeling in the past decade. They most often examined mechanisms and interventions in the areas of social network-based influences on obesity, physiology and disease state mechanics, and the role of food and physical activity environments. Usefulness for identifying common drivers of the *global syndemic* was mixed; most models represented Western settings and focused on obesity determinants close to the person (eg, social circles, school settings, and neighborhood environments), with a relative paucity in models at mesolevel and macrolevel and in developing country contexts.

KEYWORDS

agent-based modeling, global syndemic, obesity, system dynamics, systematic review

1 | INTRODUCTION

Obesity is a highly prevalent global public health problem that is largely preventable and leads to a myriad of childhood and adult morbidities.[1-3] It is also well-recognized that obesity is a complex problem, stemming from systems characterized by interdependence, mechanisms and diverse actors at varying levels of scale, and presence of feedback and nonlinearity.[4-6] In addition, taking a wider perspective on the problem of obesity, the most recent Lancet Commission on Obesity report reframed obesity as part of a larger global phenomenon—the *global syndemic*—made up of co-occurring and interacting pandemics of obesity, undernutrition, and climate change that are driven by common underlying societal drivers.[3] Climate change effects on undernutrition[7] and the interrelationship between undernutrition and obesity are well established, while the evidence around the relationship between obesity and climate change is evolving (eg, through mechanisms such as increasing sedentary behaviors due to increases

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in temperature and the impact of obesity on transport systems).[3,8] As with obesity alone, the societal drivers that generate the *global syndemic* are made up of complex adaptive systems at multiple levels that change over time and are fueled by feedback processes and multiple interactions.[3]

Given the complexity of the *global syndemic*, complex system science approaches such as agent-based and system dynamics computational modeling are particularly helpful because they are able to model feedback, interdependence, and emergence.[4,9-11] These approaches are also increasingly used in public health.[4,9,12,13] Agent-based models represent system behavior as emerging bottom-up from interactions of individual actors with each other and their environment according to a set of prespecified rules.[14] System dynamics models represent patterns of behavior of systems as a result of generalizable underlying structures whose main elements are endogenous feedback and accumulation of quantities in a system over time.[15,16] Unlike agent-based models, they are usually presented at the aggregate level (top-down) and have broader boundaries.

Existing applications of agent-based and system dynamics modeling methods to the problems of obesity, climate change, and undernutrition can serve as potential sources of insight into how common drivers of the *global syndemic* operate and the best ways to address them. This paper presents one part of a larger work that examined computational modeling studies from the fields of obesity, undernutrition, and climate change with the objective of informing the study of the *global syndemic*. The objective of the present work is to determine to what extent existing models of obesity provide insights into the drivers of the *global syndemic*. Synthesis of the climate change and undernutrition computational models will be reported elsewhere.

Two aims support the above research objective: (a) Conduct a systematic review of the use of system dynamics and agent-based modeling in understanding the challenge of obesity. (b) Determine the usefulness of this set of computational models in identifying common or related systemic drivers of the *global syndemic*.

2 | METHODS

2.1 | Overview

A systematic review of system dynamics and agent-based modeling studies of obesity was carried out, guided by the Cochrane group guidelines[17] and adapted for studies using system science methods. Peer-reviewed studies that were in English and published up to July 2018 were identified using uniform search terms related to obesity and computational modeling. Studies were selected if they explicitly used system dynamics or agent-based simulation and modeled obesity endogenously, excluding studies of a biochemical process, product development or food technology, production or supply chain of a specific food, or nonmodern populations. Due to the focus on examining the interrelated drivers of the *global syndemic*, this review purposefully excludes existing models that only incorporate obesity exogenously or include obesity-related behaviors without modeling obesity and as such is not an exhaustive review of obesity-related modeling studies currently in existence.

The study selection and identification process is illustrated in Figure 1. First, potential studies were identified through an electronic database search of relevant terms, of which duplicates were removed. Records' titles and abstracts were initially screened based on inclusion criteria, which was followed by a full-text screening. The resulting records were included in the review.

2.2 | Electronic searches

The Scopus, Web of Science, and PubMed electronic databases were searched using the following search terms in the title, abstract, and keywords fields, adapted for each database: (obes* OR overweight OR “body mass index” OR BMI) AND (“system dynamics” OR “system dynamic” OR “differential equations model” OR “differential equation model” OR “differential equations modeling” OR “differential equation modeling” OR “agent-based model” OR “agent-based models” OR microsimulation OR microsimulations). Although microsimulation is a broad umbrella of models under which agent-based modeling falls, it is at times used as a keyword for agent-based modeling studies and was included for the sake of obtaining a more complete sample.

Four-hundred fifty records were identified through electronic searches, of which 293 duplicates were removed, leaving 157 records for initial screening.

2.3 | Selection

In a two-step process to screen the identified records, titles and abstracts of each record were first screened to determine whether they met the inclusion criteria. Where information in the title and abstract was insufficient to determine inclusion, the record was provisionally included in the review. The full texts of 44 records included following the initial screen were assessed to determine if they met the inclusion criteria. A total of 38 records were included in the review, which represent 30 distinct computational models. Duplicate screening of full-text records and duplicate data extraction were carried out on at least 20% of the studies. Differences in coding were discussed, resolved by consensus, and used to improve the inclusion criteria and codebook.

2.4 | Data extraction

Data from studies were extracted using a standardized form and entered into the Qualtrics software (Qualtrics, Provo, UT). Table 1 lists extracted elements for each included study.

In addition, in order to examine to what extent the reviewed agent-based and system dynamics models of obesity could be used to examine common drivers of obesity, undernutrition, and climate change, the elements from the reviewed models were mapped onto the Global Syndemic view of the Systems Outcomes Framework,[3]

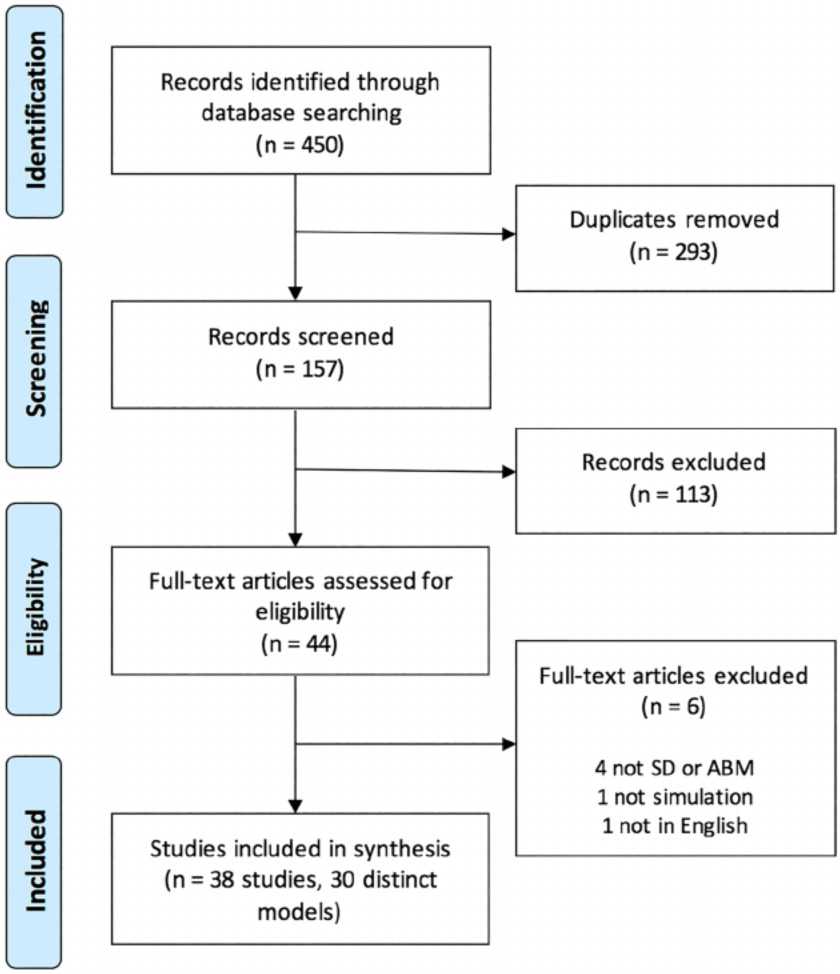

FIGURE 1 PRISM diagram of identification and selection of studies for the systematic review

TABLE 1 Data extracted from selected studies

Category	Extracted elements
Administrative details	• Author, year of publication, title • Modeling approach used • Replicability
Study details	• Study objective or purpose • Interventions tested • Study outcomes • Main results • Target setting and population[a]
Model details	• Time scale[b] • Platform • Model outputs • Key model components • Sources of information • Calibration and validation[c] • Model typology[d]

[a]Assessment regarding target setting and population of the model was made based on the stated geographical setting, aggregation level, and information regarding calibration and other data used to develop the model.

[b]Defined as the total time period that the model simulates.

[c]Categories of validation were adapted from Sterman.[15]

[d]Adapted from Hammond.[18]

adapted for the purposes of this review (Table 3). The framework organizes drivers of obesity, undernutrition, and climate change within interrelated sets of systems, at the center of which are natural systems surrounded by concentric sets of man-made systems: governance (norms, economics, and policies), macrosystems (food, transport, urban design, and land use), mesosystems (schools, hospitals, workplaces, and public spaces), and microsystems (families, social circles, and communities). In addition, existing theoretical frameworks of joint determinants of obesity, climate change, and undernutrition[7,8,19,20] were reviewed, and concepts and constructs from these frameworks were used to guide identification of relevant elements from the computational models reviewed in this study.

3 | RESULTS

Of the 30 computational models reviewed, 16 used system dynamics modeling, and 14 used agent-based modeling. The majority of studies describing these models (87%) were published in the past 10 years. Table 2 summarizes the characteristics of the included models.

TABLE 2 Summary of reviewed computational models

	Model	Objective	Temporal scale	Target setting and population	Interventions or scenarios	Outcomes / outputs	Model details	Model typology	Calibration	Validation tests
System dynamics models										
1	Abdel-Hamid (2002), Abdel-Hamid (2003)	Study and gain insight into the impacts of physical activity and diet on body weight and composition.	12 weeks	An overweight sedentary male subject, initial total weight of 100 kg and 25% body fat, daily dietary intake of 14.25 MJ (50% carbohydrate, 35% fat, and 15% protein).	Sets of intervention comparisons: 1. Food restriction versus exercise. 2. Exercising at differing intensity 3. Interaction of exercise intensity and dietary carbohydrate composition	Body weight, body composition, metabolic rate.	Key stock variables: absorbed carbohydrate. plasma glucose, glycogen in liver, glycogen in muscle, fat in adipose tissue, fat mass, fat-free mass, fat cells. Model subsystems: energy intake, energy expenditure, energy metabolism, body composition.	Etiology & intervention testing Explanatory	Not stated	Behavior reproduction
2	Intervention Childhood Obesity Dynamics model, Abidin et al (2014), Abidin et al (2014), Abidin and Jamil (2016)	1. Determine if 2000 obesity reduction targets can be met by 2020 by changes to eating. 2. Evaluate dynamic consequences of reducing meals frequency and portion size. 3. Investigate modifying either energy intake or expenditure to improve the population body weight.	60 years	English child population, 2-15 years old, calibrated to nationally-representative data.	Sets of intervention comparisons: 1. Reduction in portion size of outside meals versus number of meals eaten. 2. Reduction in macronutrients consumed from outside meals, versus reduction in frequency and duration of sedentary behavior, versus combination of the two.	Average weight, average body mass index, prevalence of obesity.	Key stock variables: Average weight, average height, prevalence of obesity, average of fat portion size from outside meal. Model components: food intake, energy expenditure, physical measurement, BMI impact. Disaggregation by gender and three age groups.	Intervention testing Predictive	Yes	Structure assessment, extreme conditions, behavior reproduction
3	Carrete, Arroyo, and Villaseñor (2017)	Analyze overweight and obesity from a sociological perspective, taking into account the influence of relevant social factors regarding the development of healthy behavior patterns of urban Mexican children.	50 years	Upper-middle class elementary school students in Mexico, 9-12 years old, model informed by data from two randomly selected schools in Toluca City, Mexico.	Scenarios: 1. Improving exo and macro level influences. 2. Family engagement (families become fully committed and actively engaged for introducing healthy habits to children). 3. Combines scenarios 1 and 2.	Overweight prevalence, obesity prevalence, change in prevalence per year	Key stocks: Exo level influence (influenced by local governmental policies, availability of recreational activities, availability of snacks and junk food), macro level influence (influenced by national culture and national governmental strategies), micro level influence (influenced by family habits and economy, friends influence), meso level influence (influenced by school intervention and local social influence), prevalence of overweight and obesity,	Etiology Predictive	Yes	Not stated
4	Chen et al (2018)	1. Study country-level dynamics between population weight status and socio-economic distribution (employment status and family income) in the US. 2. Project potential impacts of socio-economic based intervention on obesity prevalence.	50 years	US adults, calibrated to nationally-representative data	Interventions: 1. The status quo. 2. Increasing flow from unemployed to employed. 3. Increasing flow from low- to middle-income. 4. Interventions 2 and 3 combined.	Obesity prevalence	Key stocks: normal weight, overweight, obesity; lower income, middle income, high income; unemployed, employed, not in labor force.	Etiology & intervention testing Predictive	Yes	Behavior reproduction
5	Fallah-Fini et al (2013), Fallah-Fini et al (2014)	1. How dynamics of average energy imbalance gap explain changes in obesity prevalence in US adults in past 4 decades. 2. How these dynamics differ by gender, race/ethnicity, and BMI. 3. How maintenance energy gap values changed over the past 4 decades across different subpopulations.	30 years	US adults, ages 20-74 years, calibrated using nationally-representative data	None	BMI distribution and prevalence, maintenance energy gap	Key stocks: fat mass, fat-free mass. Model components: A representative individual for each of the BMI classes is modeled explicitly, based on combinations of gender, race/ethnicity, and BMI ranges.	Etiology Explanatory	Yes	Behavior reproduction, sensitivity analysis

(Continues)

TABLE 2 (Continued)

	Model	Objective	Temporal scale	Target setting and population	Interventions or scenarios	Outcomes / outputs	Model details	Model typology	Calibration	Validation tests
6	Flatt 2004	Examine effect of dietary fat content, physical activity, food availability, diversity, and palatability on adiposity and how this can be modified by inherited traits affecting the use of glucose relative to fat.	125 days	Unspecified	Scenarios: 1. Default individual, at energy balance, 65 kg weight, 1 kcal/min basal metabolic rate, 12 kg fat reserve, 2500 kcal energy expenditure, 3 meals/d (40% fat). 2. After 10 days, various levels of fat content, physical activity, and enhanced food palatability, availability, and/or diversity.	Body fat maintenance, body fat content.	Key stocks: total carbohydrate reserve, total fat/triglyceride reserve, cumulative daily fat oxidation, cumulative daily carbohydrate oxidation, gut container (calories from meals).	Etiology Explanatory	Not stated	Behavior reproduction
7	Frerichs et al 2013	1. Assess sensitivity of childhood overweight and obesity prevalence to peer and adult social transmission rates. 2. Test combinations of prevention and treatment interventions, with varying degrees of adult intervention impact on children and vice versa.	10 years	US children and adults, not necessarily representative, parametrized using existing studies and the Framingham longitudinal cohort.	Interventions: All combinations of treatment or prevention programs for adults or children (e.g., adult treatment with child prevention). Scenarios: Peer versus adult influence on child obesity, 6 combinations of 10 vs. 25% child intervention impact on adult and 25 vs. 50 vs. 75% adult intervention impact on child.	Childhood obesity prevalence	Key stocks: normal weight adults, overweight adults, and adults with obesity; normal weight children, overweight children, and children with obesity.	Etiology & intervention testing Predictive	Not stated	Behavior reproduction, sensitivity analysis
8	Diabetes System Model, Jones et al (2006), Milstein et al (2007)	1. Explore past and future burden of diabetes, its morbidity, mortality, and costs in the United States. 2. Explore incremental effects of various policy interventions on the burden of diabetes based on the Healthy People 2010 Objectives.	70 years	US adult population, calibrated to nationally-representative data.	Scenarios: 1. Improve clinical management of diabetes. 2. Increased management of prediabetes. 3. Reduced obesity prevalence. Interventions: 1. Increase diabetes diagnosis. 2. Reduce diabetes attributable death rate. 3. Reduce new diabetes diagnoses. 4. Eliminate initial onset of undiagnosed diabetes to 0.	Prevalence of diagnosed diabetes; diabetes-related morbidity, mortality, and costs.	Key stocks: normoglycemic population, undiagnosed pre-diabetes population, diagnosed pre-diabetes population, undiagnosed noncomplicated diabetes population, diagnosed noncomplicated diabetes population, undiagnosed complicated diabetes population, diagnosed complicated diabetes population, mean body weight, mean BMI.	Etiology & intervention testing Explanatory & predictive	Yes	Behavior reproduction
9	Prevention Impacts Simulation Model, Kuo et al (2016), Soler et al (2016)	1. Estimate short- and long-term benefits 2010-2020 of CPPW interventions implemented 2010-2013 in US. 2. Forecast impacts of obesity prevention strategies in the three program focus areas implemented in Los Angeles County during 2010-2012.	50 years	Original model is calibrated to US nationally, and represents gender- and race-specific averages. In reviewed studies, calibrated to: 1. six representative US communities that were awarded CPPW, 2. Los Angeles County.	RQ1. Scenarios: Model aggregates individual CPPW communities, each representing a scenario, based on completed objectives and milestones, and reported reach and intensity of interventions. RQ2. Intervention: Combined effect of implemented strategies focusing on physical activity-	Premature deaths, medical costs, and productivity costs averted, obesity prevalence, physical activity, dietary intake.	Key stocks: Obesity, smoking, high blood pressure, high cholesterol, and diabetes prevalence. Strata: Sex and age group (18-29, 30-64, and ≥65).	Intervention testing Predictive	Yes	Behavior reproduction, sensitivity analysis

(Continues)

TABLE 2 (Continued)

	Model	Objective	Temporal scale	Target setting and population	Interventions or scenarios	Outcomes / outputs	Model details	Model typology	Calibration	Validation tests
					promotion, health marketing, and healthy food environments.					
10	Lan et al (2014)	Investigate the factors affecting elementary school students' BMI values.	48 months	Unspecified	None	BMI	Key stocks: students' obesity, students' health concept, nutrition education. Model components: diet-associated parenting behaviors, implementation of school nutrition education, perception of self-body image, experience of being ridiculed for body shape.	Etiology Explanatory	Not stated	Behavior reproduction
11	Liu et al (2016)	1. Explore dynamic impacts of multiple obesity intervention and implementation options. 2. Understand the dynamics of the socioeconomic system, particularly the economic linkages between implementation strategies.	17 years	US children, model used nationally-representative data	Interventions: 1. Excise tax on SSBs. 2. Allot SSB tax revenue to safer outdoor activity spaces. 3. Allocate SSB tax revenue to subsidize youth school FV programs.	Weight gain	Key stocks: demand for SSBs, SSB tax revenue, budget for healthy environment, budget for building park, net added park land areas, energy intake from SSBs, budget for FV programs, cumulative reduced energy intake from SSB, energy expenditure from park physical activity. Model subsystems: public health, political, social, and economic.	Etiology & intervention testing Predictive	Yes	Integration error, behavior reproduction, sensitivity analysis, system improvement
12	Meisel et al (2016), Meisel et al (2018)	1. Study dynamics of overweight/ obesity prevalence over time. 2. Estimate transference between BMI categories, (inc. by age and socioeconomic status). 3. Identify population subgroups for targeting efforts. 4. Monitor potential effect of interventions across age and SES categories.	25 years	Population of Colombia, calibrated to nationally-representative data	Interventions: 1. Increase flow from overweight to not overweight categories. 2. Increase flow from obese to overweight categories. 3. Interventions 1 and 2 combined. 4. Increase flow from obese to overweight and overweight to not overweight among 5-14 year-olds. 5. Same as 4, for 15-24 year-olds.	Prevalence of overweight and obesity, transference rates between BMI categories	Key stocks: Not overweight people, overweight people, people with obesity. Model components: Includes aging chains (population aged 0–59 years divided into groups of 5 years) and socioeconomic categories.	Etiology & intervention testing Explanatory & predictive	Yes	Integration error, parameter assessment, extreme conditions, behavior reproduction, sensitivity analysis
13	Powell et al (2017)	Simulate impact of policy interventions on prevalence of childhood obesity in Georgia through 2034.	20 years	Children in the State of Georgia, model used data representative of the state	Interventions: 1. No policy change 2. Individual and combined testing of physical education and after-school interventions chosen based on legislative feasibility and evidence of efficacy.	Obesity prevalence	Not detailed	Intervention testing Predictive	Not stated by authors	Not stated
14	Sabounchi et al (2014)	Create a system dynamics model specific to weight gain and obesity in women of reproductive age that could inform future health policies and have the potential for use in preconception interventions targeting women with obesity.	2.5 years	A case of a 34-year-old, nulliparous, White woman with obesity and PCOS and associated anovulatory subfertility.	Interventions: 1. Fertility treatment only, no weight loss. 2. 10% weight loss. 3. 25% weight loss. 4. 36% weight loss.	fecundity, pregnancy weight gain, mortality	Key stocks: Pre-pregnancy weight, pregnancy weight, fetus size.	Etiology & intervention testing Predictive	Not stated by authors	Not stated by authors

(Continues)

TABLE 2 (Continued)

Model	Objective	Temporal scale	Target setting and population	Interventions or scenarios	Outcomes / outputs	Model details	Model typology	Calibration	Validation tests
15 Siegl, Lassnig, Schröttner (2014)	Investigate the influence of obesity on future need and expenses for hip replacement.	Not stated	Austrian adults, model used Austrian nationally-representative data.	None	Healthcare expenditure	Key stocks: Population by age, patients with primary hip implant, patients with 1st revision of implant, patients with 2nd revision of implant, patients with 3rd revision of implant, patients with 4+ revisions, population by BMI category.	Etiology Predictive	Not stated by authors	Not stated by authors
16 Nutrition Market Transformation Model, Struben, Chan, Dube (2014)	Analyze how supply, demand, and governmental policy collectively influence population health and dynamically shape composition of consumed food portfolios and their nutritional quality.	40 years	Canadian population, calibrated to nationally-representative data.	Interventions: 1. None, projections based on 2010 calorie consumption. 2. Industry interventions. 3. Government interventions. 4. Market and government stimuli of nutritious food product innovation.	BMI	Key stocks: serving size, propensity to consider a category, energy stored, population, attribute-related capabilities. Components: food demand, population health, food supply, and government policy; disaggregation by combinations of age and gender, firm type, food attributes (combinations by price, taste, availability, and nutritional quality).	Intervention testing Predictive	Yes	Behavior reproduction, sensitivity analysis
Agent-based models									
17 SimNCD, Aziza et al (2016)	1. Understand how individual behavior contributes to health outcomes. 2. Examine relationship between children's physical activity and BMI.	9 months	Children 7-15 years old, model validated against data from 3 research studies among children from schools in east-central Illinois, Changping District in Beijing, China, and Sydney, Australia.	Interventions (for validation purposes only): 1. 70 min/d of MVPA, 5 d/week for 9 months 2. 123 min/d of MVPA 3. 12 weeks of daily MVPA Scenarios (all under highly favorable PA environment): 1. Children are initially overweight and unmotivated. 2. Children initially have obesity and are unmotivated. 3. Children initially have obesity and are highly motivated.	BMI, cardio-respiratory fitness	Agents: Children, 6-18 y, heterogeneous by age, gender, initial BMI, motivation for physical activity. Environment: Non-spatial physical environment comprised of activities available to children with which to engage (e.g., swim, puzzles, go to school, play in the garden). Primary dynamic: Agents perceive opportunities to engage in a physical activity, choose to engage, which affects their health and BMI.	Etiology & intervention testing Predictive	Yes	Behavior reproduction
18 Beheshti, Jalalpour, and Glass (2017)	Compare conventional targeting methods (random selection, based on individual obesity risk, and vulnerable areas) with network-based targeting methods for obesity interventions.	730 days	US youth, calibrated to nationally-representative data	Targeting interventions: 1. Random targeting 2. High-risk targeting (based on BMI) 3. Centrality-based network targeting (based on number of ties) 4. Influence maximization network targeting 5. Environmental vulnerability targeting (i.e., obesogenicity) Interventions for target individuals: 1. Energy intake decreased by 15% 2. 17% increase in physical activity	Average weight	Agents: Individuals, heterogeneous by gender, age, weight and height. Environment: No spatial environment. Primary dynamic: Individuals are influenced by their friends' behaviors and their environments, combined to generate a socio-environmental influence value. If values go beyond fixed thresholds (specific and calibrated to each agent), individual will change energy intake and/or physical activity.	Etiology & intervention testing Predictive	Yes	Behavior reproduction, sensitivity analysis

(Continues)

TABLE 2 (Continued)

Model	Objective	Temporal scale	Target setting and population	Interventions or scenarios	Outcomes / outputs	Model details	Model typology	Calibration	Validation tests
19 Chen et al (2016)	Explore net energy expenditure after children in physical education class are given the choice between water and SSB consumption for rehydration and explore environmental factors that may influence the net energy expenditure.	30-60 min	8th grade students in the US, based on nationally representative data	Interventions: 1. Changing number of water fountains available for students 2. Changing number of vending machines in school 3. Changing duration of physical education class 4. Changing number of students per class 5. Changing preferences for SSBs	Average energy balance, prevalence of dehydration	Agents: 8th grade students, heterogeneous by gender, weight, height, taste preferences. Environment: Playground of rectangular area 28 x 25m, with fluid sources near the playground. Primary dynamic: Agents rehydrate when body water level is below thirst threshold, and they seek out fluid source (water or SSB) that is most time-efficient, discounting for taste preferences.	Intervention testing Predictive	Not stated	Sensitivity analysis
20 El-Sayed et al (2012)	Compare effects of targeting anti-obesity interventions at most connected individuals in a network with those targeting individuals at random.	47 years	English adults, 18-65 y old, using nationally-representative data.	Targeting interventions: 1. Selecting 10% most connected individuals 2. Randomly select 10% individuals Interventions for target individuals: 1. Preventing obesity among 10% of the population at simulation outset 2. Treating obesity among 10% of the population with obesity yearly	Obesity prevalence	Agents: Individuals, heterogeneous by gender, ethnicity, social class, educational level, initial obesity level. Environment: Six neighborhoods with differing socioeconomic and ethnic composition. Social networks based on homophily. Primary dynamic: Probability of developing obesity based on agent characteristics and whether a network contact had previously developed obesity.	Intervention testing Predictive	Not stated	Behavior reproduction
21 Hammond and Ornstein (2014)	Evaluate how social influence can affect obesity outcomes through a "follow the average" mechanism.	4 years	US youth, 12-16 y old, calibrated to nationally-representative data	None.	Mean BMI	Agents: Children, heterogeneous by BMI. Environment: Neighborhood grid, with surrounding eight neighbors as comparisons. Primary dynamic: Child compares their BMI to the mean BMI in model or network, and adjusts it by a discrete increment to approach observed mean (accounting for some falloff in motivation).	Etiology Explanatory	Yes	Behavior reproduction
22 Hennessey et al (2016)	Provide guide on developing a model to evaluate multifaceted interventions for childhood obesity prevention in multiple settings.	1 year	US children, 6-12 y old, model based on nationally-representative data	ChildObesity180 interventions: 1) Active Schools Acceleration Project: Increase child physical activity through three school-based physical activity programs. 2) Healthy Kids Out of School: Healthy out-of-school time programs for children.	BMI	Agents: Children, 6-12 y, heterogeneous by age, sex, height, weight, town type. Environment: Three town types (average, higher, and lower than average child obesity rates). Each has 56 homes, 12 schools, 3 community locations. Primary dynamic: Agents move between home, school, and community, have differing opportunities for physical activity and energy intake that affect BMI-related behavior and BMI.	Intervention testing Predictive	Not stated	Not stated
23 Virtual Population for Obesity Prevention, Lee et al (2018)	Explore impact of SSB point-of-purchase warning label policies for addressing adolescent overweight and obesity.	7 years	Children, 11-18 y, in Baltimore, San Francisco, and Philadelphia. Model incorporates geospatial grids from each city, local data for obesity, NHANES data for consumption behaviors.	Intervention: Warning labels on SSBs. Scenarios: Varying illiteracy rates, varying compliance rates of retailers.	Obesity prevalence, SSB consumption	Agents: Children, 11-18 y, heterogeneous by age, race, gender, home location, school assignment. Environment: Geospatial grids specific for Baltimore, Philadelphia, and San Francisco with households, schools, food and beverage sources.	Intervention testing Predictive	Not stated	Sensitivity analysis

(Continues)

TABLE 2 (Continued)

Model	Objective	Temporal scale	Target setting and population	Interventions or scenarios	Outcomes / outputs	Model details	Model typology	Calibration	Validation tests
						Primary dynamic: Child moves through grid and makes decisions on dietary intake locations based on distance and location attractiveness, and at each whether to consume SSB.			
24 The New York Academy of Medicine Cardiovascular Health Simulation Model, Li et al (2014)	Evaluate a lifestyle program (diet and exercise for reducing weight) among Medicare-age adults that could be implemented in primary care practice settings.	5 years	US adults of Medicare-eligible age (65+), model based on nationally-representative data	Intervention: Lifestyle program focused on improving diet and exercise and reducing weight among Medicare-age adults.	Prevalence of diabetes, hypertension, and cholesterol	Agents: Adults, 65+ years, heterogeneous by age, gender, history of and risk factors for CVD, physical activity, healthy diet, weight. Environment: None. Primary dynamic: Agents transition between behavior and health states based on normal trajectories and other behaviors and states, which influence mortality. Smoking is determined by demographic-specific trajectories.	Intervention testing Predictive	Not stated	Behavior reproduction
25 Mooney and El-Sayed (2016)	Explore mechanisms by which deviance from normative body habits may contribute to social isolation in people with obesity.	20 years	Colorado and Mississippi adults, calibrated to state-representative data	None.	Depression rates by obesity status	Agents: Individuals, heterogeneous by BMI, resistance to obesogenicity of the environment. Environment: No spatial environment. Primary dynamic: Individual updates their BMI based on resistance to environment and random weight fluctuation, drops connections with social network peers with BMI higher than population mean. Ostracization increases probability of depression.	Etiology Explanatory	Yes	Behavior reproduction, sensitivity analysis
26 Orr et al. (2014), Orr, Kaplan, and Galea (2016)	1. Explore efficacy of school quality policy for reducing racial disparities in diet and dependence of this effect on social network influence and norms. 2. Explore effects of availability of good food stores, physical activity infrastructure, and higher school quality on reduction of US Black-White BMI disparities.	2.5 generations	US Black and non-Hispanic Whites in the 100 largest metropolitan statistical areas	Intervention sets: 1. 2x2x2 factorial design comparing 8 combinations of school quality policy (policy or no policy), social network effects (present or not), and social norm type (low or high social norm threshold). 2. 125 conditions combining 3 policy types (good food stores, physical activity infrastructure, and school quality) and five levels of strength of each policy.	Diet, BMI, cardiovascular health, mortality, White/Black BMI disparity index	Agents: Black and non-Hispanic Whites, heterogeneous by race, smoking, diet, exercise, social network ties, education level, age, income, school attendance, educational attainment, earning potential. Environment: 64 neighborhoods characterized by race/economic make-up, school quality, food quality/ availability, exercise opportunity. Primary dynamics: Individuals are born, go to school, get jobs, retire, move neighborhoods, have child, die. Their health behaviors are based on individual, social network, and neighborhood characteristics, producing health outcomes.	Intervention testing Predictive	Yes	Not stated
27 Virtual Population Obesity Prevention Lab, Powell-Wiley et al (2017)	Quantify impact of crime on physical activity location accessibility, LTPA, and obesity among African American women.	1 year	African American women, 18-65 y, with their outdoor physical activity locations and recreational centers matching real geographic locations in Washington, DC.	Scenarios: 1. Baseline: 25% probability of exercising. 2. 37.5% and 50% probability of exercising. 3. 100% probability of exercising.	Obesity prevalence, LTPA	Agents: African American women, 18-65 y, heterogeneous by age, height, lean/ fat mass, household location, income, weather, social group influence, broader social pressures, baseline probability of exercising. Environment: Three location types where agents can engage in LTPA: home, outdoor locations (pools, parks, bike	Etiology Explanatory	Not stated	Behavior reproduction, sensitivity analysis

(Continues)

TABLE 2 (Continued)

Model	Objective	Temporal scale	Target setting and population	Interventions or scenarios	Outcomes / outputs	Model details	Model typology	Calibration	Validation tests
						trails and lanes), or municipal recreational centers. Primary dynamic: Women decide where to engage in physical activity among locations within radius from home (0.5 miles walking, 2.5 miles driving).			
28 Trogdon and Allaire (2014)	1. Investigate the effect of peer selection in different network types on social multipliers for weight loss interventions. 2. Explore a non-targeted policy and two policies targeting groups of people with obesity for weight loss interventions.	Unclear	US women, 30-60 y, calibrated to nationally-representative data.	Scenario sets: 1. Peer selection based on a homophily, heterophily or scale-free networks. 2. Reference weight definitions: friends' weighted average or reciprocal friends' weight average. Interventions: 1. Increase food price by 30% 2. Lower equilibrium weight (-17 lb) of five women with obesity, selected: a. randomly, or b. based on highest number of in-degree connections	Social network characteristics (clustering by weight), mean weight, weight distributions	Agents: Individuals, heterogeneous by weight. Environment: Three types of social networks. Primary dynamic: Individuals select friends using different scenarios of network-forming rules, some of which are based on friends' weight. They consume food based on their friends' weight, given food price and income.	Etiology & intervention testing Predictive	Yes	Boundary adequacy, behavior reproduction, sensitivity analysis
29 Wang et al (2014)	1. Examine dynamics between social norms and individual children's BMI and their consumption of FV. 2. Test how misperception of social norm may affect children's BMI growth.	3 years	US children in grades 5 to 8, model based on nationally-representative data.	Scenarios: 1. Qualitative deviance misperception 2. Consensus misperception 3. Probabilistic quantitative misperception	BMI, FV consumption	Agents: Children, grades 5-8, heterogeneous by gender, age, race/ethnicity, school/social network, baseline BMI, and FV consumption. Environment: No spatial environment. Primary dynamic: Children conform with socially acceptable body image and consumption behavior by observing BMI and consumption of others in social network, adapting to match social mean.	Etiology Explanatory	Yes	Behavior reproduction
30 Zhang et al (2015)	Test impact of social influence on combined overweight and obesity prevalence in population.	1 year	US children, grades 9-11, based on nationally-representative data.	Interventions: 1. Change attractiveness of high-BMI agents 2. Change BMI-related homophily 3. Change strength of peer influence 4. Shift overall BMI distribution 5. Target dietary interventions to highly connected individuals	Overweight and obesity prevalence	Agents: Children, grades 9-11, heterogeneous by sex, grade, age, income, BMI, social network characteristics, homophily parameters. Environment: No spatial environment. Primary dynamic: Children make decisions to change network ties or gain/lose BMI based on BMI status of their friends using multiple rules (e.g., homophily, peer influence on BMI, etc.).	Etiology & intervention testing Explanatory & predictive	Yes	Behavior reproduction

Abbreviations: BMI, body mass index; CPPW, Communities Putting Prevention to Work; FV, fruit and vegetables; NHANES, National Health and Nutrition Examination Survey; PCOS, polycystic ovary syndrome; SES, socioeconomic status; SSB, sugar-sweetened beverages; US, United States.

3.1 | Temporal scale

The temporal scale of the computational models varied between 30 minutes and 2.5 generations. Agent-based models more often used a time horizon of 5 years or less (median 3 years), while time horizons used in the system dynamics models were more variable (median 25 years), eg, four models used 5 years or less, two models used 15 to 20 years, and three models used 45 to 50 years. The model with the smallest time horizon of 30 to 60 minutes[21] examined behavior of children in the confines of a physical education class. The model that was run for 2.5 generations examined effects of school quality policies and built environment on disparities in body mass index (BMI) between US Black and White populations.[22,23]

3.2 | Target settings and populations

The majority of the models (67%) pertained to a US setting, while others examined Australian, Austrian, Canadian, Chinese, Colombian, English, and Mexican settings. Most models (60%) aggregated outputs at the national level, while another 17% aggregated outputs at the local (eg, city, county) level. The models were similarly distributed in examining child, adult, or general populations.

3.3 | Mechanisms, interventions, and outcomes

A large number of models (n = 9) examined *social network-based influences* on obesity and obesity-related behaviors,[22-31] most (n = 8) using agent-based modeling.

Exploring the dynamics between social norms and BMI[26,29] and fruit and vegetable intake[29] among US children, two studies focused largely on how individuals make adjustments to their own BMI or energy intake based on perceptions of BMI or energy intake of their peers. Building on one of these models,[26] Zhang et al[30] similarly modeled children's conformance of their BMI to social norms, as well as changes in children's networks (gains or losses in ties) based on peers' BMI status, and found that the effect of peer influence on BMI varied based on the underlying BMI distribution of the population. The model developed by Orr et al[22,23] incorporated the influence of friends' and parental behaviors on dietary behaviors of individuals throughout their life-course, representing US Black and White populations from the 100 largest metropolitan statistical areas. They demonstrated that upstream social policies (ie, student-to-teacher ratio in schools) reduced disparities in dietary behaviors, both independently of and in interaction with social network effects. An additional model (described below)[24] incorporated conformance of obesity-related behaviors to social norms, but the study focused on network-based targeting of obesity interventions.

Mooney and El-Sayed[27] built a similar model to Zhang et al's[30] (ie, capturing changes to one's BMI and network based on peer BMI) and expanded it to focus on the relationship between social isolation due to body-related norms and probability of depression among Colorado and Mississippi adults. They found that in contexts with lower obesity prevalence, the risk of depression in adults with obesity is higher. Similarly, the sole system dynamics model[31] that examined a social-network–based influence included a feedback loop between elementary school students' obesity status, ridicule and criticism of their body type, emotional stability and body image, obesity-related behaviors, and ultimately changes to obesity status, although this feedback mechanism was not the focus of the study.

Several studies examined the effectiveness of using network-based strategies to target individuals for obesity interventions[24,25,28,30] and found various results. Zhang et al[30] (introduced above), Trogdon and Allaire,[28] and El Sayed et al[25] simulated obesity interventions that targeted highly connected individuals in models focused on US children, US adult women, and English adults, respectively; only one study[28] found an effect compared with other strategies, specifically that targeting most popular individuals in the network resulted in greater weight loss than random targeting of individuals with obesity. In a model focused on US youth, Beheshti, Jalalpour, and Glass[24] compared random targeting to two network-based targeting strategies, targeting based on high risk (ie, high BMI), and targeting of youth in obesogenic environments, and found that the network-based strategies outperformed the other targeting strategies in terms of nutrition or physical activity intervention effectiveness.

Another large group of models (n = 8) focused on dynamics of population and individual *transitions between weight and other health states*,[32-42] all but one using system dynamics modeling.

Meisel et al[33,35] modeled the accumulation and transference of people between the normal weight, overweight, and obesity categories focusing on the urban Colombian population, and tested several interventions for increasing transference to more healthy categories. Frerichs et al[32] focused on the BMI-category dynamics in US adults and children, while expanding the model to include and explore peer versus adult influence on obesity and testing combinations of prevention and treatment interventions for children and adults. Chen et al[36] also expanded a model simulating transitions between normal weight, overweight, and obesity categories in the US population to include related transitions between income and employment categories, and tested interventions that varied transitions between the income and employment categories for effectiveness in controlling population obesity.

Similar to the weight dynamics models, the Diabetes System Model[37,38] simulated the transfer of the US population between categories of diabetes status and explored several scenarios and interventions adapted from the Healthy People 2010 Objectives that were aimed at changing the flow rates between the categories, including one scenario where population obesity rates were reduced with the goal of preventing the onset of diabetes and reversion from prediabetes to normal in the population. Siegl et al[39] applied the health status dynamics concept to accumulation and flow of patients between hip replacement categories in an Austrian population, while exploring the influence of obesity prevalence on associated health expenditures.

Three models simulated health state dynamics at the individual "below the skin" level. Fallah-Fini et al[41,42] modeled microdynamics of changes in fat- and fat-free mass in individuals representative of BMI class, gender, and race/ethnicity categories in the US population. The authors then used these representations to generate average energy imbalance gaps in the population groups and their relationship with the obesity prevalence and distribution. Sabounchi et al[40] modeled the transitions between prepregnancy and pregnancy weight and the relationship with fetus size in a case study of a 34-year-old White woman with obesity and polycystic ovary syndrome, and tested several prepregnancy weight loss interventions for impact on fecundity and pregnancy weight gain. The New York Academy of Medicine Cardiovascular Health Simulation Model,[34] an agent-based model, simulated transitions between behavior and health states of US adults of Medicare-eligible age in order to evaluate a lifestyle intervention for chronic disease control in primary care settings.

Several models (n = 7) also included interactions between individuals and their immediate *food and physical activity environments*,[21-23,27,43-46] all using agent-based modeling.

Two models examined both food and physical activity environments as determinants of obesity. Orr et al[22,23] (introduced above) simulated 64 neighborhoods characterized by different food store availability and physical activity infrastructure, racial and economic make-up, and school quality, where health behaviors of people in the model were in part driven by these environments. They tested 125 combinations of food store quality, physical activity infrastructure, and school quality, all at three intervention strength levels, on BMI and Black-White disparities in BMI. Henessey et al[44] modeled the movement of US children between home, school, and community locations with differing physical activity and energy intake opportunities. They simulated potential effect of two interventions —aimed to increase physical activity through school-based physical activity programs and healthy out-of-school time programs—on children's BMI.

Four studies focused on obesity determinants solely related to either food or physical activity. Focusing on the food environment, two studies modeled the relationship of children's food environments with sugar-sweetened beverage (SSB) intake and obesity. One model[21] simulated eight graders' decisions about beverage type in a school following physical education class and tested the impact of different configurations of the environment (ie, number of water fountains or vending machines, SSB price) and other factors on their energy balance and dehydration. The Virtual Population for Obesity Prevention model[45] used a geospatial grid of food and beverage locations associated with differing probabilities of eating and SBB consumption as an environment for Baltimore, San Francisco, and Philadelphia youth of 11 to 18 years. They tested the impact of SSB warning labels on obesity prevalence and SSB consumption while varying literacy and retailer compliance rates. Focusing on physical activity environments, Powell-Wiley et al[46] examined the relationship between varying physical activity location accessibility due to crime—based on real geographic data of Washington, DC—on physical activity levels and obesity prevalence among African American women. Aziza et al[43] presented a proof-of-concept model also focused solely on the physical activity environment that represented both children and activities available to them in the community as different types of agents, where children achieve moderate-to-vigorous activity by engaging with activities based on factors specific to themselves (eg, age, gender, and motivation to perform physical activity) and characteristics of the activity.

Finally, one study integrated agents' interactions with food and physical activity environments, but with another primary goal. Mooney and El-Sayed[27] (introduced above) modeled BMI as a function in part of adults' resistance to an obesogenic environment, but their primary focus was to explore how the relationship between weight-related social norms and BMI can lead to social isolation and depression.

A few models (n = 3) examined obesity determinants at the *economic system and governance levels* (eg, dynamics of policy implementation), all using system dynamics modeling.[47-49]

Struben et al[47] linked together the dynamics of food demand and supply with population-level energy balance and tested a series of interventions (industry-driven, government-driven, innovation stimulation, and combinations of these) for whether they are able to shift the observed resistance of the system to break out of the mutually reinforcing supply and demand for unhealthy foods into a new system state. Liu et al[48] developed a model to understand the policy implementation dynamics of a SSB tax with revenue allocation to physical activity venue construction and subsidization of fruits and vegetables, and they examined the effects of this policy on children's weight. In a model focused on obesity among Mexican elementary school children, Carrete et al[49] modeled higher level influences somewhat abstractly as stocks of macrolevel influences, driven exogenously by national governmental strategies and culture, and exolevel influences, driven exogenously by local governmental policies and availability of health environments, both of which influence the rate of change in prevalence of overweight and obesity.

Two models, both using system dynamics modeling, simulated the *energy metabolism* at the individual level.[50-52] Abdel-Hamid et al[50,51] and Flat et al[52] both modeled biological dynamics of body fat accumulation to examine the impacts of diet and physical activity in the former and diet composition and physical activity in the latter on body composition and weight maintenance.

3.4 | Model typology

Based on the typology developed by Hammond,[18] the models were assessed along two dimensions: (a) whether the model examines etiological mechanisms or tests interventions; (b) whether the model is used prospectively (predictive) or retrospectively (explanatory). The majority of the models tested interventions (70%), but a high proportion also examined etiology (67%), sometimes in the same model, which was distributed similarly between agent-based and system dynamics models. The majority of the models (73%) were used predictively, and 37% were used in an explanatory way, also distributed similarly between agent-based and system dynamics models.

3.5 | Calibration and validation

Over half of the models were calibrated (57%), which was similarly distributed by model type. At least one validation test was used on majority of the models (80%),[15] the most frequent being behavior reproduction, ie, whether the model reproduces the behavior of interest in the system.[15] Validation reporting was somewhat higher for agent-based models (86%) than system dynamics models (75%).

3.6 | Usefulness for examining common determinants of the global syndemic

Table 3 displays to what extent the reviewed computational models map onto the sets of systems of common determinants for obesity, climate change, and undernutrition that were put forth in the Systems Outcomes Framework.[3] By definition, all models examined changes in physiology related to obesity. The majority (70%) also accounted for or explored the role of behaviors that determine obesity (eg, eating behaviors, physical activity).

Half of the models also examined determinants of obesity within microsystems, which consist of influences within families, communities, and social circles. This was driven mostly by the numerous agent-based computational models that examined social network influences on obesity. Similarly, 43% of the models examined influences within mesosystems (composed of schools, hospitals, workplaces, and public spaces), and whose model components most frequently focused on school-based interventions and environments, characteristics of neighborhoods or public spaces, and access to and quality of medical care.

Fewer models (23%) included influences within macrosystems (ie, food, transport, urban design, and land use) or governance systems (ie, policies, norms, and economics). In the former group, models included elements of the built environment, urban design, and food environments. The latter consisted of government policies (eg, beverage and food taxes, warning labels) and economic determinants (eg, food demand, unemployment).

Only two computational models incorporated components representing natural systems. The PRISM model[53,54] included particulate air pollution endogenously and pollution control regulations exogenously. The Virtual Population Obesity Prevention Lab[46] implicitly incorporated weather as an exogenous factor influencing an agent's baseline probability to exercise.

4 | DISCUSSION

In this systematic review of the use of system dynamics and agent-based modeling in understanding the challenge of obesity, 38 studies were reviewed that represent 30 distinct computational models. The use of these methods has grown in the past 10 years and reflects a range of topics and time scales, with a higher median time scale for system dynamics models. Most agent-based models focused on social-network–based influences or people's immediate built and food environments. This reflects a particular strength of this type of modeling, ie, its ability to realistically represent social and spatial environments of modeled individuals. System dynamics models most often focused on population weight and health status dynamics and were able to examine determinants at the governance level. The majority of the models represented Western settings, which presents an important research gap given the high and growing prevalence of obesity in low-income and middle-income countries and the worldwide nature of the *global syndemic*.[3]

In terms of informing the study of shared drivers of the *global syndemic*,[3] the usefulness of this set of computational models was mixed. These models provide some building blocks for moving ahead, but significant gaps remain. First, long time horizons are important for understanding the *global syndemic*, and only few of the reviewed computational models have employed long time horizons. Second, the reviewed models were more likely to explore determinants of obesity close to the person (ie, microsystem and mesosystem) but less likely to address macrosystem and governance determinants, with nearly no examination of drivers in the natural systems. This reflects an important gap along the analytical scale[55] of the *global syndemic* problem. Clarifying mechanisms, testing interventions, and taking action within the governance, economic, and food supply systems have a high potential for population impact.[56] The System Outcomes Framework[3] puts forth how governance influences at the macrolevel, which determine policies, economic incentives, and societal norms, in turn create operating conditions for intermediate systems that drive the *global syndemic*—ie, food, transportation, land use, and urban design systems. Without examining such mechanisms (eg, power balance between actors, dynamics around policy implementation) or connecting the problem of obesity to changes in the natural systems, it is difficult to identify actions that will address the common causes of the *global syndemic*.

Despite these gaps, there is potential for extending some of the computational models from this review and existing climate change literature in ways that may illuminate common causes and find multiduty solutions for the *global syndemic*. For example, though the model by Struben et al[47] was developed for and calibrated to the Canadian setting, it could be adapted to settings at various stages along the nutrition transition and be expanded to include dynamics and outcomes related to undernutrition. The model developed by Liu et al[48] could be expanded to disaggregate new physical activity space construction by whether the built environment is changed in a way (eg, facilitates active transport opportunities) that mitigates greenhouse gas emissions.

Further, among existing system dynamics models of climate change, many include food systems-related components, which could be used to link mechanisms of climate change to those that produce undernutrition and obesity outcomes. Often these models include agricultural water demand or use,[57-72] crop yield and production,[62,65,73-80] agriculture-related income or profit,[57,58,65,77,81] land use,[73,74,76,82,83] agricultural energy demand or use,[80,84-86] or livestock population dynamics.[57,58,81] Notably, two studies include food

TABLE 3 Map of reviewed model elements within the adapted Systems Outcomes Framework

Computational Model	Ecological Systems	Governance	Macrosystems	Mesosystems	Microsystems	Obesity Behaviors	Physiology
System dynamics models							
1 Abdel-Hamid (2002), Abdel-Hamid (2003)							√
2 Intervention Childhood Obesity Dynamics model, Abidin et al (2014), Abidin et al (2014), Abidin and Jamil (2016)				√	√	√	√
3 Carrete, Arroyo, and Villaseñor (2017)		√	√	√	√		√
4 Chen et al (2018)		√					√
5 Fallah-Fini et al (2013), Fallah-Fini et al (2014)						√	√
6 Flatt 2004						√	√
7 Frerichs, Leah					√	√	√
8 Diabetes System Model, Jones et al (2006), Milstein et al (2007)				√		√	√
9 Prevention Impacts Simulation Model, Kuo et al (2016), Soler et al (2016)	√	√	√	√		√	√
10 Lan et al (2014)				√	√	√	√
11 Liu et al (2016)		√	√	√		√	√
12 Meisel et al (2016), Meisel et al (2018)							√
13 Powell et al (2017)[a]							√
14 Sabounchi et al (2014)						√	√
15 Siegl, Lassnig, Schröttner (2014)							√
16 Nutrition Market Transformation Model, Struben, Chan, Dube (2014)		√	√		√	√	√
Agent-based models							
17 SimNCD, Aziza et al (2016)				√	√	√	√
18 Beheshti, Jalalpour, and Glass (2017)					√	√	√
19 Chen et al (2016)				√		√	√
20 El-Sayed et al (2012)					√		√
21 Hammond and Ornstein (2014)					√		√
22 Hennessey et al (2016)				√		√	√
23 Virtual Population for Obesity Prevention, Lee et al (2018)		√	√	√		√	√
24 The New York Academy of Medicine Cardiovascular Health Simulation Model, Li et al (2014)						√	√
25 Mooney and El-Sayed (2016)				√	√		√
26 Orr et al (2014), Orr, Kaplan, and Galea (2016)			√	√	√	√	√
27 Virtual Population Obesity Prevention Lab, Powell-Wiley et al (2017)	√		√	√	√	√	√
28 Trogdon and Allaire (2014)		√			√	√	√
29 Wang et al (2014)					√	√	√
30 Zhang et al (2015)					√		√

[a]Insufficient information was provided by Powell et al (2017) about model content to assess any categories except for physiology.

consumption broadly,[78,80] and another two include consumption disaggregated by types of food,[87,88] allowing for the possibility of linking dietary patterns to climate change, undernutrition, and/or obesity in the latter. For example, Strapasson et al's model[87] examines the dynamics of land use for bioenergy, crop cultivation, and livestock on a global scale and allows for testing of multiple scenarios (eg, modifying food calories consumed, crop yields, quantity and type of meat consumed, and animal density on pasture lands) for effect on global greenhouse gas emissions and temperature. This model could potentially be expanded to allow for quantifying impact on obesity or undernutrition prevalence.

Systems science is inherently iterative, and there is a potential to draw on a repository of computational models related to the *global syndemic* that have been tested and validated across contexts and scale in order to deepen existing theoretical and empirical knowledge. This could be done serially, with models whose outputs can be used as inputs in other models, eg, using system dynamics models of climate change that incorporate food systems, as highlighted above. It could also be done by building models that have multiple levels, or hybrid modeling, eg, combining aggregate level models of markets with individual level models of consumers and their responses to environments. This review sheds light, however, on the existing challenges to synthesizing scientific knowledge using the current models due to differences in both temporal and geographical scale, as well as variability both in calibration and validation of models, limiting realism and validity, and documentation, limiting replicability.

To synthesize existing computational modeling work in the future, several innovations in system dynamics and agent-based modeling research are necessary. First, although guidelines for carrying out and reporting computational modeling exist,[89-91] no guidelines equivalent to the Cochrane group's guidelines[17] exist for performing syntheses of computational modeling research or evaluating model quality. Second, a large proportion of the models included in this review included insufficient documentation, which means that these models are not easily replicable and their assumptions cannot be examined by others. Journal requirements around the inclusion of documentation or running model files as a condition to publication would ensure that these so-called "black box" models[91] become more transparent and useful to the reader. Third, both examples of and guidelines for combining distinct computational models should be clearly explicated. Fourth, when synthesizing computational models to answer a given problem, it is important to specify the system as a whole, with a complete set of key mechanisms and levels conceptualized in advance, which enables one to use the review as was done here to verify coverage of all key elements and identify the most important gaps and overlaps.

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CONFLICT OF INTEREST

No conflict of interest was declared.

ORCID

Alexandra B. Morshed https://orcid.org/0000-0001-9960-0409

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