American Journal of
Preventive Medicine

REVIEW ARTICLE

Complex Systems Approaches to Diet: A Systematic Review

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Context: Complex systems approaches can help to elucidate mechanisms that shape population-level patterns in diet and inform policy approaches. This study reports results of a structured review of key design elements and methods used by existing complex systems models of diet.

Evidence acquisition: The authors conducted systematic searches of the PubMed, Web of Science, and LILACS databases between May and September 2018 to identify peer-reviewed manuscripts that used agent-based models or system dynamics models to explore diet. Searches occurred between November 2017 and May 2018. The authors extracted relevant data regarding each study's diet and nutrition outcomes; use of data for parameterization, calibration, and validation; results; and generated insights. The literature search adhered to PRISMA guidelines.

Evidence synthesis: Twenty-two agent-based model studies and five system dynamics model studies met the inclusion criteria. Mechanistic studies explored neighborhood- (e.g., residential segregation), interpersonal- (e.g., social influence) and individual-level (e.g., heuristics that guide food purchasing decisions) mechanisms that influence diet. Policy-oriented studies examined policies related to food pricing, the food environment, advertising, nutrition labels, and social norms. Most studies used empirical data to inform values of key parameters; studies varied in their approaches to calibration and validation.

Conclusions: Opportunities remain to advance the state of the science of complex systems approaches to diet and nutrition. These include using models to better understand mechanisms driving population-level diet, increasing use of models for policy decision support, and leveraging the wide availability of epidemiologic and policy evaluation data to improve model validation.
Am J Prev Med 2019;57(2):273−281.

CONTEXT

Complex systems methods like agent-based models (ABMs) and system dynamics models (SDMs) are well suited for examining patterns in diet and nutrition and can help identify effective policy approaches to improve diet at the population level. Identifying and intervening upon the mechanisms that shape population-level diet will likely require considering how multiple multilevel influences interact to comprise a complex and dynamic system.[1] These multilevel influences include factors at the community (e.g., social norms), environment (e.g., food access), household (e.g., income), and individual (e.g., preferences) levels. Complex systems can include feedback loops (e.g., access to

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0749-3797/$36.00
https://doi.org/10.1016/j.amepre.2019.03.017

healthy food impacts individuals' diets, but the collective food purchasing patterns also influence food retail), heterogeneity (e.g., individuals differ in important ways that affect their diet choices), nonlinear effects (e.g., tipping), and dependencies (e.g., peer influence on diet).Complex systems methods are useful precisely because they are intended for examining elements of complexity that are important for diet and for which other simulation-based approaches (e.g., Markov models or microsimulation) are not intended.[2] An ABM is a flexible simulation framework in which "agents" make decisions and pursue goals according to simple decision rules.[3] An ABM can include one or multiple types (e.g., individuals and food stores) of agents, each agent can have heterogeneous characteristics (e.g., income levels), and agents can interact with each other and their environments. For example, Zhang and colleagues[4] developed an ABM to understand how social norms, food pricing policies, and zoning impact people's choices regarding where to shop for food and what to purchase. Although the rules that guide the decisions of a single agent are generally simple, they can lead to emergent patterns at the population level.As described by Homer and Hirsch,[5] the SDM approach involves development of simulation models that portray processes of accumulation and feedback. SDMs typically include stock variables that represent the accumulation of resources (e.g., people, revenue, and disease), as well as a series of equations that govern flows into and out of these stocks.[5] Understanding feedback loops and the flow and accumulation of resources can generate insights regarding the systems that influence diet, as well as potential policy approaches. For example, Liu and colleagues[6] developed an SDM to examine the flow and accumulation of revenue if a city were to pass a beverage tax to fund various combinations of policies to improve diet and physical activity (e.g., healthy food subsidies and new parks).Previous systematic reviews have examined complex systems approaches to noncommunicable disease and obesity.[7,8] No systematic review has specifically examined the application of complex systems methods to diet and nutrition, although the literature regarding complex systems approaches to diet has expanded in recent years.[9−14] The purpose of this study is to conduct a systematic review of studies that have used ABMs or SDMs to understand the complex systems that influence population diet, with particular emphasis on identifying the complex system structures explored and methods used by each study. The paper reports key data extracted from each study, including its purpose, the main examined diet and nutrition outcomes, integration with empirical evidence and data, and model design elements. The paper also overviews the main results and insights reported in each study. This review and the data extracted from each study will be useful for modelers working in this area, who can build upon, refine, and extend the concepts and methods employed in previous models.[15] Based on the findings, the paper concludes by discussing key methodologic and substantive opportunities via which complex systems approaches can advance understanding of population-level patterns in diet and nutrition.

EVIDENCE ACQUISITION

The authors searched the PubMed, Web of Science, and *Literatura Latino-Americana e do Caribe em Ciências da Saúde* (LILACS) databases to identify peer-reviewed manuscripts that used ABMs or SDMs to explore diet and other nutrition behaviors. The authors included the LILACS database because they have interest in developing systems models to inform nutrition policy in Latin America. The search was conducted in two rounds; the initial search took place in November 2017. After completing data extraction for the identified studies, the search was repeated in May 2018 to identify studies published in the intervening period. In each database, all combinations of one of the following modeling terms and one of the following food terms was queried: *agent based model*, *agent based simulation*, (*system dynamics AND model*), *computational model*; *AND diet, nutrition, food, eat, drink, soda, beverage*. The search strategy was refined iteratively by screening results to assess coverage of a set of papers meeting the inclusion criteria of which the authors were aware a priori. Search results were limited to those that included the search terms in the title, abstract, or keywords fields. Two ABM studies authored by team members were not included in the database results. Hammond et al.[16] referred to their model as a "computational model" in the abstract, rather than an "agent-based model", and the term "agent" did not appear in the title, abstract, or keywords. As a sensitivity analysis, the term "computational model" was added to the search of Web of Science and identified no further studies to include beyond the paper by Hammond and colleagues; because the addition returned several hundred studies that did not meet the inclusion criteria, the term was excluded from the final search. Langellier et al.[17] were published in a new journal that was not indexed in any of the databases at the time of the search, though it has since been indexed by PubMed. No review protocol is available.

Studies were included in the review if they met the following inclusion criteria:

1. They implemented an ABM or SDM.
2. They included a diet- or nutrition-related behavior as either a primary or secondary outcome of the study.

3. The manuscript was published in full-text format in a peer-reviewed journal (i.e., conference abstracts and book chapters were excluded).

Studies were excluded if they reported exclusively on a physiological simulation,[18,19] owing to this study's focus on understanding drivers of population-level patterns. One author screened the title and abstract of each study to determine whether it met the inclusion criteria. If eligibility was unclear, two authors then reviewed the full-text version of the study. No studies were excluded based on the date of publication, largely based on the desire to include all pertinent studies and because of the authors' background knowledge regarding the relatively nascent state of the literature that applies complex systems models to address issues of noncommunicable disease. The authors adhered to PRISMA guidelines for conducting and reporting on the literature review.[20] Table 1 describes the data extracted from each ABM and SDM study and terms used throughout the manuscript.

EVIDENCE SYNTHESIS

Twenty-seven studies met the inclusion criteria, including 22 ABMs and five SDMs. Figure 1 includes further information regarding the identification, screening, and inclusion process, including reasons for exclusion. Appendix Table 1 (available online) shows detailed information on the purpose; dietary outcomes; design; use of data for parameterization, calibration, and validation; and types of insights generated for ABMs. Appendix Table 2 (available online) shows the same information for SDMs.

Purpose

Thirteen of the 22 ABMs explored mechanisms that shape diet,[11,13,16,17,21−26] including social norms and social influence,[17,22,24,25,27] food price and budgets,[12,23,24] food reward learning,[16] methods of targeting interventions,[11,27] residential segregation,[17,28] and environmental influences.[13,25,26] Twelve of the ABMs were policy-oriented[4,9,10,14,29−33] and explored policies related to residential segregation,[28,29] food and beverage pricing,[4,10,12,14,27−29] food access and the food environment,[4,10,28,32,33] media campaigns and social norms,[4,29,30] youth education,[14,31,32] and food labeling.[9]

Three of the SDM studies sought to examine multiple integrated processes and systems that work in combination to influence diet or related outcomes.[6,34,35] The purpose of three SDMs was to inform healthy diet or obesity prevention policies.[5,6,36] For example, Liu and colleagues[6] developed an SDM to inform decisions related to obesity prevention policies to be funded by revenue generated by a sugar-sweetened beverage (SSB) tax.

Parameterization and Calibration

All of the SDMs and most of the ABMs leveraged empirical data to inform parameter values. Those that did not were highly stylized mechanistic models.[16,17,25,28] Several studies used longitudinal data to estimate the values of parameters related to either the population (i.e., initialized the population based on demographic and health data from the baseline observation of a cohort study) or processes under investigation.[11,13,14,22,29] Many studies also identified values for parameters from the peer-reviewed literature or previous simulation studies.[4−6,9,10,12−14,24,27,30−34,36] This included, for example, the own-price elasticities of certain categories of food[12,14] and effect sizes of interventions.[6,14,30] Values derived from the literature typically originated from a range of intervention, longitudinal, and cross-sectional studies.

Nine ABM studies and three SDM studies used calibration methods to estimate the values of parameters for which data were not available.[5,11,22,24,26,27,29,31−35] Wang and colleagues[22] calibrated the values of parameters describing the effect of social norms on children's BMI and fruit and vegetable consumption. Typically, calibration targets were based on data collected among the population under study or a similar population. Wang et al.[22] calibrated the social norm effects in their ABM to descriptive statistics (i.e., deciles, means, and SDs) regarding BMI and fruit and vegetable consumption among participants in the Early Childhood Longitudinal Study Kindergarten Cohort. Meisel and colleagues[35] calibrated the transition rates between BMI categories in their SDM using data regarding the distribution of BMI observed in national data in 2005 and 2010.

Validation

Eleven ABM studies and one SDM study conducted validation through behavioral reproduction, or comparison of model output to external data observed in the systems under investigation.[4,9−12,14,21−23,26,29,36] This typically involved comparisons at a single point in time to descriptive statistics produced from one or more data sets. For example, Lee and colleagues[9] used their ABM to assess the potential effect of a policy to place point-of-purchase warning labels for SSBs in three U.S. cities. The study compared overweight and obesity prevalence produced by the ABM in a baseline, nonintervention scenario to prevalence data collected in each city. Liu et al.[6] noted that data did not exist to validate the policy predictions of the model, because the policies were counterfactual and had not been implemented.

Agent-Based Model Design

The most common classes of agents were individuals and households, one of which was included in all of the ABMs; these agents made food purchasing or consumption decisions. Five ABMs also included a class of food store agents

Table 1. Description of Data Extracted From Agent-Based and System Dynamics Modeling Studies

Data extracted	Description
ABM and SDM	
Model type	Agent-based model or system dynamics model
Purpose	Stated purpose of the model, as described by study authors
Primary outcome	Main outcome of the model (e.g., mean BMI)
Diet and nutrition outcomes	Main diet and nutrition outcome, if different from the primary outcome (e.g., mean sweetened beverage consumption)
Subgroup estimates	Whether outcomes are presented separately for subgroups of interest (e.g., by race/ethnicity)
Parameters and relationships	Description of key parameters, variables, and relationships that drive the dynamic changes that occur as the model runs
Parameterization data	Data used parameterize the model, meaning to assign the values of parameters in the model.
Calibration data and methods	Calibration is an iterative process through which the values of unknown parameters are “tuned” to align specified output produced by the model with data describing the “real” system.
Validation data and methods	Validation refers to the process and tests used to assess the suitability of the proposed model, and can include sensitivity analysis, uncertainty analysis, and behavior reproduction.
Model design method	Authors’ description of the process through which the structure of the model was designed, including the model boundary (i.e., which variables, relationships, and dynamic processes to include). Common methods include via a literature review, stakeholder engagement processes (e.g., group-based modeling), or face validation (e.g., content experts reviewed the structure).
Feedback loops	Bidirectional relationships involving two or more variables that create circles or loops of influence, and can be either reinforcing (i.e., vicious or virtuous cycles) or balancing (i.e., regulating)
Findings	Summary of findings as interpreted and reported by authors
ABM only	
ABM class	A classification of models as either policy, mechanistic, or a combination of the two, based on the stated purpose of the model
Empirical anchoring	A qualitative assessment of anchoring to empirical data using a three-category system: (1) low, if the environment, agents, or parameters were stylized (i.e., implausibly simplistic) rather than linked to empirical data; (2) medium, if some but not all factors of the environment, agents, or parameters were linked to empirical data; (3) high, if the environment, agents, or parameters were all linked to empirical data. Note that empirical anchoring is not intended as an assessment of the quality of the study, but rather as a useful piece of information regarding a model’s purpose and applicability across populations and contexts (e.g., a model that is highly anchored to data from a particular context may produce insights about the context that are precise but highly specific, whereas a less empirically anchored model may be less applicable to a specific context or population but have implications that are more broadly applicable)
Agent classes	Types of agents (e.g., individuals, food stores) present in the model
Agent processes and rules	The processes, rules, and objectives that drive agent behaviors over time
Social networks	Whether agents were organized in social networks, characteristics of the network, and use of the network. Key characteristics include the network formation model (e.g., small world), average degree, clustering, and reciprocity. An example use for a social network is to enable a mechanism of social influence on diet
Dependencies	Mechanism through which the outcome of an agent is directly influenced based on the outcomes of other individuals (e.g., social influence)
Spatial sensing	Description of whether the model is spatially explicit, use of space (e.g., distance between an agent and a food store), and representation of space in the model environment (e.g., GIS space, a grid of cells, continuous space)

ABM, agent-based model; GIS, geographic information systems; SDM, system dynamics model.

that made periodic decisions (e.g., whether to go out of business) based on their own set of rules.[4,10,28–30]

Ten of the ABMs connected agents via social networks to explore the implications of social influence on diet.[4,10,11,17,22,25,27,30–32] Typically, social influence was operationalized via a “follow-the-average” (FTA) mechanism,[37] whereby each agent’s behavior (e.g., diet) was periodically adjusted to align with the mean behavior of the social network.[4,10,11,17,22,27] Beheshti and colleagues[11] used a modified FTA mechanism, in which behavior change only occurred if the joint pressure of both social influence and environmental influence exceeded a prespecified threshold. In contrast to the FTA mechanism, Orr et al.[31,32] implemented social influence via a threshold mechanism (i.e., the more “healthy” friends one has, the more one is likely to make healthy changes).

Fourteen of the ABMs included spatial sensing, meaning that agents’ decisions or behaviors were influenced by

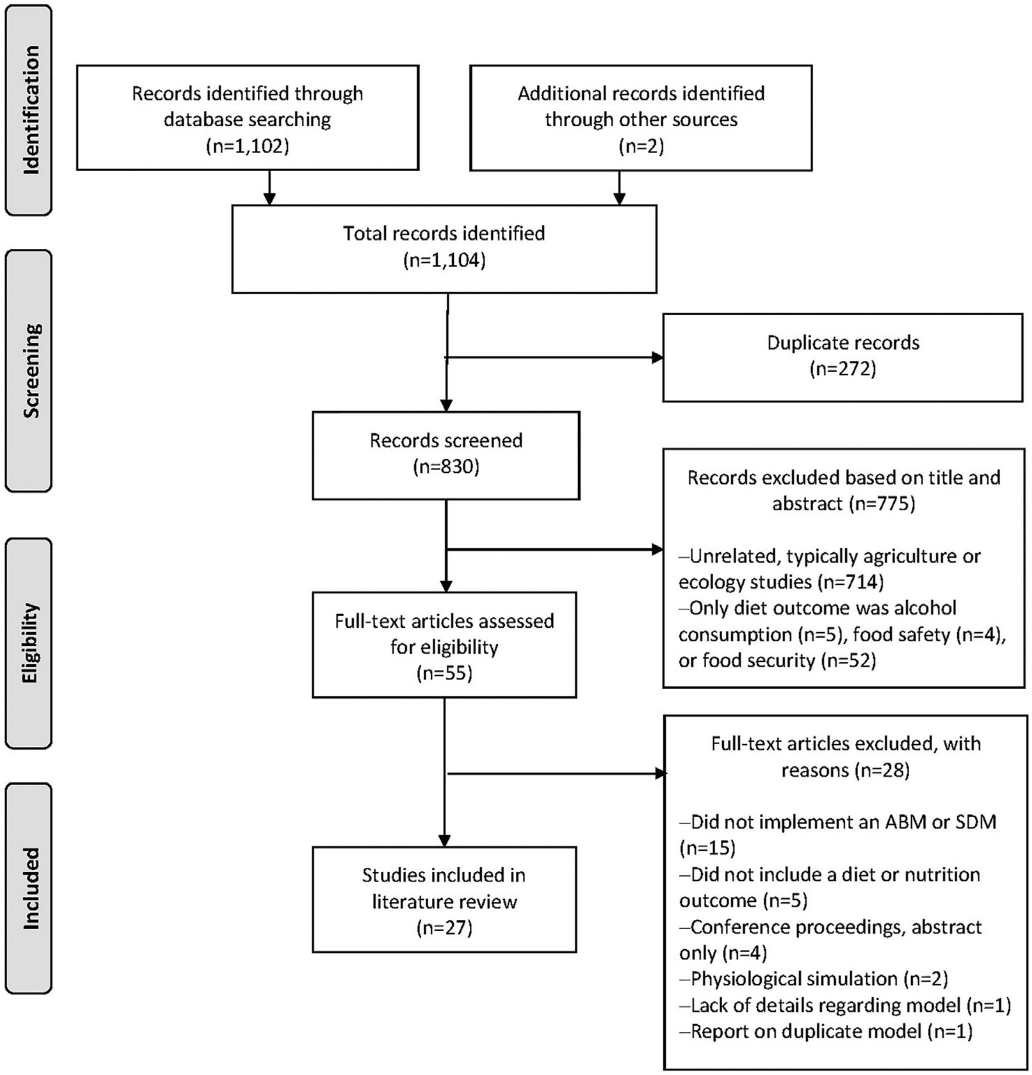

Figure 1. PRISMA 2009 flow diagram.
ABM, agent-based model; SDM, system dynamics model.

distance to other agents (i.e., individual or store agents) or features of the environment.[4,9,10,13,16,17,25,26,28–33] In several models, distance was operationalized via a dichotomous rule such as "individual agents can shop at food stores within one mile of their location."[10] In others, the influence of distance was continuous (e.g., individual agents were more likely to shop at nearby stores or to be friends with agents that lived nearby).

System Dynamics Model Design

All of the SDMs were composed of several subsystems. The model of Abidin and colleagues[36] included subsystems related to food consumption by source, energy intake, energy expenditure, and body composition. Four of the models explicitly included balancing or reinforcing feedback loops.[6,34–36] An example of a reinforcing feedback in the SDM of Struben et al.[34] is that increased consumption of a category of food by an individual increased the population's exposure to the food. This increased exposure, in turn, increased each person's propensity to consume the food.

Types of Insights Generated

Several of the ABM and SDM studies generated insights about the implementation of one or multiple policy interventions.[4–6,9,10,12,14,27–34,36] For example, Orr and colleagues[32] found that an intervention to improve the quality of the lowest-performing schools in a community had the potential to reduce disparities in healthy diet between black and white students, and that improvements in diet were greatest when the policy was paired with healthy social norms. The SDM of Struben et al.[34] demonstrated that single-pronged interventions are ineffective and that curbing the obesity epidemic will likely require a combination of multiple, aligned efforts. Abidin and colleagues[36] found that achieving the British Government Offices' goal to reverse childhood obesity prevalence to their 2000 levels will likely require policies that go beyond the individual level, particularly those that create an environment that makes it easier to make healthy choices. Collectively, these studies suggest the importance of considering how policies can be most effectively combined, as well as considering how mechanisms like social influence and feedbacks can impact policies' effectiveness.

Other studies looked at potential mechanisms driving dietary patterns, such as aging[5] and residential segregation.[28,29] The mechanistic studies, particularly ABMs, examined heuristics or rules that guide diet and nutrition decisions; this is important, because these rules can have difficult-to-predict consequences (i.e., emergence) for health outcomes and the effectiveness of interventions. Hammond et al.[16] explored the process of food reward learning as a potential food choice heuristic that, in combination with high access to unhealthy food, could explain secular trends in unhealthy eating. Studies can also help adjudicate among multiple, reasonable heuristics. Beheshti and colleagues[23] developed an ABM to examine multiple price heuristics (e.g., price per calorie versus price per serving) that guide food purchasing decisions. By comparing diets generated using the different price heuristics to diets observed using data from a national study of diet, they concluded that price per calorie is likely the dominant price metric used in guiding food purchasing decisions.

DISCUSSION

Complex systems approaches can add to an understanding of diet and nutrition, but there are still clear challenges and opportunities. Findings from this review suggest opportunities for complex systems research to make contributions in the following areas: (1) mechanisms that drive population-level patterns in diet and nutrition; (2) decision support for diet and nutrition policy, including examination of the conditions necessary for policy success; and (3) model validation.

First, several studies illustrate the utility of complex systems methods for elucidating mechanisms that shape population patterns in diet.[38,39] For example, Homer et al.[5] used their SDM to estimate the health effects of population aging, a demographic shift underway in most developed and many developing countries. Complex systems models like that of Homer and colleagues can help explore how population aging and other demographic (e.g., migration and fertility) and social processes are likely to shape population-level patterns in diet. For example, research suggests that the dietary patterns of Latinos in the U.S. change as immigrants acculturate, though the specific mechanisms through which this occurs are not well understood.[40,41] Complex systems models can help test hypotheses regarding the dynamic mechanisms through which immigrants both adapt to and influence the food behaviors of their communities.

Collectively, the studies illustrate how multiple elements of complexity can interact to drive changes in population diet. Beheshti et al.[20] used an ABM to determine that price per calorie is likely the dominant price metric used by low-income individuals in deciding what to eat, whereas Auchincloss and colleagues[23,28] explored the important role of residential segregation in producing income disparities in diet. Taken together, these studies may suggest an explanation for the dearth of full-service supermarkets in poor versus nonpoor neighborhoods that has been observed in many cities.[42,43] Residential segregation, combined with poor consumers' purchasing preferences for cheap, energy-dense food, may produce comparatively low demand in low-income neighborhoods for healthy foods with a high price per calorie, like fresh produce. These studies highlight the utility of complex systems approaches for examining the etiology of diet at the population level, and particularly for understanding the implications of interactions between policies, people, and their environments.

Several of the ABMs examined social influence as an important driver of diet and nutrition.[4,10,11,17,22,25,27,30−32] Generally, these studies used or adapted an FTA mechanism first introduced by Hammond and Ornstein,[37] in which agents periodically adjust their preferences to conform with those of their social network. Hammond[44] describes the empirical evidence suggesting that social norms play an important role in shaping diet, but also suggests that social influence is not the only mechanism through which social ties have an impact. Future work could iterate from these existing models to explore how social influence combines with other mechanisms such as social capital (i.e., the resources, information, and people accessible through a social network) and social stress (i.e., stress generated by social relations) to influence diet.[44]

A second opportunity is to increase use of complex systems models as a decision support tool for nutrition policy. Homer et al.[5] describe how a locally calibrated version of their SDM has been adopted by county collaborators to inform local strategies to address chronic disease. The study employed several approaches that, if more widely adopted, could lead to greater policy impact of complex systems models of diet and nutrition. The study engaged stakeholders early in the modeling process to identify a set of interventions relevant within the context of local public health systems and used local data to calibrate the model to increase relevance for local policy decisions. Complex systems simulations have also informed policy decisions related to tobacco control, infectious disease control, natural resource management, and agricultural policy.[45,46] If complex systems modeling is to become more mainstream, it is critical to engage local stakeholders early in the modeling process and to tailor models to be most relevant to local contexts and policy decisions. Similarly, modelers should work with dissemination scientists to develop a framework for effectively and appropriately disseminating results of complex systems studies to nonresearch audiences (e.g., policymakers and community members).

A particular area where complex systems models can be useful for informing policy is in helping to identify the conditions necessary for policy success. A salient example is recent efforts to implement excise taxes on energy-dense, nonessential food items like SSBs. Early results show that a 1-peso/liter excise tax on SSBs in Mexico has resulted in a decrease of >7% in per-capita sales of SSBs and a 5% increase in water sales.[47] Jou and Techakehakij[48] argue that taxes are most likely to be effective in contexts like Mexico where obesity prevalence and SSB consumption is high and existing food and beverage taxes are low or modest. Implementing SSB taxes in contexts where existing taxes are already high or where SSB consumption is low may have minimal impact on obesity prevalence but cause backlash from the beverage industry (e.g., lobbying against nutrition standards and increased advertising) or the public, and have negative unintended consequences. The models that examined beverage consumption,[6,9,14] food and beverage pricing,[4,6,12,23] and food advertising[30] could serve as a foundation for future work examining how context and starting conditions impact the success of beverage taxation policies.

As noted by Tracy and colleagues[49] and others,[50,51] validation of complex systems models in public health has been underdeveloped. An illustration of the challenge in validating complex systems models of diet can be drawn from the multiple policy-oriented ABM studies that sought to predict the effects of counterfactual food and beverage taxation policies.[4,14] These studies, as well as most policy-oriented studies, were validated via comparison of model output to data collected in nonintervention, baseline scenarios. Though this approach builds credibility in a model's ability to produce reasonable output when no intervention is implemented, it provides few checks for understanding whether the model is appropriate for predicting how a specific nutrition policy will impact a population's diet. The lack of robust validation of models' capacity for policy prediction is particularly concerning for studies in which parameters driving the policy effects were derived using data or estimation methods that are insufficient for identifying a causal relationship (e.g., use of cross-sectional estimates of the relationship between food beliefs and diet as an estimate of the causal effect of a change in beliefs on diet).

A third opportunity exists to build more-credible models for policy prediction, specifically within the field of diet and nutrition. One approach available to modelers is to leverage data from a diverse range of epidemiologic studies of population patterns in diet, as well as evaluation data from a diverse range of nutrition policies that have already been implemented. For example, SSB taxes have been implemented in the last several years in Berkeley, Philadelphia, Mexico City, and other contexts. Models like those of Zhang and colleagues[4] and Langellier et al.,[14] which sought to evaluate the effects of food taxes in specific local contexts, could use evaluation data from these taxes for retrospective validation. If such a model were able to reproduce patterns observed as these other taxes were implemented, it would be a step in the right direction for building credibility in the model's capacity for addressing related policy questions (e.g., implementing a tax in a different context, or estimating the effect over a longer time horizon or on different health outcomes). If the model were unable to reproduce empirical patterns, this may indicate misspecification of the values of key parameters or that the causal structure underpinning the model does not adequately represent the policy's mechanisms. A challenge to this approach may be that models often do not explicitly include or examine barriers to implementation that impact the effectiveness of policies and programs implemented in the real world. For retrospective evaluation to work, modelers will likely need to work with stakeholders to identify important implementation factors that should be included in their models.[52] Challenges notwithstanding, retrospective validation represents an opportunity to leverage past policies and existing dietary data sets to develop credible and insightful models.

Another approach that could prove useful in advancing validation is iterative studies that integrate complex systems modeling with policy intervention research. An example of this is the Childhood Obesity Modeling for Prevention and Community (COMPACT) study, which pairs complex systems approaches with community-wide child obesity interventions in several communities.[53,54] The benefits are synergistic: the model can be recalibrated and updated as new implementation and evaluation data become available, and the intervention can be iteratively refined based on the insights of the model. Although this study is not specific to diet and nutrition, the approach could be replicated with diet-oriented policies, interventions, and environmental changes taking place in cities across the globe.

Limitations

This literature review has strengths and limitations. Strengths include the systematic nature of the database search and data extraction, the focus on models with a diet or nutrition outcome, the otherwise inclusive search terms used, and use of multiple databases. A limitation is that the search may have omitted relevant studies that were not in English (PubMed, Web of Science), Spanish (LILACS), or Portuguese (LILACS), or that did not include the search terms in the title, abstract, or keywords. No studies were included that employed social network analysis, nor were conceptual SDMs that were not implemented within a simulation framework (e.g., those developed by stakeholders using participatory methods such as group model building). Similarly, because the purpose of the review was to understand how elements of complexity (e.g., feedback loops, dynamic processes, and heterogeneity) impact population diet, studies were not included that used other simulation-based approaches (e.g., the CHOICES microsimulation).[55]

CONCLUSIONS

Complex systems approaches can help to elucidate drivers of population diet, and to understand the implications of complex systems for nutrition policy. The studies conducted to this point underscore the high potential of the approach, yet opportunities remain to build on this success to expand evidence and bring insights to policy.

ACKNOWLEDGMENTS

We thank Krystal Lobban for assistance with the literature search and data extraction.

The *Salud Urbana en América Latina* (SALURBAL)/Urban Health in Latin America project is funded by the Wellcome Trust [205177/Z/16/Z]. More information about the project can be found at www.lacurbanhealth.org. The Wellcome Trust played no role in the design of this study. FM was funded by NIH FIC D43TW010540. JM was funded by the Research Office at the Universidad de Ibagué.

All authors contributed to the development of the research question and conceptualization of the study. BAL conducted the literature search. BAL, UB, FM, JDM, and LOC extracted data for the studies. All authors contributed to the writing of the manuscript and all authors approved the final version.

No financial disclosures were reported by the authors of this paper.

SUPPLEMENTAL MATERIAL

Supplemental materials associated with this article can be found in the online version at https://doi.org/10.1016/j.amepre.2019.03.017.

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