REVIEW

Applications of Complex Systems Models to Improve Retail Food Environments for Population Health: A Scoping Review

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ABSTRACT

Retail food environments (RFEs) are complex systems with important implications for population health. Studying the complexity within RFEs comes with challenges. Complex systems models are computational tools that can help. We performed a systematic scoping review of studies that used complex systems models to study RFEs for population health. We examined the purpose for using the model, RFE features represented, extent to which the complex systems approach was maximized, and quality and transparency of methods employed. The PRISMA-ScR (Preferred Reporting Items for Systematic reviews and Meta-Analyses extension for Scoping Reviews) guidelines were followed. Studies using agent-based modeling, system dynamics, discrete event simulations, networks, hybrid, or microsimulation models were identified from 7 multidisciplinary databases. Fifty-six studies met the inclusion criteria, including 23 microsimulation, 13 agent-based, 10 hybrid, 4 system dynamics, 4 network, and 2 discrete event simulation models. Most studies ($n = 45$) used models for experimental purposes and evaluated effects of simulated RFE policies and interventions. RFE characteristics simulated in models were diverse, and included the features (e.g., prices) customers encounter when shopping ($n = 55$), the settings (e.g., restaurants, supermarkets) where customers purchase food and beverages ($n = 30$), and the actors (e.g., store managers, suppliers) who make decisions that influence RFEs ($n = 25$). All models incorporated characteristics of complexity (e.g., feedbacks, conceptual representation of multiple levels), but these were captured to varying degrees across model types. The quality of methods was adequate overall; however, few studies engaged stakeholders ($n = 10$) or provided sufficient transparency to verify the model ($n = 12$). Complex systems models are increasingly utilized to study RFEs and their contributions to public health. Opportunities to advance the use of these approaches remain, and areas to improve future research are discussed. This comprehensive review provides the first marker of the utility of leveraging these approaches to address RFEs for population health. *Adv Nutr* 2022;13:1028–1043.

Statement of Significance: This is the first review to synthesize and evaluate the use of complex systems models (e.g., agent-based, system dynamics, network, and discrete event simulation models) to study retail food environments for addressing population health.

Keywords: food environment, healthy retail, nutrition interventions, systematic review, agent-based modeling, system dynamics, simulation, microsimulation, networks

Introduction

Unhealthy diet is a leading cause of mortality worldwide (1), and federal and private budgets are burdened by growing health care expenditures for diet-related chronic disease (2). Pronounced disparities in access to healthy, affordable foods have been documented in retail food environments (RFEs) of economically deprived, Black, indigenous, and people of color (BIPOC), and other marginalized communities (3–7). Some evidence also suggests associations between health behaviors and unhealthy RFE neighborhoods (8–10) as well as links between consumer-level RFE features, such as product placement, and the healthfulness of customer purchases (11–15). However, inconsistent relations between RFEs and health in the literature exist (16–18), which may reflect a limited consideration of the complexity of RFEs in prior research.

Local RFEs and their impact on health have historically been investigated using observational research designs and

 Adv Nutr 2022;13:1028–1043; doi: https://doi.org/10.1093/advances/nmab138.

TABLE 1 Descriptions of the modeling approaches included in the review of studies using complex systems models to study retail food environments for population health

Model approach	Description
System dynamics models	An aggregate- (versus individual-) level modeling approach that uses specific techniques (e.g., differential equations, state variables, stocks and flows) to capture and understand endogenous sources of complex system behavior. It centers on the principles of feedbacks and accumulation and is well-suited to simulating and capturing a macroscopic view of system behavior in large populations (24–26, 30, 31)
Discrete event simulations	Simulations with individual actors that are passive entities whose behavior is modeled as a sequence of discrete events in a setting over time. In this approach, events are the priority over the individual entities. Models are commonly used to examine resources and system constraints in meeting a target, and health sciences often use these to determine patient flows through clinical care settings (25, 26, 31)
Network analyses	Models with individual entities (e.g., people, organizations) that measure and analyze the relations and/or flows among them. Models can be used to analyze the network structure as well as how the transfer of information, behaviors, or diseases across connections change as relations for each individual entity change (23–25, 30)
Agent-based models	Simulations with individual actors (i.e., agents) that are active entities which make decisions and/or behave based on a set of rules. Individual actors may interact with each other and their environment and can adapt to these interactions producing emergent properties of the system that make them effective at capturing complex social phenomena (22–24, 31)
Microsimulations	Simulations with individual actors that are passive entities without interactions. Experiments often modify the attribute(s) of individual actors to understand the effect the change has on an individual over time. Common method in the economics field and tends to focus on estimating the detailed predictions of a specific policy/intervention on a target outcome as well as determining its cost-effectiveness (22, 23)
Hybrid models	Combined use of 2 or more model approaches in the same simulation. Offers the advantage of balancing the strengths and shortfalls of each approach to improve the effectiveness of a model in capturing aspects of a complex system (26, 31)

analytic methods such as regression modeling. Although customary, such approaches are limited when examining both the complexity of RFEs as well as their impacts on health. In particular, RFEs are multilayered, bridge numerous disciplines, and span an array of settings (e.g., grocery stores), modalities (e.g., online ordering), products, and other characteristics (e.g., prices) (19). Underlying these complexities are also a multitude of interrelations between factors, which may be dynamic, reciprocal, and interdependent, and together may be better understood as a system (20, 21). Although traditional statistical approaches are useful for many research questions, they often prioritize identifying average effects of an isolated relation (22–24), making them ineffective in capturing the holistic interconnectedness within a system. Further, as complex systems are not easily explained by studying their individual parts (25), additional methods are necessary to study the links between RFEs and health.

A set of methods that has received growing attention in this area is complex systems computational modeling. Complex systems modeling involves a series of diverse computational tools that capture the nature of a system, including its processes, behavior, and evolution (20, 26). These approaches are well-suited for capturing various dimensions of dynamic systems and population-level patterns that emerge from them (20, 21, 23), and their use is increasingly encouraged by health and scientific authorities (27, 28). In addition, as many of these approaches involve the use of simulations, they can be leveraged to estimate future effects of proposed policies and interventions (29), augmenting the retrospective (i.e., "has happened") knowledge gained from traditional study designs. Examining such "what if" scenarios and other forms of complexity could help facilitate additional insights necessary to inform policy and health efforts to improve RFEs and address diet-related chronic disease.

In this review, we focused on 6 specific approaches of complex systems computational modeling. Although variation remains in what is considered the core approaches (22, 24–26, 29–32), for this review we considered complex systems approaches to include agent-based models (ABM), system dynamics (SD), discrete event simulations (DESs), networks, and any hybrid of the above. We also include the approach of microsimulation, given its similarities to ABM (22, 26, 29). Both similarities and differences exist in the ways each approach handles complex systems, which are described in **Table 1**.

Prior reviews have examined the use of complex systems methods to study noncommunicable chronic disease, obesity, and health behavior (25, 33–35). Yet, to our knowledge, no prior review has examined the contributions of these approaches to understanding the specific role of RFEs in population health. Thus, the purpose of this systematic review was to examine research to date that used a complex systems

Research reported in this publication was supported by the National Heart, Lung, and Blood Institute, of the National Institutes of Health under Award Number K99HL144824 (Principal Investigator: MRW). The content is solely the responsibility of the authors and does not necessarily represent the official views of the NIH.
Author disclosures: The authors report no conflicts of interest.
Supplemental Methods A, B, and C, Supplemental Tables 1–2, and Supplemental References are available from the "Supplementary data" link in the online posting of the article and from the same link in the online table of contents at https://academic.oup.com/advances/.
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Abbreviations used: ABM, agent-based model; DES, discrete event simulation; OECD, Organization for Economic Co-operation and Development; PRISMA, Preferred Reporting Items for Systematic Reviews and Meta-Analyses; RFE, retail food environment; SD, system dynamics; SSB, sugar-sweetened beverage.

computational modeling approach to study the RFE for population health. We focused on addressing the following questions: why was the model used (i.e., model purpose); what RFE characteristics were included in the model and to what breadth; to what extent were use of complex systems approaches maximized (i.e., models included complexity characteristics, such as feedback loops, that distinguish them from statistical models); and what was the quality of modeling methods employed? We conclude by summarizing the strengths observed in the use of these approaches and by identifying areas of improvement for nutrition research to fully benefit from them when investigating how RFEs could improve population health.

Methods

We performed a systematic scoping review due to the multidisciplinary nature of studying RFEs and our broad research questions. We followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) Guidelines for Scoping Reviews (36) to conduct the review and analysis. Prior to executing our search strategies, we developed a review protocol (**Supplemental Methods A**), including objectives, inclusion criteria, and methods. Investigators agreed upon iterative changes to the methodology, and we present the final strategy below.

Search strategy

Guided by the team, a university public health librarian (SH) created the search strategy for 7 databases: MEDLINE via Ovid, PsycINFO, AGRICOLA, CAB Abstracts, Business Source Premier, PAIS Index, and Scopus. These databases represent literature from multiple relevant disciplines, such as medicine, public health, psychology, agriculture/food, business, and public policy. The searches were run from March to April 2020, and there were no publication date restrictions used in the search.

Supplemental Methods B details the full electronic search strategies. The final search strategy was developed based on results of preliminary searches in MEDLINE via Ovid, team input, and keywords and phrases from relevant articles known in the literature (37–47). Terminology focused on 2 concepts: retail food environment and complex systems approaches. The search was designed to be specific to identify the 6 complex systems modeling approaches, while more comprehensive to identifying RFE concepts.

To capture citations missed by electronic searches, we performed hand searching methods in October–November 2020. We reviewed reference lists (backward search) and performed citation searches (forward search) of all included studies, and reviewed reference lists of key literature reviews (33, 34, 48–53).

Study selection

Studies were included if: *1*) published in English; *2*) empirical in nature (i.e., an empirical research study with results); *3*) published in an academic journal; *4*) implemented or developed an SD, DES, network, ABM, hybrid, or microsimulation model that included an aspect of the local or regional RFE; *5*) studied the RFE aspect in a high-income (54) and/or Organization for Economic Co-operation and Development (OECD) country (55); and *6*) studied a diet-related behavior or noncommunicable disease (e.g., food purchases, obesity) or otherwise were explicitly specified as related to population health. We limited studies to high-income and/or OECD countries to capture RFEs operating in similar economic and trade environments. Concepts from the Retail Food Environment and Customer Interaction framework (19) were used to guide the RFE aspects that met inclusion criteria. These included RFE settings where people purchase food/beverage products (e.g., stores, restaurants); the RFE features customers experience once at a setting (e.g., price, product availability, promotion); and/or the people who make decisions that influence the RFE (e.g., store managers, distributors) (19).

Studies were excluded if they: *1*) only studied food safety (e.g., acute foodborne illness) or alcohol retail; *2*) did not study the RFE separately from other environments (e.g., examined an overall built environment); *3*) were the wrong publication type (i.e., literature review); or *4*) involved nonhuman research.

Duplicate studies were removed, and items were uploaded to Rayyan (56), a web application for independent title/abstract screening. Screeners (MW, YM, MT) first tested screening agreement and then completed independent title/abstract screening once adequate agreement was reached (i.e., 85% on 20 records). Each title/abstract record was independently screened by 2 reviewers, and disagreements were resolved through discussion. Two screeners, then, independently reviewed full texts against eligibility criteria and resolved discrepancies through discussion. **Figure 1** presents the study selection flow and reasons for exclusion.

Data extraction and transparency evaluation

Data were extracted from included articles and their published supplemental materials. Data were charted into a matrix using Microsoft Excel, following a list of definitions and guidelines for all items (**Supplemental Methods C**). Initial documents were informed by prior systems science literature reviews (23, 34) and then trialed by MW, YM, and MT on 5 articles that used different modeling approaches. Documents were refined based on inconsistencies and additional feedback sought and incorporated from the study team. Reviewers then assessed independent data extraction agreement, and once adequate (i.e., 85% across 5 additional articles), independently extracted the remaining articles with a second person verifying.

Although assessing study quality is not generally part of scoping reviews (36), insights from complex systems computational approaches may be most useful if trustworthy practices are used in the modeling process and made transparent in the publication (57–60). Thus, we assessed the transparency of each study using 10 items inspired by Jalali et al. (58, 59) (**Supplemental Table 1**). All included articles were appraised by one reviewer and verified by a second. We

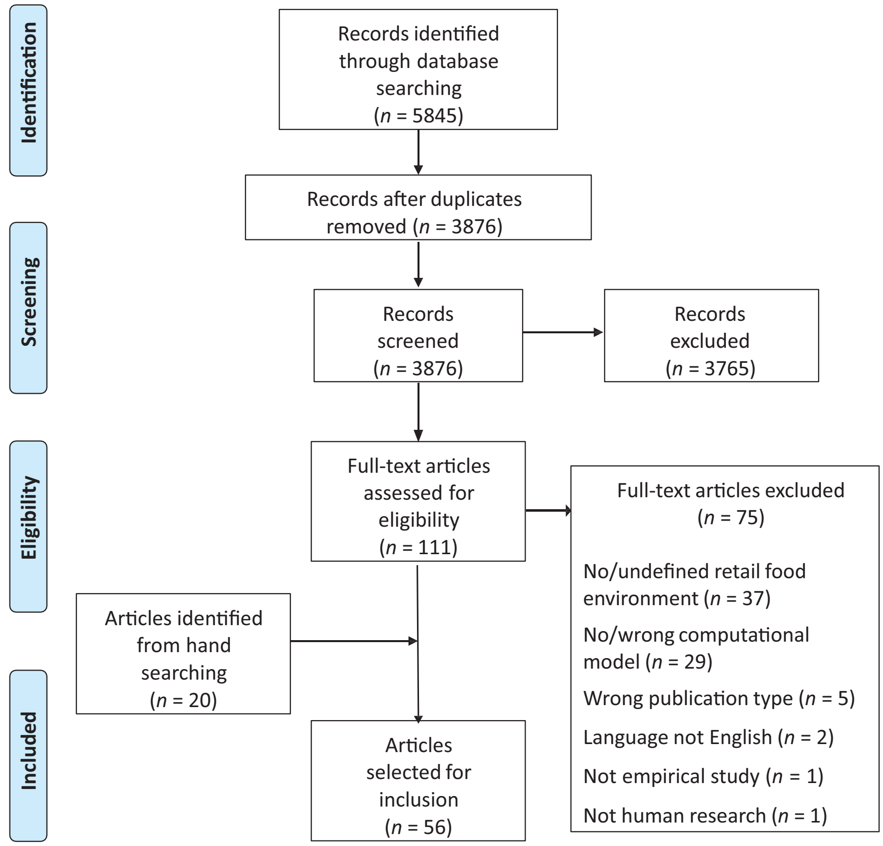

FIGURE 1 Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) study selection flow diagram of studies using complex systems models to study retail food environments for population health.

examined the presence of each item across studies as well as by a total score; the number of "Yes" answers was divided by the number of applicable criteria to derive a total percentage score. As the criteria only examined presence and not quality or extent, we ran the risk of overestimating the transparency of studies; thus, we selected a stricter qualitative assessment of overall transparency with <70% of items present defined as low, 70–89% as adequate, and ≥90% as high transparency.

Data synthesis

Synthesis included both quantitative and qualitative approaches, which were finalized once the relevant content from all included studies was extracted. We used a priori definitions from our data extraction guide (Supplemental Methods C) and the Retail Food Environment and Customer Interaction model (19) to categorize the model purpose and the RFE characteristics included in models, and then used a thematic approach to identify inductive patterns within categories. We also performed simple counts to summarize information across our areas of interest—model purpose, RFE characteristics included, complexity characteristics represented, and model methods employed. Given the enormous diversity in research questions, we did not synthesize study findings and instead prioritized the utilization, benefits, and limitations of employing these models to study the RFE for population health.

Results

Description of included studies

Our initial database searches identified 5845 records (Figure 1). We screened 3876 unique records and assessed 111 full-text articles for eligibility. An additional 75 articles were excluded after full-text review, and we identified 20 additional articles from hand searching. The final 56 articles that met our review criteria were published between 2010 and 2020 with the number of publications increasing over time (**Figure 2**).

Eight OECD countries were represented across studies, though most studied populations in the USA ($n = 46$) (37, 40–47, 61–97). All 6 complex systems modeling approaches were represented with 23 microsimulations (74–91, 98–102), 13 ABMs (37–39, 41, 44, 47, 67–73), 10 hybrid models using ABM coupled with DES or networks (40, 42, 43, 61–66, 103), 4 SDs (95–97, 104), 4 network models (45, 92, 93, 105), and 2 DESs (46, 94). We also identified 25 studies that used the same model or a modified version (**Supplemental Table 2**), which included 6 microsimulation models used across 17 studies (75–79, 81, 83, 85–90, 99–102), 2 hybrid models used

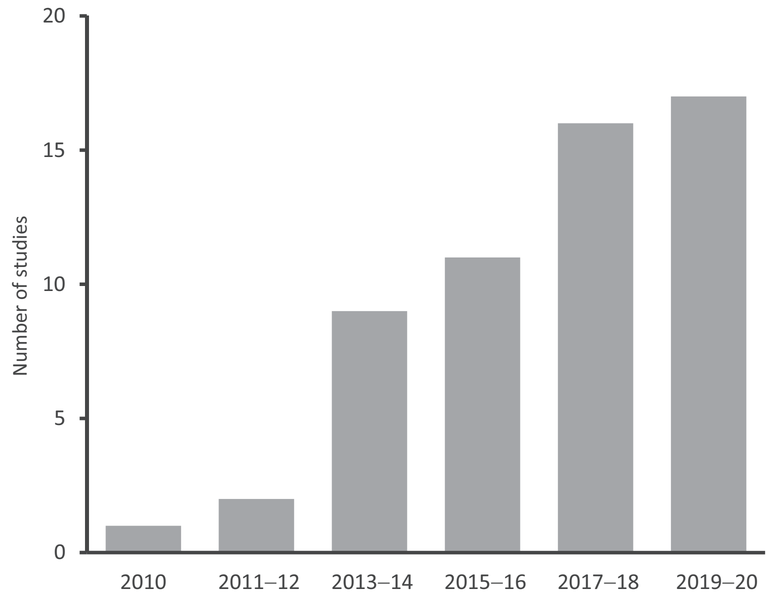

FIGURE 2 Publication year of studies ($n = 56$) using a complex systems model to study retail food environments for population health.

across 6 studies (40, 42, 43, 62–64), and 1 ABM used across 2 studies (47, 68).

Why was the model used?

Across a wide range of research questions (Supplemental Table 2), studies implemented complex systems models for 3 primary purposes—descriptive ($n = 4$) (45, 92, 93, 105), mechanistic ($n = 7$) (41, 47, 66, 71–73, 97) (i.e., to understand the system's etiology), and experimental ($n = 45$) (37–40, 42–44, 46, 61–65, 67–70, 74–91, 94–96, 98–104). Studies with descriptive purposes employed network models and aimed to characterize relations among supply chains (45, 92), product label messages (105), or procurement locations used by food assistance program participants (93). Seven studies used models for only mechanistic purposes, including ABM ($n = 5$) (41, 47, 71–73), hybrid ($n = 1$) (66), and SD ($n = 1$) (97). The mechanisms of interest ranged widely and depended on the specific research question [e.g., understanding the effects of neighborhood income segregation on healthy food access (72), understanding customer and producer features that make alternative food hubs sustainable (41)].

Implementing models for experimental purposes, including evaluating potential effects of proposed policies and interventions, was most common ($n = 45$), and all types of complex systems models were used for this purpose except network models (Supplemental Table 2). Some investigations only examined interventions or policies specific to the RFE, such as Wong et al. (46) which only simulated the effects of cooler and shelf placement on customer purchasing of nonsugar-sweetened beverages (non-SSBs); whereas, others examined interventions targeting RFEs as well as individuals [e.g., modifying resident's willingness-to-walk (61), product bans for food assistance benefits (75, 76, 87, 88)] or other environmental features [e.g., increased transportation options (44), improved school quality (43)]. Of the 42 studies (37–40, 43, 44, 46, 61, 64, 65, 67–70, 74–91, 94–96, 98–104) examining ≥1 proposed RFE policy or intervention, over half ($n = 24$) (38–40, 64, 65, 68, 70, 74–76, 78, 81, 84, 85, 87, 88, 90, 91, 94–96, 98, 101, 104) included scenarios that involved modifying food prices (e.g., SSB taxes, reducing produce prices); 11 examined scenarios resulting in product reformulation (67, 77, 79, 80, 83, 86, 89, 99–102); 7 studied scenarios involving product labels (e.g., SSB health warning) (37, 81–83, 86, 101, 104); 6 simulated scenarios that added neighborhood retail sources (e.g., increase supermarket density) (40, 43, 44, 61, 64, 103); 5 included scenarios that increased healthy food availability within sources (e.g., increase produce offerings in convenience stores) (44, 69, 81, 95, 104); 1 examined in-store product placement scenarios (46); and 1 examined product marketing scenarios (104). Most studies examined multiple scenarios to either understand the dose of a particular intervention [e.g., food industry compliance with sodium reformulation targets under optimal, modest, and pessimistic scenarios (89)] or to facilitate comparisons among different interventions [e.g., compare effects of adding farmer's market vendors to mobile markets (44)].

In addition, although all studies explicitly contextualized their study purpose as relevant to health, there was variation in the primary outcomes of interest (**Figure 3**). Forty-five studies (37–40, 42–44, 46, 47, 62–68, 70, 71, 73–91, 95, 96, 98–102, 104) used models to examine health and/or behavior outcomes (e.g., obesity, dietary intake) of which 6 (38, 39, 42, 43, 66, 70) were primarily interested in disparities between population groups. Other outcomes of interest included the cost-effectiveness of proposed policies ($n = 15$) (74, 75, 78–81, 83, 85–90, 95, 102), business interests like revenue and store survivability ($n = 5$) (41, 72, 94, 103, 104), food

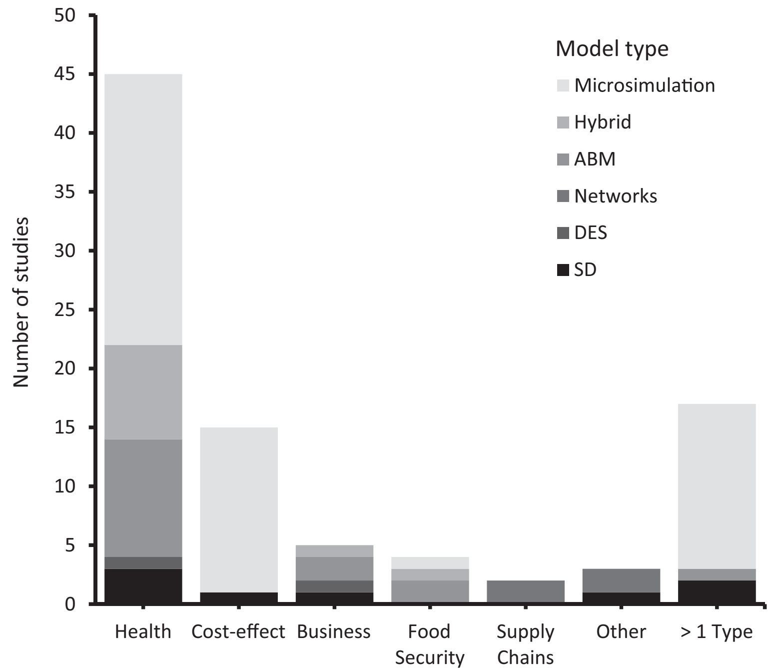

FIGURE 3 Primary outcome of interest across studies ($n = 56$) by model type. Categories of the primary outcomes are not mutually exclusive; studies with >1 primary outcome of interest are represented within each applicable category. >1 Type, studies with multiple primary outcomes of interest; ABM, agent-based model; Business, retail outcomes including store revenue and survivability; Cost-effect, cost-effectiveness of simulated policy or intervention; DES, discrete event simulations; Health, population health behavior or outcome; Hybrid, >2 model approaches used; SD, system dynamic models.

security and access ($n = 4$) (61, 69, 72, 75), RFE supply networks ($n = 2$) (45, 92), or other factors [$n = 3$ (93, 97, 105), e.g., implementation and maintenance of a restaurant intervention (97)]. Seventeen studies (72, 74, 75, 78–81, 83, 85–90, 95, 102, 104) examined more than one of these outcomes, mostly health and cost-effectiveness.

What RFE characteristics were included in models?

We identified a diverse breadth of RFE characteristics that were represented and simulated in model scenarios (Supplemental Table 2). We grouped characteristics using concepts from the Retail Food Environment and Customer Interaction model (19), including characteristics related to the customer retail experience, retail sources (e.g., grocery stores, fast food), and retail actors (e.g., managers) (**Figure 4**).

Customer retail characteristics.

Customer retail characteristics comprised features customers encounter when they acquire a product (19), such as price, product availability, and promotion, and 55 models (37–47, 61–92, 94–105) included ≥1 customer retail characteristic (Figure 4). Product characteristics were represented in nearly all models ($n = 54$) (37–47, 61–64, 66–92, 94–105), which varied from general characterizations of product healthfulness [e.g., "healthy" (45, 95)] to specific products [e.g., SSBs (94), fruits and vegetables (44, 78)] and nutrients [e.g., added sugars (83)]. Price was also a common feature represented in models ($n = 32$) (38–41, 47, 62–65, 68–72, 74–76, 78, 81, 84, 85, 87, 88, 90, 91, 94–96, 98, 101, 103, 104) varying from general classifications [e.g., "inexpensive" or "expensive" food store prices (39)] to specific values [e.g., 1-peso-per-liter beverage tax (98)]. Promotion features, like product labels and in-store marketing, were less common ($n = 7$) (37, 81–83, 97, 104, 105), whereas product placement ($n = 1$) (46) and other customer features, like service ($n = 1$) (103), were rarely represented.

Retail sources.

Retail sources involved the settings where customers purchased food and beverages (e.g., restaurants), which were included in 30 models (37–46, 61–64, 66, 69, 71–74, 77, 81, 86, 87, 92–94, 96, 97, 103) (Figure 4). Across these studies, the presence of grocery stores, supermarkets, and discount clubs were most commonly represented ($n = 12$) (37, 38, 42–44, 61, 69, 72, 87, 92, 93, 103) followed by convenience or corner stores ($n = 10$) (37, 44–46, 61, 69, 87, 93, 94, 103), restaurants ($n = 6$) (37, 73, 77, 81, 86, 92), farmers' markets/produce vendors ($n = 5$) (38, 44, 92, 93, 103), fast food/carry-outs ($n = 4$) (37, 38, 87, 97), and other sources [e.g., community-supported agriculture (74, 92), food hubs (41), vending (71, 81)]. Seven models (39, 40, 62–64, 66, 77) included a generic classification of "food stores," though additional specification was provided by assigning customer retail features (e.g., store prices, products available).

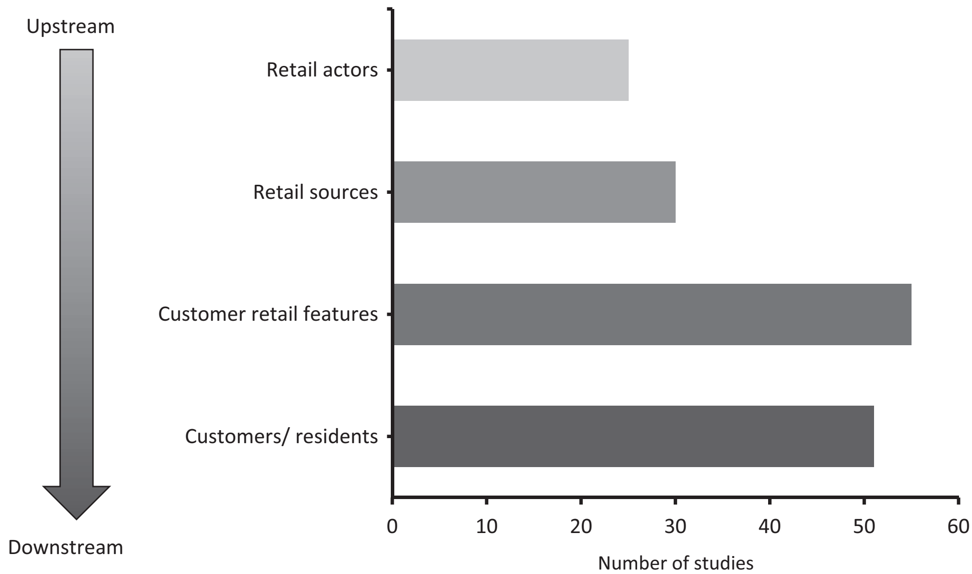

FIGURE 4 Number of studies that examined different retail food environment (RFE) characteristics and incorporated customers in model scenarios. Upstream indicates RFE features that are more distal to customers for which they have limited control, interaction, or influence; downstream indicates RFE features that are proximal to customers.

Retail actors.

Retail actors are individuals (e.g., store managers, suppliers) that behave and make decisions which create the RFEs experienced by customers and were included in 25 models (38–41, 45, 62, 63, 67, 72, 77, 79, 80, 83, 85, 86, 89, 90, 92, 94, 97, 99–102, 104) (Figure 4). The majority ($n = 17$) (41, 45, 67, 77, 79, 80, 83, 85, 89, 90, 92, 94, 99–102, 104) represented food producers and/or suppliers, largely by examining scenarios of product reformulation or supply chain relations. Managers and owners were less commonly included ($n = 10$) (38–40, 45, 62, 63, 72, 86, 94, 97) and typically represented via decisions to modify prices or products sold at a source or whether to close a store site. In contrast, nearly all models ($n = 51$) (37–44, 46, 47, 61–91, 93, 95, 96, 98–104) included customers (Figure 4 and see **Supplemental Table 2** for study population details).

Breadth of RFE characteristics.

As RFEs are complex, multilayered entities, we also examined the breadth of RFE features incorporated into the same model scenario, which allows the dynamics and interdependencies between RFE features to be simulated. Overall, 35 studies (37–41, 44, 45, 47, 61–64, 66–69, 72, 73, 83, 85, 86, 88, 90, 92–97, 99–104) simulated >1 RFE feature in the same scenario (**Figure 5**), which was performed among all SD ($n = 4$) (95–97, 104) and most ABM ($n = 11$) (37–39, 41, 44, 47, 67–69, 72, 73) models. For example, Struben et al. (104) used SD to simulate scenarios that examined changes in the prices and promotion of both healthy and unhealthy products; whereas Gouri Suresh et al. (72) used ABM to simulate multiple retailer behaviors, such as choosing where to locate a new store and the prices of store products. In contrast, the majority of microsimulation studies (74–82, 84, 87, 89, 91, 98) only examined a single RFE feature (Figure 5), such as Pitt et al. (91) that simulated price changes for a single product category (i.e., meat).

To what extent were use of complex systems approaches maximized?

To understand the extent to which studies maximized their complex systems modeling approach, we examined the presence of specific complexity characteristics in models. **Table 2** presents the definition of these characteristics and their existence across studies. Although complexity was present in all studies, it was captured to varying degrees. Variation was driven by investigator modeling decisions and research questions in addition to the constraints of the specific modeling approach selected [e.g., microsimulation does not allow individual actors to interact (22)].

Nearly all models ($n = 54$) (37–47, 61–93, 95–104) conceptually represented multiple levels (e.g., RFE features and individual customers); however, only half ($n = 30$) (37–47, 61–64, 66–73, 92, 93, 95–97, 103, 104) explicitly operationalized those levels in the model and connected them in some way (Table 2). For example, Blok et al. (38) studied various neighborhood and RFE interventions on inequalities in healthy food consumption among residents, which conceptually represent distinct environmental and individual levels; authors then explicitly quantified the interactions between levels, as residents were simulated to select which food stores to shop based on store-to-home distances, and stores were simulated to respond to residents' purchasing (e.g., store closes if insufficient revenue). Alternatively, Lee et

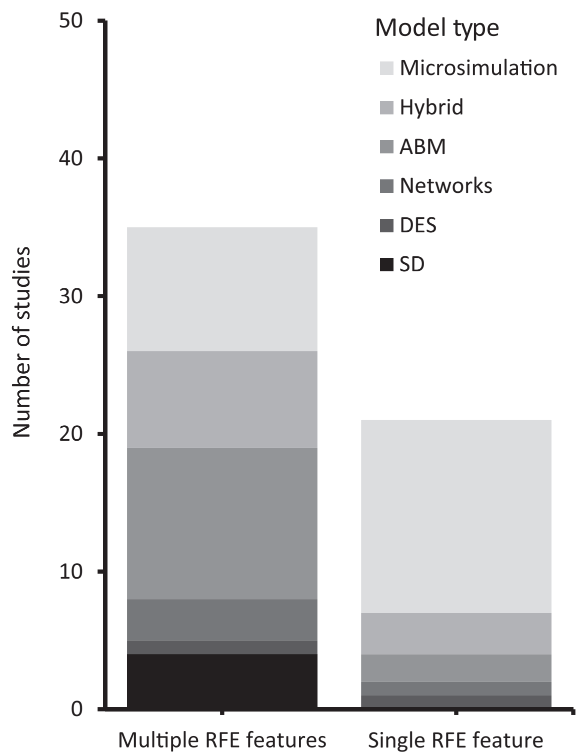

FIGURE 5 Studies that simulated a single retail food environment (RFE) feature or multiple RFE features in the same scenario by model type. ABM, agent-based model; DES, discrete event simulation; Hybrid, >2 model approaches used; RFE, retail food environment; SD, system dynamic model.

al. (85) examined the effects of various SSB tax policies on cardiovascular disease, which also involve concepts that represent distinct policy and individual levels; however, authors used individual-level SSB intake to quantify the effects of the tax policy as opposed to incorporating environmental price changes of SSBs, for example. A similar pattern was observed among the incorporation of heterogeneous individual actors in models (Table 2), which was common (n = 51) (37–47, 61–93, 98–103, 105), but only one-third (n = 18) (38–43, 62–67, 70–72, 92, 103, 105) had connections or interactions between actors to allow for potential influence [e.g., an individual's behaviors are influenced by peers in their network (40)].

The remaining complexity characteristics demonstrated distinct patterns by model approach (e.g., lack of explicit space included in SD) (Table 2), confirming some of the obvious constraints of certain models. In contrast, ABM and hybrid models enabled extensive versatility as all complexity characteristics were commonly included in studies using these models. Even so, studies using ABM did not universally incorporate some key characteristics relevant to RFEs and population health that they can model, like feedbacks (e.g., between customers and stores) and interactions among heterogeneous actors (e.g., customer purchasing behavior that influences others). In addition, although spatial representations were more regularly incorporated in both ABM and hybrid models, we noted that most representations were limited to home-to-store distances (38–40, 44, 61–64, 69, 72, 73, 103), neglecting additional nonresidential food environments (e.g., work) individuals navigate.

We also noted a marked pattern in the complexity of model construction between microsimulations and other models, especially ABM, SD, and hybrid models. A key advantage of microsimulations is their ability to simulate intervention effects in a heterogeneous population while incorporating dynamic and probabilistic conditions. Yet, other models such as ABM and hybrids, possess these and additional capabilities which can facilitate a richer exploration of the conditions under which interventions may be effective. For example, Grummon et al. (82) and Lee et al. (37) both examined the effects of an SSB warning label policy on individuals' weight status using microsimulation and ABM, respectively. Although both examined the simulated effects of different efficacy rates, Lee et al. (37) also explored these effects while incorporating customers' daily travel patterns, probabilities of purchasing SSBs at different neighborhood retail sources (e.g., corner stores, supermarkets), and other conditions that precede SSB purchasing and intake (e.g., store compliance with the policy, warning label literacy rates). Alternatively, Grummon et al. (82) only looked at individual effects downstream of SSB intake (e.g., caloric intake and weight).

What was the model quality and transparency?

We assessed model quality by examining the rigor and inclusivity of methods across studies (**Table 3**). All studies used empirical information to develop and parameterize models, with most (n = 53) (37–47, 61–91, 94–104) using datasets and/or prior literature (e.g., published estimates) and a few (n = 5) (41, 92, 93, 97, 105) collecting primary data either to augment other data sources or model alone. Few studies (n = 10) (61, 81, 84–87, 95, 96, 100, 103) reported consulting with experts during model development, and Koh et al. (69) conducted the only study that explicitly engaged stakeholders in the modeling process via a group model building approach. Most studies specified additional methods of rigorous modeling, including sensitivity analyses to increase confidence in the robustness of their results (n = 40) (37, 39, 40, 42, 43, 46, 47, 61, 63, 66–72, 74, 75, 77–80, 82–86, 88–91, 94–100, 102, 104) and steps of model verification or external validation to ensure models ran as intended and/or accurately captured observed phenomenon (n = 37) (37–40, 42, 43, 47, 61–64, 67–70, 73, 75–78, 80–82, 84–86, 88, 90, 92, 96, 97, 99–104). We noted one-third of studies (n = 20) (38, 39, 42–44, 61, 65, 69, 73, 79, 81, 83, 89, 91, 95, 96, 101–104) used calibration to "tune" unknown parameters or create a synthetic population. Relatedly, this meant most studies (n = 40) (37, 38, 40, 45–47, 62–64, 67–69, 73–90, 92–94, 97–102, 105), especially those with microsimulation, network, and DES models, displayed a high degree of empirical anchoring (i.e., all model features are linked to empirical data), which facilitates precise insights but potentially limits generalizability to the data sources

TABLE 2 Complexity characteristics[1] overall and by model type[2] across included studies using complex systems models to study retail food environments for population health

Complexity characteristic	Overall ($n = 56$) N (%)	SD ($n = 4$) N (%)	DES ($n = 2$) N (%)	Networks ($n = 4$) N (%)	ABM ($n = 13$) N (%)	Hybrid ($n = 10$) N (%)	Microsimulation ($n = 23$) N (%)
Multilevel: model includes heterogeneous elements that are conceptually aggregated at distinct levels (e.g., individuals, stores, products, neighborhoods)	54 (96)	4 (100)	1 (50)	3 (75)	13 (100)	10 (100)	23 (100)
Multiple levels interact: elements explicitly operationalized at distinct levels connect (e.g., network ties) or influence one another through active or passive interactions (e.g., customers modify travel behavior in neighborhood when food store closes)	30 (54)	4 (100)	1 (50)	3 (75)	13 (100)	9 (90)	0 (0)
Spatial: model includes elements that are located in an explicit definition of space (e.g., graphic or numeric representations)	21 (38)	0 (0)	1 (50)	1 (25)	10 (77)	9 (90)	0 (0)
Dynamic: model includes elements that evolve over time and are not static	47 (84)	4 (100)	0 (0)	0 (0)	12 (92)	10 (100)	21 (91)
Stochastic: model includes elements that are specified probabilistically using random inputs or conditions rather than all elements being deterministically specified	42 (75)	0 (0)	0 (0)	0 (0)	12 (92)	10 (100)	20 (87)
Feedbacks: model includes a sequence of variables or equation functions that form a bidirectional effect or loop of influence	19 (34)	3 (75)	0 (0)	0 (0)	6 (46)	10 (100)	0 (0)
Heterogeneous individual actors: model includes individual entities that are differentiated (e.g., customers with different demographic characteristics)	51 (91)	0 (0)	1 (50)	4 (100)	13 (100)	10 (100)	23 (100)
Actors connect/interact with each other: individual entities within an agent type (e.g., among customers) connect (e.g., network ties) or influence one another through active or passive interactions (e.g., products unavailable to later customers due to prior customers purchasing stock)	18 (32)	0 (0)	0 (0)	2 (50)	7 (54)	9 (90)	0 (0)

[1]Complexity characteristics were adapted from Speybroeck et al. (23) and definitions informed from additional sources (22, 24, 26, 31, 34).
[2]Abbreviated model types include: ABM, agent-based model; DES, discrete event simulation; Hybrid, >2 model approaches used; SD, system dynamic model.

TABLE 3 Summary of computational modeling methods employed overall and by model type[1] across included studies using complex systems models to study retail food environments for population health

Characteristic	Overall ($n = 56$) N (%)	SD ($n = 4$) N (%)	DES ($n = 2$) N (%)	Networks ($n = 4$) N (%)	ABM ($n = 13$) N (%)	Hybrid ($n = 10$) N (%)	Microsimulation ($n = 23$) N (%)
Model development methods[2]							
Literature review/data sources	53 (95)	4 (100)	2 (100)	1 (25)	13 (100)	10 (100)	23 (100)
Primary data collection	5 (9)	1 (25)	0 (0)	3 (75)	1 (8)	0 (0)	0 (0)
Consulted experts/advisory group	10 (18)	2 (50)	0 (0)	0 (0)	0 (0)	2 (20)	6 (26)
Engaged stakeholders in modeling	1 (2)	0 (0)	0 (0)	0 (0)	1 (8)	0 (0)	0 (0)
Additional methods[2]							
Calibration	20 (36)	3 (75)	0 (0)	0 (0)	5 (39)	5 (50)	7 (30)
Verification/external validation	37 (66)	3 (75)	0 (0)	1 (25)	9 (69)	8 (80)	16 (70)
Sensitivity analyses	40 (71)	4 (100)	2 (100)	0 (0)	9 (69)	6 (60)	19 (83)
Empirical anchoring[3]							
High	40 (71)	1 (25)	2 (100)	4 (100)	7 (54)	4 (40)	22 (96)
Medium	13 (23)	3 (75)	0 (0)	0 (0)	4 (31)	5 (50)	1 (4)
Low	3 (5)	0 (0)	0 (0)	(0)	2 (15)	1 (10)	0 (0)
Transparency appraisal[4]							
High	24 (43)	2 (50)	0 (0)	0 (0)	6 (46)	1 (10)	15 (65)
Adequate	22 (39)	1 (25)	1 (50)	3 (75)	5 (39)	5 (50)	7 (30)
Low	10 (18)	1 (25)	1 (50)	1 (25)	2 (15)	4 (40)	1 (4)

[1] Abbreviated model types include: ABM, agent-based model; DES, discrete event simulation; Hybrid, >2 model approaches used; SD, system dynamic model.

[2] Categories are not mutually exclusive. Multiple methods may be employed by authors in a single study; studies using >1 method are represented within each applicable category. Definitions for each method type are available in Supplemental Methods C.

[3] Assessment based on Langellier et al. (34) definition of the degree of anchoring a model has to empirical data. Low consists of models that are primarily stylized or simplistic and do not directly link to empirical data; medium involves models that have some but not all features (e.g., parameters) linked to empirical data; and high consists of models that are entirely linked to empirical data sources. Categories are mutually exclusive.

[4] 10 items inspired by Jalali et al. (58, 59) (See Supplemental Table 1). The number of "Yes" answers was divided by the number of applicable criteria to derive a percentage score qualified as low (<70%), adequate (70–89%), or high transparency (≥90%). Categories are mutually exclusive.

used. Only 3 studies (39, 65, 72) developed models that were simplistic and highly stylized.

Last, we assessed the transparency of studies which facilitates model clarity, reproducibility, and verifiability (Table 3). Twenty-four studies (47, 62, 68, 69, 71–74, 77–80, 82–86, 88, 89, 97, 98, 101, 102, 104) had a high degree of transparency; however, transparency criteria only examined presence and not extent, creating a potential ceiling effect for overall scores. Individually, the least common transparency criteria we identified across studies ($n = 12$ studies) (47, 68, 69, 74, 77, 78, 97, 98, 101–104) was providing a way for replication (e.g., public access to model code; see **Supplemental Table 1**).

Discussion

This systematic scoping review examined studies that used a complex systems computational modeling approach to address the RFE for population health. Across the literature, we examined the purpose for using the model, the RFE features studied, the extent to which complex systems approaches were maximized, and the quality and transparency of model methods employed. Below we summarize what has been accomplished across these applications of complex systems models by highlighting key strengths and areas for improvement.

Strengths

Several strengths were identified in our review. First, we identified more eligible studies than anticipated, with a total of 56 meeting inclusion criteria. Without imposing publication date restrictions, the earliest publication year was 2010 (95), which coincided with public health's growing interest in the use of complex systems approaches (24). Our review captures the early progress in applying complex systems approaches to study RFEs and demonstrates a clear acceleration in their utilization over the past decade (Figure 2). Such progress suggests research teams are finding effective ways to overcome the challenges inherent in transdisciplinary work to leverage the benefits of these models, including their use as policy and intervention laboratories (29), the primary use identified in this literature.

We also observed key strengths related to the outcomes studied using these models. Following health as the primary outcome of interest, the next most common outcomes were cost-effectiveness and business interests, like store revenue (Figure 3), which are important for making a compelling case for policy or intervention implementation. In addition, multiple outcomes were examined in 17 studies, reflecting the growing attention in the field to address multiple societal outcomes of RFEs (19, 106), and were most typically examined using microsimulation models that provided precise estimation of costs and health. At the same time, these microsimulation studies often only simulated a single RFE feature with few model dynamics, which limited novel or unexpected insights. In contrast, other approaches like ABM and hybrid models simulated both individuals and the systems that surround them. This facilitated a deeper exploration of the dynamic conditions that may affect policy and intervention effectiveness and provided a different but additionally useful strength in facilitating insights into the strategies that should be prioritized to best address health and other goals.

Other strengths were related to the extent models maximized complex systems approaches (Table 2) and the quality and transparency of methods used (Table 3). As the focus of this review was on RFEs and population health, it was unsurprising that nearly all models conceptually represented multiple levels (e.g., RFEs and individual customers). We also noted strong maximization among studies specifically using hybrid models (40, 42, 43, 61–66, 103), as all complexity characteristics were regularly incorporated, reflecting their strengths in realistically representing multiple levels, spatial and social features of RFEs, as well as individual heterogeneity among customers. Across all studies, there was also consistent use of empirically informed models and sensitivity analyses, which increased the rigor of both models and their results. Authors also displayed a consistent priority of transparency when reporting their investigations, as most had an overall adequate or high score (though, the criteria only measured presence not quality).

Areas for improvement

Across this review of literature, we also identified areas for improvement as these approaches are used in future research. One of the most concerning limitations we identified was the infrequency with which collaboration and community engagement were employed in developing models and informing investigators' assumptions (Table 3). Proponents of systems science models have argued the advantages of using these tools to improve community health, inform structural changes, and reduce health disparities (20, 21, 29, 107–109). Yet, without a coproduction of models with decision-makers, food system players, customers, and other community members to help ensure sound assumptions and inform feasible change, it may be difficult to achieve these goals (107–109). Such limited stakeholder engagement has been identified in other reviews of systems science models for health behaviors (34, 35), like physical activity, indicating a gap that is not unique to the RFE literature. Intentionally addressing this gap is needed in future work, and although the tradition of community engagement is better established among some approaches, like SD, examples of cobuilding using other complex approaches, like ABM (110, 111), are increasingly demonstrating what is possible.

Another area for improvement identified was the dominant focus in models on individual customers and relatively limited focus on more upstream factors of the RFE and larger food system (Figure 4). Most models ($n = 45$) examined health and behavior outcomes, making the incorporation of customers key. Yet, in several studies using microsimulation models, RFE features (e.g., product label, taxes) were operationalized at the customer level using change in dietary intake. In addition, less than half of studies explicitly included RFE actors like managers and distributors, which may be a product both of author decisions and potential data gaps (112). Expanding models to consider RFE actors in addition to customers, such as performed by Basu and Lewis (67) which examined population health effects of the food industry's behavior within a cap-and-trade system on sugar, are important next steps. Similarly, models that focus only on RFE actors using a public health lens like Mui et al. (45), where distributor networks of corner stores were examined by product healthfulness, are critical to comprehensively understand how RFEs influence health.

In addition to a limited incorporation of upstream RFE factors, we observed a relatively limited incorporation of complexity into models themselves (Table 2) as well as the extent of RFE components examined among certain model types (Figure 5). For example, several studies using microsimulation only examined a single element of the RFE (e.g., nutrient reformulation), limiting understanding of the dynamics between other RFE components (e.g., price) that are relevant to purchasing as well as supply (e.g., industry response to reformulation policy). The limited complexity incorporated among microsimulations highlights some of their distinct limitations as a tool to study systems and explore unknown or emergent effects, which have been previously described (22). Other approaches like ABM and hybrid models are better equipped to handle this complexity and are quite versatile in addressing each study's unique RFE research question. Yet, which model to select and the degree of complexity to incorporate must be decisions guided by the research question and purpose (113). Adding additional complexity because a team can is not necessarily useful and might unintentionally obscure answers (113)—a scenario we did not observe in this literature. At the same time, drawing boundaries of the model too narrowly and not incorporating important complexity features can lead to setbacks in understanding (113) that may reflect similar challenges produced from relying only on traditional statistical models. Thus, each team is tasked with identifying the degree of complexity most relevant to their research problem and their intended purpose of the model (e.g., produce precise estimates, explore future policy scenarios).

Despite the greater versatility, ABMs and hybrid models used in this literature also displayed some limitations in capturing RFE complexity (Table 2). Some applications inconsistently incorporated feedbacks (e.g., between customer purchasing and store behavior) and assumed residential neighborhoods are the only relevant food environment for health (50) (i.e., neglecting other food environments at school and work). Future ABM and hybrid models that incorporate these key characteristics of RFE complexity will be able to be more fully utilized to answer RFE-related questions as well as enhance insight into unintended or unexpected effects.

Lastly, as noted by other authors (30, 34), issues remain around the methods employed when applying complex systems models, especially around validation and certain aspects of transparency (Table 3). External validation was common across studies, however, it was not universal; and when employed, was at times underdeveloped, as similarly identified in a review by Langellier et al. (34). Finally, although most studies demonstrated adequate transparency, only 12 studies (47, 68, 69, 74, 77, 78, 97, 98, 101–104) specified how to replicate their model (e.g., public access, pseudocode)—a gap that has been documented among ABMs at large (114). This, along with a need to make graphic representations of model relations a universal practice, is critical to help make complex systems modeling more reproducible, verifiable, and clearer to a wider audience. Setting author expectations to publish studies using existing model-specific reporting guidelines, such as the ODD (Overview, Design concepts, and Details) protocol (115, 116) and the PARTE (Properties, Actions, Rules, Time, and Environment) framework (117) for ABMs, and expanding these to include additional elements (e.g., graphical representations) that enhance transparency may be important future approaches.

Strengths and limitations of this review

This review has strengths and limitations. This review is the first of its kind to evaluate the utility, benefits, and limitations of using complex systems science approaches to examine RFEs for population health. Strengths included the extensive database search led by a public health librarian, and the implementation of PRISMA guidelines to select studies and extract data. We limited study inclusion to 6 specific complex systems computational approaches, which excluded other simulation and stochastic analytic methods, such as Markov models, and we omitted gray literature and studies that were not in English. Thus, results may have failed to provide a full synthesis of research to date that has used a complex systems computational modeling approach to study the RFE for population health. In addition, given the vast diversity of research questions and experiments simulated, we were limited in our ability to synthesize results across studies (e.g., which policies consistently demonstrated positive effects on nutrition-related health), and the lenient criteria of our transparency score may have overestimated the overall transparency among studies.

Conclusion

Tackling complexity within RFEs can be challenging if done unaided. Complex systems computational models are a useful tool to study this complexity and understand its potential solutions for health. The 6 approaches reviewed here all demonstrate potential in unraveling complexity, understanding RFEs as systems, and providing insights into future RFE policy and intervention effects. As these approaches become more common, it will be important for investigators to select the approach that best addresses their specific RFE research question, design models that adequately capture real-world complexity, better engage stakeholders, and provide greater transparency. Although room for improvement remains, this review helps demonstrate the utility of using these approaches to understand complex relations between RFEs and population health and inform future decision-making that improves RFEs.

Acknowledgments

We would like to thank Mohammad S Jalali of MGH Institute for Technology Assessment, Harvard Medical School, for sharing a preprint of the evaluation criteria used to assess reproducibility of simulation models.

The authors' responsibilities were as follows—MRW: was responsible for leading the literature review including research inception, study design, study selection and data extraction, data analysis, and manuscript writing; YM: contributed to study design, performed study selection and data extraction, and contributed to data analysis; SH: performed and designed the database search; MNL: contributed to the research inception, study selection, and data analysis approach; JG: contributed to data analysis approach; MT: performed study selection and data extraction and contributed to the research inception, study selection, and data analysis; and all authors: critically revised the manuscript for intellectual content, and read and approved the final version.

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