**Evaluation of public health interventions from a complex systems perspective: a research methods review**

## ABSTRACT

**Introduction:** Applying a complex systems perspective to public health evaluation may increase the relevance and strength of evidence to improve health and reduce health inequalities. In this review of methods, we aimed to: (i) classify and describe different complex systems methods in evaluation applied to public health; and (ii) examine the kinds of evaluative evidence generated by these different methods.

**Methods:** We adapted critical review methods to identify evaluations of public health interventions that used systems methods. We conducted expert consultation, searched electronic databases (Scopus, MEDLINE, Web of Science), and followed citations of relevant systematic reviews. Evaluations were included if they self-identified as using systems- or complexity-informed methods and if they evaluated existing or hypothetical public health interventions. Case studies were selected to illustrate different types of complex systems evaluation.

**Findings:** Seventy-four unique studies met our inclusion criteria. A framework was developed to map the included studies onto different stages of the evaluation process, which parallels the planning, delivery, assessment, and further delivery phases of the interventions they seek to inform; these stages include: 1) theorising; 2) prediction (simulation); 3) process evaluation; 4) impact evaluation; and 5) further prediction (simulation). Within this framework, we broadly categorised methodological approaches as mapping, modelling, network analysis and ‘system framing’ (the application of a complex systems perspective to a range of study designs). Studies frequently applied more than one type of systems method.

**Conclusions:** A range of complex systems methods can be utilised, adapted, or combined to produce different types of evaluative evidence. Further methodological innovation in systems evaluation may generate stronger evidence to improve health and reduce health inequalities in our complex world.

**Keywords:** systems thinking, complexity science, evaluation methodologies, public health, practice

INTRODUCTION

It has been suggested that a complex systems perspective can help public health researchers generate evidence that better accounts for the complex nature of real-world environments1-6. A ‘complex systems perspective’ involves considering the “bigger changing picture” within which attempts to improve population health occur7. Such a perspective is not necessarily intervention focused8,9, but it can be used to inform decisions about interventions. For example, it can potentially improve understandings about how an intervention’s interactions with the wider system in which it is embedded contribute to impacts relevant to health and health inequalities2,8,9. However, there remains uncertainty amongst public health researchers about what applying a complex systems perspective to intervention evaluation entails, the different methods involved, and the kinds of evaluative evidence they produce8,10-13.

**Complex systems**

Aristotle’s phrase “the whole is greater than the sum of its parts” has been used to explain what is meant by the term ‘complex system’14. A system is made up of inter-related parts, but these parts alone do not make it ‘complex’. A complex system is dynamic – its behaviour changes over time. These behavioural patterns or properties emerge when the parts of a system interact within a wider whole; they are not reducible to the functions of the individual components within the system. Complex systems cannot be fully known, controlled, or predicted – but researchers and stakeholders can analyse what makes a system behave in a certain way and how it can be shifted towards more desirable behaviour patterns1.

Numerous terms are used to describe complex systems; Table 1 explains those used in this article. Cause-and-effect relationships within a complex system are likely to be ‘non-linear’; that is (and unlike simpler dose-response relationships), inputs into one part of the system can lead to disproportionate impacts over time. An action within a complex system may have its impacts diminished or amplified depending on how the rest of the system responds. For example, an intervention to restrict availability of certain alcoholic beverages may (hypothetically) find its health impact diminished if producers, retailers, and customers adapt by switching to producing, promoting, and purchasing other alcoholic products15,16. Conversely, the impacts may be amplified if the intervention encourages retailers to promote healthier products, consumers to make healthier choices, and policy-makers to consider further restrictions on alcohol availability.

**Insert Table 1 here**

Complex systems have both a long academic tradition (dating back to ancient philosophy) and a more recent (dating from the 20th century) resurgence as a mathematical discipline. Gates (2016) has used the terms ‘systems thinking’ and ‘complexity science’ respectively to describe these two intersecting traditions17.

Systems thinking draws on a somewhat loose collection of inter-disciplinary fields17. Researchers select methods, theories and concepts from these fields to help them examine the wider influences and causal pathways relevant to a particular phenomenon of interest. Systems thinking is concerned with the structure of a system, understanding and defining its ‘boundaries’, and making sense of the relationships between ‘agents’ and the wider system. Many systems thinking approaches gain insight from multiple perspectives of different stakeholders and facilitate stakeholders and evaluators in restructuring their individual and collective understanding of the system in question17-20.

Complexity science typically takes a dynamic system as its principal unit of analysis. Often, such research defines and models systems, using computer simulation, to draw conclusions about how systems might behave over time. There are various ways a complex system can be modelled21; the aim of such models is not to precisely replicate the ‘real world,’ but rather to create a helpful abstraction in order to evaluate its potential changes and the mechanisms that drive them.

Systems thinking and complexity science are intersecting research traditions, and there are potential risks and limitations of implementing one approach without the other. For example, a computational model that is developed without a multi-perspective understanding of the system may be viewed as flawed by stakeholders, while a systems thinking approach without some formal modelling may overlook key uncertainties and system behaviour that a computational approach could identify.

**Public health evaluation**

Most public health evaluations do not reflect either of these two traditions8,22,23. Instead, where complexity is mentioned at all, public health evaluations have tended to focus on the complexity of interventions (i.e. interventions with multiple components, stakeholders, and outcomes)24. Increasingly, there have been calls for evaluative public health research to move beyond thinking of complexity solely as a property of an intervention2,5,8,23,25. If complexity is a property of the system within which an intervention is implemented, even an apparently simple intervention can result in complex interactions and emergent outcomes across that system8.

In this review, we synthesise evidence from studies that report applying a complex systems perspective to evaluations of *population-level interventions that seek to modify social determinants of health to impact on non-communicable disease outcomes*. As shorthand, we use the term ‘public health intervention’ when referring to such interventions. We define the term ‘public health evaluation’ to refer to studies of public health interventions. ‘Systems methods’ refers to methodological approaches used to apply a complex systems perspective to evaluations. Within the public health field, previous reviews of complex systems research have focussed on specific public health issues14,18,26-30 or on particular approaches31,32. Three previous reviews have involved a wider scoping of literature relevant to complex systems-oriented evaluation in public health, although none limit themselves to intervention evaluations18-20. One review focused on ‘whole system interventions’, a term that is sometimes used to describe complex interventions that attempt to change many different parts of a system simultaneously32.

This review aimed to: (i) describe and classify different types of systems methods applied in published public health evaluations; and (ii) examine the kinds of evaluative evidence generated by these different methods.

## METHODS

**Study design**

We applied systematic review and critical interpretive synthesis approaches to conduct a review of systems methods used in public health evaluations. The study protocol is provided in the Supporting Information 1 file. Critical reviews have been described by Dixon-Woods et al. (2006) as ‘interpretive’ in that they synthesise relevant examples from a complex body of literature with an intent to generate new concepts, theories, or interpretations33. Interpretative synthesis may involve purposive sampling that seeks to capture the diversity of relevant examples. Interpretative synthesis is contrasted with ‘aggregative’ synthesis (e.g. systematic reviews of effectiveness) that attempt to test specific research hypotheses by synthesising findings from all the relevant high quality studies that can be identified33.

**Data sources and searches**

We employed a variety of search methods to identify studies. We consulted experts (n=32) with an interest and expertise in systems-oriented public health research. We also conducted citation searches of relevant published systematic reviews beginning with two we had pre-identified19,20. For our electronic search, we adapted search terms (Supporting Information 2) from those reviews and searched Scopus, Medline and Web of Science, searching after the time period covered by the published systematic reviews19,20. The databases were searched from January 2014 to September 2019.

**Study screening**

Identified studies were screened for relevance, supported by Covidence software34. A study was included if it met all of the following criteria:

1. Self-identifies as taking a systems or complexity-informed approach.
2. Focuses on a public health-relevant subject. We developed the following non-exhaustive list of topic areas to guide us: housing, policing, community safety, health promotion, community health, built environment, urban planning, regeneration, alcohol, obesity, food, trading standards, illicit substances, tobacco, social welfare, employment, transport, education, and environmental health. We focused on interventions that sought to modify social determinants of health and impact on non-communicable diseases.
3. Reports empirical findings to inform decision-making (i.e. not simply methodological discussion) from an evaluation of an existing or hypothetical intervention. We defined the term ‘intervention’ to refer to policies, initiatives, services, and activities that may be important for population health. We deliberately took a broad view of ‘evaluation’ that included any research intended to increase understanding of an intervention’s impacts, mechanisms for impact, context, or implementation.

Primary studies from any country were eligible for inclusion, although the search was limited to English-language publications. Initially, titles and abstracts were screened to identify obviously non-eligible studies. Full text articles were then screened for relevance by two independent reviewers; a third reviewer reconciled disagreements.

**Data extraction**

Data extraction for each study was conducted independently by two reviewers using a table developed to capture information on each study’s aim, intervention type, methods, findings, and recommendations for policy and practice. Disagreements were reconciled through consultation with a third reviewer.

**Data analysis and synthesis**

We developed a framework for mapping included studies onto different stages of an evaluative process from a close reading of the included studies, informed by our prior understandings of systems and evaluation. This combination of inductive and deductive interpretation fits with that found in critical interpretive synthesis and recognises that researchers cannot (and may not consider it desirable to) ‘unknow’ what they already know of the topic being reviewed33. Within this framework, we categorised studies by their methodological approach and purposively selected ‘case study’ papers that provided clear accounts of methods, and reported findings intended to inform policy and/or practice.

**Researcher contributions**

EM, TP, and VE led the review’s search, selection, and data extraction process with further input from ME and MP to discuss issues and disagreements. M White, EM, ME, and TP led on the development of the framework. All authors suggested potential studies to include from their own knowledge, and provided input on the review protocol, case study selection, framework development, and manuscript drafts.

## FINDINGS

Seventy-four unique studies reported in 85 publications were included in the review (see Figure 1), covering topic areas such as urban planning, transport, nutrition/obesity, sexual health, tobacco, substance abuse, school health promotion, strategies for tackling non-communicable disease, crime, violence, and anti-social behaviour. Table 2 shows the main characteristics of each included evaluation and is organised by the relevant methodological approach.

**Insert Figure 1 here**

**Insert Table 2 here**

Table 3 presents a framework that includes (in the rows) five stages in an evaluation process ordered to parallel the theorising, planning, delivery, assessment, and further delivery phases of the interventions they may seek to inform. The ‘theorising’ and ‘prediction (simulation)’ stages refer to studies that generate evidence to inform intervention development. The process evaluation and impact evaluation stages relate to studies that aim to generate evidence about implemented interventions; the former focuses on how the intervention is delivered, the latter on assessing its impacts. The ‘further prediction (simulation)’ stage relates to studies that provide evidence to inform longer-term decisions including decisions to deliver an already implemented intervention in new settings. We present this framework as a heuristic and do not suggest that the evaluative stages must occur in a sequential fashion, or all be a part of every evaluation. A particular type of systems method can be applied to more than one evaluative stage.

The columns of Table 3 describe the types of systems methods we identified from the included studies. Our typology is intended to differentiate between (i) studies that theorise and illustrate a system’s boundaries and inter-related parts (‘system mapping’); (ii) studies that focus on relationships between individuals or organisations relevant to a system (‘network analysis’); (iii) computational models that simulate changes within a complex system over time (‘system modelling’); and (iv) approaches that have emerged from the systems thinking tradition or from attempts to apply systems theories and concepts to other evaluation methods (‘system framing’). This typology is, we accept, contestable given that studies often use multiple methods and the systems literature includes a large (and growing) number of methodological approaches – not all of which are amenable to simple classification. In the sections below, we provide more details of each type of systems method and consider how they have been used across the five stages of evaluation in our heuristic framework.

**Insert Table 3 here**

Theorising

Theory has an important part to play across all the stages of an evaluative process, but ‘Theorising’ appears first in the framework because systems approaches often begin by theorising the structure of the system of interest – its boundaries, the elements that comprise it, and the way they relate to one another. Theorising research can identify potential points of intervention in the system and suggests ways in which it might interact with that system.

System mapping approaches are frequently used at this stage, particularly maps generated from structured stakeholder mapping workshops. Forty-five evaluations included in this review reported some form of system mapping, or presented some form of diagrammatic representation of a system (see Table 2). Three of these studies (including Case Study 1) gave a particularly prominent role to system mapping35-38. However, most used system maps as a tool within the context of another method. In such studies, they were developed at an early or interim stage of an evaluation to aid study design and provide a framework for further modelling or qualitative analysis. Mapping workshops were also used to bring stakeholders together to help them understand each other’s perspectives and encourage joint decision-making37,38.

System maps are well established within complexity science and take various forms. System maps developed for modelling presented variables known as ‘stocks’ and ‘flows’ (see Table 1)37,43,51,52,54,57,66,68,70,76,77. Twelve evaluations presented causal loop diagrams, which omit some of the details found in stock and flow diagrams and have a particular focus on identifying feedback loops35,38,43,46,47,51,53,54,57,66,80,103. Six studies presented concept maps, used to illustrate a wide array of factors relevant to a particular intervention35,40,48,62,66,67. Two network analysis studies presented sociograms: maps showing relationships between agents such as people or organisations37,39.

Eleven studies presented *ad hoc* systems diagrams, designed by evaluators specifically for their studies15,84,89-92,97-99,107,109,113. The studies that developed these maps did not appear to have collected data using formally structured mapping workshops. Instead, they typically collected data through a range of qualitative methods (document analysis, interviews, and focus groups). Three studies drew on systems frameworks originally developed for business and administration (soft systems methodology95,96; ‘Cynefin’88; and the ‘viable systems model’37) and presented visual aids associated with the literature on these frameworks.

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| Case Study 1**: System mapping** **Systems thinking in 49 communities related to healthy eating, active living and childhood obesity (Brennan et al., 2015)**  **Aim**  To develop causal maps for 49 Healthy Kids, Healthy Communities (HKHC) in order to create a synthesised causal map that identifies the common variables and major system feedback structures.  **Intervention**  A community partnership implemented in 49 areas in the US and Puerto Rico to create policy, system, and environmental changes to improve eating and promote active living. The intervention was aimed at children and families, with a particular emphasis on children at highest risk of obesity.  **Methods**  In each HKHC area, a half-day group model building workshop was held with a range of participants, including: residents, elected officials, representatives from government, community organisations, businesses, and researchers. Participants created behaviour-over-time graphs to map variables that affect or are affected by healthy eating, active living, and childhood obesity. Participants then created a causal loop diagram which mapped the causal relationships between the variables identified. Evaluators subsequently created a synthesised causal loop diagram based on each community’s diagram.  **Findings**  The creation of the maps allowed participants to share and develop theories of change from a systems perspective and prompted participants to consider how best to intervene in the system and further reinforce what was already working within the system. |

Prediction (simulation)

Most of the modelling studies included in this review were used to simulate the impacts of interventions yet to be implemented (see Table 2). Models cannot truly capture the complexities and unpredictability of the real world, but they may be of use to decision-makers in anticipating likely impacts of interventions. Agent-based models (ABMs) were typically used to hypothesise and simulate how agents within a system might react and interact in response to an intervention40,41,44,45,49,50,58-62,64,65,72,74,78,79,81. System dynamics (SD) modelling was used to hypothesise and simulate how an intervention may impact on and interact within a wider complex system42,43,46-48,51-57,63,66-70,73,75-77,80. Other forms of modelling could also potentially inform decisions about planned interventions (e.g. microsimulation), but here we have focused on modelling approaches found in studies that met our review’s inclusion criteria.

Although different in their approach, both ABMs and SD models allow researchers to run ‘what if” simulations – varying values in parts of the model to simulate the unfolding effects of interventions118,119. Different interventions or combinations of interventions can be modelled and compared55, or tested in models designed to simulate different contextual characteristics. For example, we identified studies that simulated the impact of a hypothesised sugar-sweetened beverage intervention in three cities64 and the impact of high street tobacco restrictions in different communities49.

Agent-based modelling is a bottom-up modelling approach, where behaviours at the micro-level (individual agent) lead to macro-level changes emerging over time120. The aim of the method is to observe whether simple, rule-based patterns of behaviour can be identified that, collectively and over time, generate complex system behaviour. Researchers define behavioural rules according to a pre-specified hypothesis or theory. They can then test the degree to which, if the agents in the model act according to the rules, the emergent behavioural and outcome patterns in the model resemble the observed real-life system behaviour121. ABMs are sometimes used to examine agents’ spatial movements, and this was reflected in some of our included studies 64,72,79,81, whilst others focused on agent behaviours within social environments.

In contrast, SD modelling is a ‘top-down’ modelling approach, used to analyse problems from a macro perspective and develop a more holistic view of the structures behind a complex phenomenon122. It typically involves an initial mapping of a system followed by computational modelling of causal relationships between system elements quantified using evidence from primary or secondary data, or expert-elicited assumptions. Twenty-three SD modelling studies were included in this review. Most (n=16) were used to model hypothetical interventions. Case Study 2 gives an example of a SD model that compared the predicted impacts of multi-intervention policies for reducing cardiovascular disease55.

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| Case study 2: System dynamics modelling **A system dynamics model for planning cardiovascular disease (CVD) intervention (Hirsh et al., 2010)**  **Intervention**  The study simulated three hypothetical strategies for reducing CVD in El Paso County, Colorado: (i) 14 lifestyle and environment interventions; (ii) those 14 interventions and (for those with CVD) 5 health care interventions; (iii) the 14 lifestyle and environment and 5 health care interventions – but this time the health care interventions were available to the whole population.  **Aim**  To evaluate the potential impacts of various intervention strategies for reducing the county’s CVD burden.  **Data**  The authors took an existing model of CVD causal factors and recalibrated it to reflect the local population. Data from a wide range of sources were used including local population estimates, public health surveillance data, and health service data relevant to CVD risk factors, prevalence, and outcomes.  **Findings**  Strategy 3 combining lifestyle, environment, and health care for all produced the largest reduction in CVD events and deaths as well as total consequence costs by 2020. However, it required a large expansion in primary care considered potentially unfeasible by the researchers. In comparison, Strategy 2 was found to be almost as effective but required a much smaller (and so potentially more feasible) increase in primary care. |

Process evaluation

Process evaluations, as described in our framework, focus on assessing *how* an implemented intervention impacts upon a system, considering contextual factors, implementation, and how the wider system responds and adapts. We recognise that there is some subjectivity involved in decisions as to what constitutes a process and what constitutes an impact; depending on the theory of change or the goal of an intervention (which may vary for different stakeholders), some process indicators may well be considered impacts.

All the methodological approaches we categorised in this paper were used to examine processes from a complex systems perspective; arguably, this is an inherent feature across systems approaches2. For example, studies that map or model implemented interventions can potentially generate insights into implementation processes, and how contextual factors may have influenced implementation38,57,59.

Process evaluations are a common feature of public health intervention evaluation123, but they do not typically include system maps, modelling or the explicit application of systems theories and concepts. They are more likely to involve qualitative or mixed-methods approaches (e.g. qualitative data from implementers and users, and quantitative data on intervention delivery)123. However, our review identified 16 qualitative studies82,83,88,91-94,97,98,104-106,108,109,111,112 and a smaller number of mixed methods process evaluations15,16,84,85,89,90,99-103 that did explicitly seek to apply a complex systems perspective. These studies are included under the heading ‘system framing’ as they seek to gain insights from different stakeholders’ perspectives and consider how an intervention interacts with different elements of a theorised wider system. The application of systems thinking concepts and theories played a relatively minor role in some of the included studies82,100, but a greater role in others.

Examples of process evaluations that substantially incorporated system framing into the study design include Case Study 3108, which described how specific systems theories and concepts were integrated into its methods and analysis. In addition, Grant (2015) conducted a realist analysis of city planning and urban design interventions that identified barriers and facilitators across system levels.

Studies that draw from the systems thinking tradition often includes an element of participatory action research124, bringing stakeholders together and providing opportunities for them to learn from each other and from research about ongoing processes affecting their work, so that they can take action to improve problem situations. Soft systems methodology and developmental evaluation are well known examples of this kind of approach95,96,125,126. Amongst the studies included in this review, there are examples of what could be broadly described as action research. Rosas and Knight (2019) developed continuous learning cycles for their evaluation of a youth development intervention, where a series of different methods (e.g. system mapping, viable system modelling and network analysis) were applied to examine emerging issues identified through stakeholder participation. Burman and Aphane (2016) applied the Cynefin framework to help stakeholders understand processes and act during the implementation of a school health intervention.

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| Case Study 3**: System framing** **Systems theory as a framework for examining a college campus-based support program for the former foster youth (Schelbe et al., 2018)**  **Aim**  To describe the application of systems theory as a framework for examining a college campus-based support program for former foster youth.  **Intervention**  The Student Enrichment Program (STEP) was a community programme embedded in a local community college. The programme aimed to improve post-secondary educational outcomes for former foster youth at a community college. Students were provided with financial, academic, and social/emotional support.  **Methods**  Interviews with current and former STEP students, mentors, collaborative members, and independent living program staff. Member checking was also conducted with the programme leader and programme coordinator.  **Findings**  The authors utilised systems theory as a framework to understand how the STEP functioned. Systems theory focussed their analysis on the programme’s components, how different stakeholders related to each other, with a specific emphasis on the boundaries between stakeholders the impact of those boundaries on their interactions. The authors drew on the concepts of closed and open systems, and feedback, to explore how the programme interacted and was influenced by its location in the broader context of a community college. |

Impact evaluation

In our framework, we describe impact evaluations as studies that seek to quantify the impacts of interventions on key system parameters in the real world. Our emphasis on ‘real world’ rules out modelling studies that use simulations to examine potential impacts. Simulations can (to greater or lesser degrees) incorporate ‘real world’ data obtained from research and other sources. However, we felt it important to distinguish simulations from evaluations that focus on calculating estimates of effect based on directly observed measurements of impact.

We identified relatively few studies to populate the impact evaluation stage of our framework39,86,87,113-115,117. This is partly a result of our decision to locate the modelling studies elsewhere in the framework. It also reflects a historic lack of engagement from public health evaluators with complex systems approaches8,22,127. Impact evaluations are sometimes framed as antithetical to complex systems approaches9. For example, Mowles (2016) argues that they insufficiently account for the complex, emergent, and unpredictable nature of human interaction.

However, this review does include examples of public health impact evaluations that self-report applying a complex systems perspective. Two studies by Blackman et al. (2011, 2013) used qualitative comparative analysis (QCA) to assess impacts of contextual variation on impacts of interventions relevant to cardiovascular disease (2011) and sexual health (2013). QCA is a methodology that combines qualitative and quantitative analysis to examine how combinations of contextual factors affect impacts across multiple cases128. In our expert consultations for this review, opinions differed as to whether, or to what extent, QCA should be considered a complex systems approach. QCA does consider how combinations of factors interact to influence outcomes, but does not generally explore aspects of complexity such as emergence in detail. Many QCA studies make no explicit claim to be taking a complex systems approach and were therefore excluded from this review.

Fuentes et al. (2018) conducted a network analysis evaluation of a school intervention that measured impacts on social relationships. Network analysis involves identifying agents (sometimes called ‘actors’) within a network, collecting data on their relational links with each other, and analysing these links through data visualisation (e.g. a network map called a ‘sociogram’) and statistical modelling129. In public health research, the agents in question tend to be individuals or organisations – often key stakeholders within a particular system of interest. Fuentes et al.’s study is unique amongst the network analyses we identified as it involved a pre- and post- controlled design (see Case Study 4). The other network analysis studies we included had no control and were used within the context of a process evaluation to study diffusion of information, behaviours or innovative practices21,37,40.

We also identified published studies from an ongoing evaluation (projected end date December 2021) of the impacts of ‘UK Treasury Soft Drinks Industry Levy (SDIL).’ So far, the evaluation has reported intermediate outcomes116,117 and economic impacts114,115, and plans to report on the system mapping process that underpins the evaluation, as well as findings on health relevant impacts, modelling of longer term health impacts, and evidence synthesis of these multiple approaches in future publications113.

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| Case Study 4**: Network analysis** **Development and complex dynamics at school environment (Fuentes et al., 2018)**  **Aim**  To evaluate behavioural plasticity of social relationships between peers in 6-7-year-olds who participated in an intervention with cooperative and self-awareness activities, conducted in a school context.  **Intervention**  Children (aged 6 and 7) engaged in 8 one-hour long sessions, which included mindfulness-based practices and social/collaborative activities. The control group engaged in their normal classroom activities.  **Methods**  Children were individually interviewed before and after the intervention using a sociometric questionnaire. Children were asked which peers they would and would not like to play with in order to create a sociogram for each child. Complex network and game theory were used to evaluate pre-post-intervention variations compared to the control.  **Findings**  Social network diversity and the quality of positive relationships improved after the intervention in the experimental group, whereas no such changes were observed in the control group. |

Further prediction (simulation)

Not all the included modelling studies tested hypothetical interventions. Some agent-based and system dynamics modelling studies focused on previously implemented interventions and simulated system-level impacts in new scenarios, where an intervention was rolled out to a different locality and population40,59,78,42,46,56,57,63,66,73. As these kinds of modelling methods have already been presented in the section on prediction (simulation), we will not discuss them further here. However, we do provide an example (in Case Study 5) of an ABM that simulated the further implementation of an intervention in 3 different cities.

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| Case Study 5: **Agent-based modelling** **Simulating the impact of sugar-sweetened beverage warning labels in three cities (Lee et al., 2018)**  **Aim**  To model the impact of sugar-sweetened beverage (SSB) warning labels on overweight and obesity prevalence among adolescents in three U.S. cities.  **Intervention**  Scenarios modelled how adolescent overweight/obesity prevalence could be affected by different levels of efficacy for a food labelling intervention (based on findings from previous studies), compliance of food retailers, compensatory eating, and population characteristics such as illiteracy rates and socio-economic status.  **Methods**  ABMs were developed to represent the intervention’s implementation in three cities, using data from a wide range of sources, including the National Health and Nutrition Examination Survey for height, weight, and SSB consumption and purchasing habits, the U.S. Census Bureau for sociodemographic characteristics, and sources for the location of food retailers.  **Findings**  Modelling estimated that implementing SSB warning labels at all SSB-retailing stores would lower overweight/obesity prevalence and BMI among adolescents in all three cities. The reduction persisted in varying circumstances (i.e. lower store compliance, literacy and label efficacy, low social economic status population, and compensatory eating), with literacy rate and label efficacy identified as potential drivers. |

## DISCUSSION

We have reviewed public health evaluations that reported applying a complex systems perspective. We have categorised the methodological approaches used in these studies, which included system mapping, network analysis, system modelling, and system framing. We then mapped these methods onto a framework that summarises the functions such studies have in generating evidence at different stages of an evaluative process: 1) theorising; 2) prediction (simulation); 3) process evaluation; 4) impact evaluation; and 5) further prediction (simulation).

Several of these types of methods – notably the structured system mapping and modelling methods – are well established within complexity science17, although they may be new to many public health evaluators. Other study methods we identified demonstrate a particular tension evident in efforts to apply complex systems perspectives to evaluation: namely, a fuzzy and contested sense of what constitutes and what does not constitute a complex systems approach. This tension is evident in impact evaluations, but we also found it in some of the process evaluation methods. It is, perhaps, to be expected as different research traditions and paradigms intersect, with the result that new approaches are developed, established methods are adapted and disciplinary boundaries become contested130.

While we identified a large number of examples of complex systems approaches to public health evaluation, we also recognise that such approaches are relatively uncommon2 and present challenges to evaluators and decision makers, including possibly long evaluative time scales2, the need for adaptive and agile evaluation methodology131, and the ability to determine and capture multiple impacts that cannot be reduced to a single outcome measure22.

The task of identifying public health evaluations that take a systems perspective involves a number of challenges and decision-points: notably, deciding (i) whether or not some studies that explicitly reported taking a complex systems perspective were justified in doing so132; and (ii) whether the inverse applied (i.e. some studies were compatible with a complex systems perspective but were excluded from the review because they did not explicitly report doing so). This tension around the reporting of methods is not unique to systems evaluations, but is arguably amplified by the large number of approaches associated with systems thinking and complexity science traditions, as well as by research innovations that seeks to apply a systems perspective to methods that were not originally developed with that perspective in mind84,87,99.

We also note that there are a number of other approaches to researching systems that have been used in public health, but did not meet the inclusion criteria to be included in this review. They include (to name a few): critical system heuristics133, microsimulation134, and strategic assumption surfacing and testing 21.

Taken together, we suggest that there are a number of areas for further development in public health evaluation from a complex systems perspective. First, we identified relatively fewer examples of complex systems impact evaluations. This could be an area for future methodological development. Second, there are a number of complex systems methodological approaches that have not yet been applied to public health evaluation, but may generate useful evidence for decision-making. Evaluators wishing to apply a complex systems perspective could usefully test out and reflect on the application of these methods in public health evaluation. Finally, more consideration could usefully be given as to how to present findings from complex systems evaluation so that they can be used by decision makers to improve public health decision making.

**Review Strengths and Limitations**

The aim of this review was to contrast different methods in complex systems evaluations of public health interventions, rather than attempt to identify every published example of an evaluation that met a pre-specified definition. We conducted a systematic search which included expert consultations. Nevertheless, there may be relevant studies that our search did not identify. We searched for studies that self-identified as taking a systems or complexity-informed approach, rather than searching for specific methods associated with a complex systems perspective. We may therefore have missed papers that do not use language and methods that are compatible with systems thinking. We kept our definition of a public health evaluation broad and are aware that some evaluators would limit their definition to process and impact evaluations. We think our decisions are justifiable; had we only focused on a narrowly conceived definition of process and impact evaluations we would have excluded the modelling methods, which have a prominent position in complexity science. If public health evaluation is to embrace complexity science, we suggest that a willingness to broaden definitions of ‘evaluation’ may be a pre-requisite.

## CONCLUSIONS

We have reviewed studies that self-identified as applying complex systems approach to public health evaluation, developed a framework that maps this body of literature onto five different stages of the evaluative process, and categorised studies by their predominant methodological approach. We believe the findings of this review could help introduce a wider public health audience to the different kinds of systems evaluation that have been used within their discipline and provide some guidance to evaluators wishing to engage with this innovative area of public health evaluation. Through methodological innovation, it is hoped that better evaluations can lead to better informed decisions on how to improve health and reduce health inequalities in our complex world.

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