Complexity in Epidemiology and Public Health

Addressing Complex Health Problems Through a Mix of Epidemiologic Methods and Data

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FROM PANACEAS TO COMPLEXITY

The way public health problems are conceptualized shapes the kind of solutions we seek and the methods we use. The classical paradigm of public health, dating back to the nineteenth century, seeks “magic bullet” interventions that operate with the idea that there is a universal, necessary cause of disease.1,2 This framework enabled breakthroughs such as vaccination and water treatment against infectious diseases and some deficiency diseases. However, this way of thinking has proved unsuited to many public health challenges, including health inequalities, mental health, obesity, polypharmacy, and even infectious disease phenomena such as the COVID-19 pandemic.

Epidemiologists have long searched for ways to improve on the “magic bullet” paradigm, using terms such as multifacality, multifactorial disease, and web of causation to indicate the complexity of the problems they confront.3–9 As a result, epidemiology has to some extent become a process of accumulating information about risk factors in the hope of eventually tracking down an appropriate public health intervention. However, risk-factor epidemiology has been criticized for making causal claims that are unreliable, unclear, or nonactionable.10,11 Recent methodologic work has offered detailed mathematical frameworks for causal inference enforcing much clearer standards for inferring causality.9,12,13 Formal causal inference frameworks place the intervention front and center, insisting that all causal effects be expressed as the consequences of interventions9,14 even if merely hypothetic ones.15,16 However, even if that framework becomes better developed and more widely applied, the problem of translating epidemiologic research into public health interventions

Public health and the underlying disease processes are complex, often involving the interaction of biologic, social, psychologic, economic, and other processes that may be nonlinear and adaptive and have other features of complex systems. There is therefore a need to push the boundaries of public health beyond single-factor data analysis and expand the capacity of research methodology to tackle real-world complexities. This article sets out a way to operationalize complex systems thinking in public health, with a particular focus on how epidemiologic methods and data can contribute towards this end. Our proposed framework comprises three core dimensions—patterns, mechanisms, and dynamics—along which complex systems may be conceptualized. These dimensions cover seven key features of complex systems—emergence, interactions, nonlinearity, interference, feedback loops, adaptation, and evolution. We relate this framework to examples of methods and data traditionally used in epidemiology. We conclude that systematic production of knowledge on complex health issues may benefit from: formulation of research questions and programs in terms of the core dimensions we identify, as a comprehensive way to capture crucial features of complex systems; integration of traditional epidemiologic methods with systems methodology such as computational simulation modeling; interdisciplinary work; and continued investment in a wide range of data types.

We believe that the proposed framework can support the systematic production of knowledge on complex health problems, with the use of epidemiology and other disciplines. This will help us understand emergent health phenomena, identify vulnerable population groups, and detect leverage points for promoting public health.

Keywords: Complex systems; Epidemiology; Methods; Public health; Theory

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Complexity in Epidemiology and Public Health. Addressing Complex Health Problems Through a Mix of Epidemiologic Methods and Data

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will persist, because of the sheer difficulty, perhaps impossibility, of addressing complex health phenomena within the formal causal inference framework. According to critics, that framework is destined to simply leave out the most difficult and pressing public health problems, such as health inequalities. This is because the causal inference framework is designed to replicate the randomized controlled trial, which is intended to isolate the difference made by single factors. In its essence, it is a methodology that is difficult to reconcile with the complexity of public health phenomena. Thus, it is unsurprising that attempts to fit fields such as health inequality research into the causal inference framework have had limited success.

To overcome this problem, several authors have argued for the benefit of applying complex systems thinking, which conceptualizes “poor health and health inequalities as outcomes of a multitude of interdependent elements within a connected whole.” The causal drivers of complex health problems are multifaceted and constantly evolving. They emerge from the complex and messy real world, where elements interact and interfere with each other over time. Take polypharmacy as an example. Elderly people are often treated with two or more drugs at the same time and often for multiple disorders. Although each of these drugs have been tested in isolation in randomized controlled trials, such evidence cannot stand alone in a real-world setting, where polypharmacy represents a complex phenomenon. Complex systems thinking can help us systematically address such complex health issues by applying a complex systems lens to public health, as summarized in Figure 1. This change of perspective allows us to embrace complexity, while benefitting from the important conceptual and methodologic developments of modern epidemiology, including the causal inference framework.

This article introduces a systematic framework for interdisciplinary knowledge production, which conceptually relies on complexity theory while harnessing the interdisciplinarity of public health. Our goal is to provide an overarching framework, which integrates and advances knowledge that is currently produced in different disciplinary silos of public health and epidemiology. Although the framework promotes interdisciplinarity, in this article, we specifically relate it to examples of methods and data traditionally used in epidemiology. This is not to disregard the need for interdisciplinarity, but simply as a starting point for finding practical ways of applying complex systems thinking.

HEALTH COMPLEXITY FRAMEWORK

We suggest that a first, but important, step towards understanding and intervening in complex public health phenomena is to systematically generate and integrate the knowledge of the system(s) that give rise to these phenomena. To operationalize this for public health, we propose an interdisciplinary framework that organizes this knowledge production according to three core dimensions, capturing seven critical features of complex systems (Figure 2). The framework builds upon the idea of methodologic pluralism, and is intended as an overarching framework for interdisciplinary and collaborative research.

The three dimensions involve:
1. patterns: describing the health patterns that emerge from complex systems;
2. mechanisms: understanding the mechanisms that produce these emergent patterns; and
3. dynamics: exploring the dynamics that make mechanisms and patterns change over time.

Each of these dimensions is directly related to key features of complex systems, which are often highlighted in relation to public health. These features include emergence, interactions, nonlinearity, interference, feedback loops, adaptation, and evolution.

The first dimension, patterns, captures the emergence of complex health issues as an outcome of the mechanisms and dynamics of the underlying systems. Investigation of patterns may involve identifying vulnerable populations with clustering of diseases or risk factors, identifying geographic clustering of

FIGURE 1. Applying a complex systems lens on public health issues.
risk, or identifying changing risk patterns over time. Studying such patterns allows us to identify vulnerable populations for targeted intervention or identify emergent health phenomena in need of public health attention. Epidemiology and data science are exemplary in identifying such patterns in large-scale empirical data.

The second dimension, mechanisms, allows us to understand how elements of a system interact at multiple scales to create complex public health issues. It relates to the study of interactions, nonlinearity, and interference. Studying biologic, social, psychologic, and cultural mechanisms can help us understand interactions between diseases and risk factors at multiple levels, critical thresholds, phase transitions, and clustering and spread of diseases or risk factors in social networks. Lab-based and clinical biomedical studies are exemplary in disentangling the biologic mechanisms underlying disease, whereas the social sciences provide deep insight into social mechanisms.

The third dimension, dynamics, aims to explore how complex public health issues change because of dynamic processes. This dimension involves studying feedback loops between diseases or risk factors over time, adaptation to change, and evolution across generations. Studying dynamics helps us, for instance, to identify and intervene on vicious circles that generate excessive burdens of disease. Systems methodology, including formal conceptual model building and computational simulations, and intervention research are exemplary in creating such evidence.

Complex systems often transcend different levels, and some have even argued that population health should be understood as a complex adaptive system of multiple systems.29 This implies interactions between complex subsystems at the molecular, individual, group, and population levels. Aiming to understand the full complexity at all levels is impossible—and probably not even desirable, and we always need to make sure that problem is analyzed at the right level(s), similar to when geographers, for example, define the relevant image resolution of a map for each given problem.

As illustrated in Figure 2, the three dimensions are interlinked in a dynamic circle to highlight that knowledge on all three dimensions is essential to understand and eventually intervene on complex health issues. Leaving out one or more dimensions may leave blind spots that will render our understanding incomplete and may impact the efficiency of interventions. There are many examples of interventions that work in one place or in an experimental setting but fail in a target population. For example, condoms are effective in preventing the spread of HIV, but condom promotion has proved ineffective at preventing female infection in sub-Saharan Africa (where young women bear the greatest HIV burden). In this case, understanding the wider social situation was a necessary precursor to developing a more effective intervention.30 For condoms to offer protection to women, the social context must enable women to enforce their use; otherwise, the
mechanisms by which condoms prevent HIV infection will not operate.

**USING COMPLEX SYSTEMS THINKING AS AN ANALYTICAL FRAMEWORK FOR EPIDEMIOLOGY**

Epidemiologists have acknowledged the need for this reorientation towards complex systems thinking for some time, but there is still potential for a more widespread uptake of complex systems thinking in mainstream epidemiology. Towards this end, we will map epidemiologic concepts and techniques onto the three organizing dimensions outlined above. Although this reorientation naturally introduces new systems methods such as simulation models, we believe that methods and approaches already used in modern epidemiology are equally important for understanding complex health phenomena. Table 1 provides an overview of how these dimensions, the features of complex systems, and research aims are related, combined with examples of analytic methods and data needed to support such research.

Patterns: Describe the Emergence of Complex Public Health Issues

Looking for population disease patterns is a classic epidemiologic approach, which remains central when applying a complex systems lens, where patterns of disease and risk factors are assumed to emerge from the mechanisms and dynamics of the underlying systems. Identifying patterns across spatial–temporal scales allow us to empirically identify space and time clustering of disease or risk factors. This can help us delineate complex health problems and identify vulnerable groups that would benefit from targeted interventions. Understanding mechanisms requires studying directly to pattern recognition and descriptive epidemiology. We will discuss interactions under the mechanisms below.

Emergence in persons

This research aims to identify vulnerable populations with clustering of diseases and risk factors. There is a long tradition in epidemiology for identifying such clustering of risk and identifying vulnerable populations. More recent developments in artificial intelligence-based methodology and flexible machine-learning models such as deep neural networks allow for high-dimensional exploration of large and complex data patterns. While some of these methods have been criticized for being black boxes, other approaches are being developed to decompose risk and identify vulnerable subgroups from multi-dimensional data. Such analyses ideally require large data sets with multi-dimensional genetic, social, biologic, and environmental data. They must also be understood within their limitations: they cannot take us beyond the data they are provided with, and their applicability always requires qualitative assessment and sense-checking.

Emergence in Geographic Place

This research aims to identify the geographic clustering of disease risk and risk factors. Early work includes John Snow’s seminal work on the cholera epidemic in London in 1854, where he identified the clustering of disease risk in geographic areas directly supplied by a specific water pump. More recent work shows that many diseases and risk factors for diseases cluster in geographical areas; examples include spatial fluctuations in COVID-19 fatality rates related to geographic inequality and shortage in health care capacity, or geographic clustering of air pollution being associated with higher mortality. Analytical methods for spatial analysis include disease mapping, geographic correlation studies, and disease clustering analyses. Such analyses require spatial data and data linkage between geographic data and health data via geocoding.

Emergence in Time

This research aims to identify patterns of disease or risk factors over time, and it relates to surveillance of time trends in disease risk and associated risk factors at the population level, which is a core public health task. Prominent examples include the global burden of disease studies, which compile information on the development of major disease groups globally. Emergence over time is also examined in studies aimed at identifying emergent patterns of disease or risk factors over time. Examples include studies on trajectories of social adversities as they emerge during childhood, or trajectories of multi-morbidity in primary care. Examples of analytical methods which are well suited to study emergence over time include functional data analysis, growth mixture, and latent class models. Obviously, such analyses require time series or longitudinal data.

Mechanisms: Understand How Elements of a System Interact at Multiple Scales

Understanding the mechanisms that give rise to complex health phenomena is essential to identify effective interventions. Understanding mechanisms requires studying interactions, nonlinearity, and interference. Where once it was assumed that elucidation of mechanisms was outside the domain of epidemiology, the study of mechanisms via epidemiologic tools has become an area of increasing interest. Still, it is an area of research where epidemiology to some extent meets its limit and where interdisciplinary collaboration is needed. To fully understand the biologic and social mechanisms underlying complex health issues, epidemiology can benefit from a closer collaboration with, for example, biomedicine and social sciences. Only by such interdisciplinary work can we begin to understand how different elements of a
TABLE 1. Overview of Dimensions and Features of Complex Systems Underlying Complex Public Health Issues in Relation to Analytical Methods and Types of Data used in Epidemiology

<table>
<thead>
<tr>
<th>Goals</th>
<th>Complex Systems Properties</th>
<th>Research Aims</th>
<th>Analytical Methods (examples)</th>
<th>Types of Data Required</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Patterns</strong></td>
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<tr>
<td>Describe the emergence of complex public health issues</td>
<td>Emergence across spatial-temporal scales</td>
<td>Person</td>
<td>Identify vulnerable individuals or groups with clustering of diseases or risk factors</td>
<td>Descriptive epidemiology Flexible AI-based methods</td>
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<td></td>
<td></td>
<td>Place</td>
<td>Identify geographical clustering of disease or risk factors</td>
<td>Disease mapping Geographical correlation studies</td>
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<tr>
<td></td>
<td></td>
<td>Time</td>
<td>Identify patterns of disease risk or risk factors over time</td>
<td>Functional data analysis Latent class models</td>
</tr>
<tr>
<td><strong>Mechanisms</strong></td>
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</tr>
<tr>
<td>Understand how elements of a system interact at multiple scales to create complex public health issues</td>
<td>Interactions</td>
<td>Understand interaction and mediation effects of disease risk factors</td>
<td>Additive interaction Mediational analysis</td>
<td>Multi-dimensional data</td>
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<tr>
<td></td>
<td>Non-linearity</td>
<td>Understand critical thresholds (tipping points) and phase transitions</td>
<td>Compartmental models Life course models</td>
<td>Longitudinal data</td>
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<tr>
<td></td>
<td>Interference</td>
<td>Understand clustering, spread of diseases, and risk factors in social networks (families, communities, schools, and workplaces)</td>
<td>Network analysis Multi-level analysis</td>
<td>Social network data</td>
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<td><strong>Dynamics</strong></td>
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<tr>
<td>Explore how complex public health issues change over time because of dynamic processes</td>
<td>Feedback loops</td>
<td>Explore feedback loops between diseases or risk factors over time</td>
<td>Causal loop diagrams/computer simulation models (e.g., system dynamics models/agent-based models)</td>
<td>Integration of epidemiological data into computational models</td>
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<tr>
<td></td>
<td>Adaptation</td>
<td>Explore how complex public health phenomena adapt to change</td>
<td>Computer simulation models Parametric g-formula Natural experiments</td>
<td>Time-series data</td>
</tr>
<tr>
<td></td>
<td>Evolution</td>
<td>Explore how diseases and risk factors track across generations</td>
<td>Life course models</td>
<td>Multi-generational life-course data</td>
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</table>
system interact at multiple scales and identify leverage points for intervention. While interdisciplinary work is needed, epidemiology has still made some progress in this area, as summarized below.

Interactions

This research aims to understand the interactions of diseases or risk factors that lead to the emergence of complex health issues. The conceptual notion of interaction has been acknowledged for some time in epidemiology, such as, for example, in the Sufficient Component Cause model, which has been translated into empirical studies of additive interaction between a few single risk factors. Interactions and mediation are closely linked over time, and newer methodologic developments in counterfactual-based mediation analysis, such as the four-way decomposition approach, are aimed more directly at disentangling causal pathways and how they interact over time. A core challenge in this line of research is the lack of data to support such analysis, as interaction and mediation analyses ideally require large data sets with multidimensional data measured over time with a suitable time resolution.

Non-linearity

This research aims to understand critical thresholds (tipping points) and phase transitions. A classic example is the compartmental models, for example, the S (susceptible) I (infected) R (recovered) model is used to study the progression, spread, and control of infectious diseases at the population level. Such models are used to understand phase transitions and identify threshold conditions above which, for example, outbreaks become epidemic and below which they die out. From a public health perspective, it also becomes relevant to characterize the processes that make some individuals or groups of individuals more vulnerable/resilient than others to transition into a disease stage. Such thresholds for developing disease may vary between individuals and are closely related to interaction, as described above. Life-course epidemiology has introduced concepts of risk accumulation, critical time windows for exposure (e.g., during pregnancy), and vulnerable periods often related to life transitions (e.g., puberty), and methods that are able to incorporate multiple interacting factors across longer periods of time such as structural equation models have been quite prominent in this line of research. Such analyses require longitudinal life-course data.

Interference

This research aims to understand the clustering and spread of disease risk or risk factors in networks. Networks can be defined at several levels, but the social networks of families, friends, schools, workplaces, and communities are probably the most relevant for understanding the complexity of health at the population level. Seminal work includes that of Christakis and Fowler, who used dense network data from the Framingham Heart Study to show that, for example, smoking behavior and obesity spread in social networks. Others have tried to capture social interference and network clustering of diseases or risk factors in multi-level analyses in families, schools, or workplaces. Apart from these influential lines of work, and a growing body of technical work in this area, most empirical epidemiologic studies are still based on an unrealistic assumption of no interference between individuals in social networks, probably because highly granular network data is not available. This constitutes a knowledge gap in epidemiology and calls for investment in data collection that will match the technical developments.

Dynamics: Explore How Complex Health Issues Change Over Time Because of Dynamic Processes

Building evidence on dynamic processes of change over time will allow us to identify and intervene on vicious circles associated with particularly high morbidity in the population. Ignoring such dynamics may result in simplistic misinterpretations of the causes of complex health problems and create ineffective or unintended effects of interventions. Apart from a branch of influential work on population dynamics in infectious disease epidemiology, such systems dynamics are rarely studied in epidemiology. This calls for the study of feedback loops, adaptation to change, and evolution over generations and it necessitates research designs and analytical methods not typically employed in public health.

Feedback Loops

This research is aimed at exploring dynamic feedback loops between disease risks or risk factors over time and it is particularly useful to identify target points for interventions in settings with highly dynamic behavior and feedback that evolves over time and at different scales. Examples include reinforcing feedback loops between sleep impairment, gnathic system functioning, and neuronal dysfunction in Alzheimer’s disease, or amplifying feedback loops linking socioeconomic conditions with chronic stress through learned helplessness, deterioration of access to coping resources, and susceptibility to external stimuli against a background of early stress. Complex systems science methods are useful in identifying and understanding such feedback loops. Causal loop diagrams are conceptual models that map the hypotheses of system structures between variables across relevant scales, and such qualitative models often provide the conceptual basis for a computational simulation model which incorporates cross-scale dynamics. System dynamics models and agent-based models are the two most commonly used computer simulation models in complexity science, and in principle, they mimic a virtual laboratory for public health where population health outcomes can be compared under hypothetical interventions. A core challenge with applying such systems

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models is that they heavily rely on assumptions about how the world works, which can be difficult to validate. Also, the approach is often most informative in creating an understanding of the dynamics of smaller sub-systems due to the inevitable complexity of the matter. These models can incorporate and integrate multi-layered empirical real-life data on complex systems as the ones outlined under patterns and mechanisms above, but such data is unfortunately not always available.

Adaptation

This research aims to explore how complex systems adapt to change. Adaptation is therefore closely related to the feedback loops, and the computer simulation models outlined above can be useful to simulate scenarios of adaptation. In addition, g-methods such as the parametric g-formula offers a middle ground between simulation and data, as it uses a mathematical model to estimate the effects of a hypothetical intervention in a single data set. An actual intervention into a complex system, such as the introduction of new health policies or social legislation, often carries important insights into the dynamics of the system. As an example, social policies such as schooling or unemployment benefit reforms are introduced to the whole population and can be leveraged as quasi-experiments to assess the causal effect of these policies including their unintended outcomes. Methods to assess the impact of natural experiments include instrumental variables, difference-in-differences, and regression discontinuity designs, and they require time series of longitudinal data.

Evolution

This research aims to explore how disease risk tracks across generations. Reproduction is the ultimate example of a complex interplay between individuals (the mother, the father, and the fetus), which may lead to the transmission of biologic and social vulnerability across generations. According to the Developmental Origins of Disease theory, parental exposures and disease status preconception and during pregnancy contribute to shaping the child’s mental and physical health. In a similar vein, the concept of evolutionary public health provides a conceptual framework for understanding physiologic and behavioral trade-offs between growth, maturation, reproduction, and survival, and how this shapes life histories of health and survival across generations. Analytically, such research relies on similar models as those used in life-course epidemiology, but with a specific focus on reproduction, health, and survival across generations. These analyses require multi-generational life-course data.

BUILDING AND INTEGRATING EVIDENCE ON COMPLEX HEALTH ISSUES

Applying complex systems thinking to public health science is an emerging field, but there is still a gap between recognizing the need for complex thinking and finding practical ways to apply it when designing studies or interpreting data. We have outlined a knowledge production framework, which is aimed at supporting the implementation of complex systems thinking in public health research by relying on methods and data that to a large extent are well-known to epidemiology. Still, this reorientation has major implications for the way we phrase research questions, which data and methods we use, and how this evidence is synthesized, as summarized in Table 2.

The word “complexity” is often confused with “complicated,” and some may be concerned that the focus on complexity will end up paralyzing action. However, only by understanding the complex systems that generate health will we be able to zoom out and understand public health as a connected whole, where universal (and often simple) interventions may have multiple effects across societal, social, and biologic scales. We essentially need to step back and embrace complexity—that is, acknowledge, analyze, and understand it—to eventually be able to identify solutions that are actionable and likely to produce systems change. These solutions are likely to be different than the ones we would have identified if we had ignored complexity in the first place. When identified, their causal effect may be tested in more traditional setups such as a randomized trial or other appropriate methods of evaluation. Thus, by systematically addressing dimensions of complexity, as proposed in the article, we aim to generate knowledge on how complexity can be understood, even if such understandings will always be partial and temporary.

Epidemiology has traditionally focused on empirically testing predefined hypotheses of single exposures and single outcomes, which allow for a relatively straightforward evidence synthesis through, for example, systematic reviews.

<table>
<thead>
<tr>
<th>TABLE 2. Implications of a Reorientation Towards Complex Systems Thinking in Epidemiology and Public Health</th>
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<tr>
<td>Complex research questions. Formulate research questions and programs in such a way that they systematically gather evidence on the core dimensions of the complex health phenomena, i.e., patterns, mechanisms, and dynamics. Leaving out some dimensions may leave blind spots that will render our understanding incomplete and may impact the efficiency of interventions, which build on this evidence.</td>
</tr>
<tr>
<td>Methodologic pluralism. Utilize the full spectrum of methodology from epidemiology and other disciplines to systematically assess all dimensions of complex health issues, but also introduce complex systems methodology as part of the standard epidemiological curriculum and acknowledge the need for interdisciplinary work and mixed methods.</td>
</tr>
<tr>
<td>New types of data. Identify major data gaps and promote the collection of new types of data. The systematic production of knowledge on complex health issues requires several types of data including multidimensional data, spatial data, time-series data, life-course data, network data, and multi-generational data.</td>
</tr>
<tr>
<td>Dynamic evidence synthesis. Synthesize evidence on complex research questions in a dynamic manner with a constant focus on which dimensions remain unresolved and understudied.</td>
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and meta-analyses. Even where studies address multiple exposures and outcomes, the relationships between these tend to be assumed to be fixed rather than dynamic, and the presence of nonlinearity, feedback loops, and other familiar traits of complex systems are not generally considered as a target of inquiry but as a potential source of error. Where clearly outlined relations between causes and effects exist, this traditional approach has proved useful. However, this approach meets its limits when trying to understand the dynamics of complex health problems. Thus, we need to radically change our perspective from pure hypothesis testing to an evolving process of data-driven discoveries, hypothesis testing, and theory building, as outlined in this article. This will allow us to synthesize evidence on complex research questions in a dynamic manner with a constant focus on which dimensions remains unresolved and understudied. Such unresolved or understudied dimensions or features should be guiding for future studies and research programs.

As an example, if we already have abundant epidemiologic studies on the association between the level of physical activity and obesity, future studies may add more value by focusing on understanding and exploring other dimensions of obesity, such as the role of social networks in determining physical activity levels, the adaptation to more bike lanes and healthy food outlets in specific city districts, and feedback between socioeconomic background, social norms, availability of green space and body composition. Of course, some of these examples are themselves highly contextual to the context of a relatively affluent developed city. In an area with poor adherence to traffic regulations and high levels of crime, creating bicycle lanes and a bike “borrowing” service is unlikely to be effective at reducing obesity: the bicycle lanes would be violated or blocked, and the bikes would be stolen. These points underscore the fact that discovering and even quantifying a cause-and-effect relationship between, for instance, the installation of bicycle lanes and a reduction in urban obesity, is of little use beyond the context in which it is identified. An understanding of the wider situation, in which the intervention is effective, is required for transportability as well as initial intervention design.

We are not the first to argue for the need for methodologic pluralism to address health complexity,18 and triangulation has, for example, previously been suggested as a way of strengthening causal evidence by integrating evidence across different dimensions.76 The current approach adds to this by specifically applying complex systems thinking as a theoretical framework. The framework allows us to utilize our extensive toolbox of methods and data in epidemiology to systematically gather evidence on complex health issues across the dimensions of complexity. But there is of course still plenty of room for development. We can, for example, continue to learn from other disciplines such as economics and physics, which have similarly found that, to acknowledge the complexity in the phenomena they study, their conceptual foundations needed to be adjusted or rebuilt.77,78

CONCLUSION

The key goals of public health are to control and prevent disease. Public health and the underlying disease processes are multifactorial, involving the interaction of biologic, social, psychologic, economic, and other processes at multiple levels and time scales, that may be nonlinear and adaptive. Applying complex systems thinking to public health science adds to this goal by providing an overarching framework that can help us integrate and advance the existing conceptual and methodologic frameworks of epidemiology and public health towards an approach that takes this complexity of public health problems into account. Thus, epidemiology should not only concern itself with isolating specific causal effects between exposures and outcomes but also with understanding the underlying dynamics to identify leverage points for interventions. Formalizing this branch of public health requires a reorientation of our research questions and knowledge production. We have highlighted three core dimensions and seven related key features of complex systems, which can be used as a framework for systematically producing evidence on complex health issues. These dimensions are directly related to the (1) identification of vulnerable groups that would benefit from intervention, (2) target points for interventions, and (3) vicious circles that may generate an excessive burden of disease. A reorientation towards complex systems thinking in public health also implies investments in new types of data, interdisciplinary work, and capacity building in systems methodology. The good news is that we are at the brink of a promising time where such conceptual reorientation can for the first time be matched with stringent empirical analysis. Such promises include large-scale initiatives aimed at integrating data across systems and national borders, and massive methodologic development in flexible data modeling. At the same time, it should be acknowledged that the multidimensional data requirements argued for in this article may leave blind spots where such data is not available, for example in marginalized populations or in areas with less-developed data infrastructure.

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