Bringing ALife and Complex Systems Science to Population Health Research

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Abstract Despite tremendous advancements in population health in recent history, human society currently faces significant challenges from *wicked* health problems. These are problems where the causal mechanisms at play are obscured and difficult to address, and consequently they have defied efforts to develop effective interventions and policy solutions using traditional population health methods. Systems-based perspectives are vital to the development of effective policy solutions to seemingly intractable health problems like obesity and population aging. ALife in particular is well placed to bring interdisciplinary modeling and simulation approaches to bear on these challenges. This article summarizes the current status of systems-based approaches in population health, and outlines the opportunities that are available for ALife to make a significant contribution to these critical issues.

Keywords: Population health, ALife and society, agent-based modeling, societal impact

1 The Population Health Challenges Facing 21st-Century Society

Few would dispute that population health research has achieved significant strides in recent human history. The human life span has lengthened repeatedly beyond the upper bounds thought possible by health scientists and demographers. Communicable diseases are far less of a scourge in many countries than they used to be, thanks to huge advances in immunization and sanitation. In recent decades, health problems due to noncommunicable diseases—tobacco-related illness, for example—have been tackled through the deployment of health policy interventions that target behavior and lifestyle across society.

However, major population health challenges still remain: the rapid graying of populations, leading to concerns around healthy aging and social care demand; widespread increases in obesity, causing increased rates of heart disease and diabetes; and inequalities in health, a strikingly persistent problem even in societies that go to great effort to reduce inequity (e.g., Scandinavian countries). These problems all share a common trait—these are issues driven by complex, interacting mechanisms, not by the simple causal mechanisms that population health and epidemiologic methods are designed to address.

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In population health, these are called *wicked* problems, where causal links between risk factors and outcomes are not well defined, and unearthing the mechanisms that drive these processes is difficult [6]. As efforts to address these wicked challenges with traditional methods have floundered and failed to produce effective and actionable policies, population health scientists have increasingly turned toward the conceptual frameworks of complex systems science and simulation methods to find a way forward.

2 Complex Systems and ALife for Health

The hunger for systems-based perspectives in population health has culminated recently in a call to arms from Rutter et al. published in *The Lancet*, one of the most-cited public health journals, which concluded that "reshaping public health research, policy, and practice to incorporate complex systems approaches will be essential for improving population health and reducing health inequalities" [5, p. 2].

As heartening as that sounds, Rutter et al. also outline the challenges faced by complex systems approaches: the bias of publishers in the field toward individual-level health interventions; wariness of funders about new approaches; and policymakers' desire for easily actionable policy recommendations. Population health researchers remain skeptical of the benefits of complex systems approaches to health systems; Naimi, for example, contends that epidemiological methods can cope with producing causal effect estimates even in the presence of nonlinearity, so simulation models are an unnecessary addition to the population health toolbox [3].

3 The Case for Modeling and Simulation

Naimi's criticisms do hold some weight, in that standard epidemiological models are perhaps more efficient tools when seeking causal effect estimates relating to a health challenge where the causal mechanisms are more visible. But the presence of these wicked problems demonstrates that systemic understanding is necessary to make progress on some of the biggest challenges facing population health. As Rutter et al. describe, developing policy that addresses these challenges "requires more than single interventions, such as traffic light food labeling or exercise on prescription, many of which require high levels of individual agency, have low reach and impact, and tend to widen health inequalities" [5, p. 1]. Policy tools have the potential to reach far greater numbers of people, and to address population health problems through innovative means, such as environmental change interventions or social programs. Yet without an in-depth understanding of the diverse and interacting causes that drive these problems, those policy solutions can lead to flawed outcomes.

Alcohol misuse research provides an instructive example here. A variety of programs in American universities have tried to reduce alcohol misuse amongst students, as it causes numerous deaths each year and can lead to profound social and academic consequences. Normative reeducation programs are a common approach that shows students that the real alcohol consumption levels amongst their peers are lower than they might assume, in order to encourage moderation in alcohol consumption. However, evaluations of these programs "find no meaningful differences at schools with social norms programs" and suggest they have "the lowest level of effectiveness." Further, these programs can actually lead to "boomerang effects wherein those exposed to normative reeducation programs actually increase their alcohol consumption" [1, p. 356]. Ultimately these programs fail to take account of the multiple interacting factors that drive college drinking, focusing instead on addressing a single element of this complex web of causes. Apostolopoulos et al. propose that viewing alcohol misuse through a complex systems lens rather than a linear causal one "can better capture the dynamic complexity of these problems and facilitate substantive advances in both basic and applied knowledge" [1, p. 360].

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So while Naimi may be correct in thinking that systems-based simulation approaches may not be the most expedient answer to less wicked problems, this critique ignores the capacity for our methods to explain and describe more complex issues, and in the process help build more effective policy. Systems-based approaches to population health allow for the design and evaluation of health interventions that address the complexities of these issues, rather than attempting to simplify them out or focus on singular aspects. Simulation models can demonstrate the multi-layered interactions between individual agents and their physical, social, and even emotional environments, allowing stakeholders to test out policies that have the potential to affect broad swathes of the population [7]. Using simulation enables us to develop a more comprehensive picture of these complex health issues, and in turn avoid interventions and policy prescriptions that can lead to unintended adverse consequences.

4 Benefits for ALife

From what we have seen so far, the outlook for a systems-based approach to population health seems positive, but we still face an uphill battle. While some clearly accept the power of systems-based approaches and simulation modeling in particular, funders, journal editors, and researchers themselves remain biased toward statistical studies of linear causal models. Anyone in our community who sought to join the fight against wicked health issues could face a difficult journey, punctuated by rejections of their ideas and approaches—even amongst their own peers, some of whom may bemoan stretching the boundaries of ALife beyond its perceived remit.

I propose however that artificial life is particularly well suited to take on this challenge. ALife is thoroughly steeped in the language and conceptual frameworks of complex systems, and many of our approaches and models incorporate interacting layers of agents, environments, and processes. Terms that are slowly entering the population health discourse include foundational ALife concepts like emergence and adaptive behavior. In any interdisciplinary endeavor there is the danger of reinventing the wheel, as core concepts in other disciplines are rediscovered, renamed, and reapplied without the benefit of years of advancement that has already occurred elsewhere; ALife is in a position to help steer and motivate these embryonic extensions into complex systems viewpoints and methods, providing the benefit of our experience and knowledge.

In turn, these changes in approach can lead to profound shifts in the nature of intervention development and evaluation. Currently the population health landscape is shaped largely by reductionist statistical approaches, carving complicated problems into manageable chunks that can be turned into actionable policy solutions. As we have seen, however, these linear approaches to complex, nonlinear problems can produce policies that are ineffective or even counterproductive. By demonstrating the benefits of modeling populations as multi-layered complex adaptive systems, we can start changing the lens through which society is viewed by policymakers, and in the process develop more effective solutions.

More pragmatically, applying ALife methods to population health can have significant benefits in turn for our own efforts to bring models to data. Models of complex adaptive systems, particularly agent-based models, can be difficult to parameterize and analyze. Population health is a profoundly empirically focused discipline, and any systems-based approach will need to address these challenges in order to make headway with researchers and policymakers in the area. This challenge will help us develop more robust methods for mapping complex population data to our models, which will pay dividends in other disciplinary interfaces. As an example, take the ODD protocol for documenting agent-based models, first conceived in 2006 in ecological modeling circles, then later expanded to ODD+D for social models and recently ODD+2D for data-rich social simulations; as the method spread, new norms and techniques developed that have helped ABM become a more trusted tool across numerous disciplines [2].

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5 Building a Movement

Research groups and projects in population health incorporating complex systems methodologies are growing by the day, and opportunities to get involved are ever more plentiful. Simulation modeling is gaining acceptance, through high-profile projects like CASCADE, a five-year project at the University of Sheffield using agent-based modeling to study alcohol use and misuse. Here at the Complexity in Health Improvement Programme in the MRC/CSO Social and Public Health Sciences Unit at the University of Glasgow we have hired four complex systems scientists in the last eight months, have been granted capital funding for significant expansion of our scientific computing resources, and are building a UK-wide network of simulation modelers in population health spanning multiple universities. New research groups focused on complex systems approaches to health are appearing with greater regularity, such as the Complexity and Computational Population Health Research Group at Texas A&M University, while established groups in computational health sciences are beginning to expand further into population health. Increasing interest in the use of machine learning to work with big data in health is also likely to drive engagement with computational methods more generally.

On the whole, the field seems to be on the cusp of a significant shift toward systems-based approaches, and as these efforts expand and funders begin taking note, this is an ideal time for the ALife community to get involved. Along with Penn [4], I would also suggest that since we have the ability to help these research efforts develop, we also have a responsibility to do so. The wicked health problems, such as obesity, opioid addiction, and inequalities in health, all cause incalculable damage to life and society. As consensus grows that new approaches are needed, we should step up and do what we can to help develop smarter policy to address these issues.

Given recent trends in population health research, and widespread calls for a new approach to major health challenges, the artificial life community has an opportunity to make a significant contribution. Health scientists may contend our methods are complex, difficult to analyze, and poorly suited for causal effect estimates—and we can concede these points happily. What we offer instead are the tools to answer new questions, to model and evaluate policy in ways epidemiological methods cannot, and to address challenges that require an understanding of complexity, emergence, and adaptive behavior. If we reach across this disciplinary divide, we can help transform population health into a vibrant model-based science, and in the process demonstrate the societal impact of our ideas and methods.

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