Reducing Social Inequalities in Health: The Role of Simulation Modeling in Evaluating the Impact of Population Health Interventions

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The Munk School of Global Affairs at the University of Toronto seeks to be an internationally recognised leader in interdisciplinary academic research on global issues and to integrate research with teaching and public education. We place special emphasis on the fostering of innovative interdisciplinary knowledge through the exchange of ideas and research among academics as well as the public, private, and voluntary sectors.

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Reducing Social Inequalities in Health: The Role of Simulation Modeling in Evaluating the Impact of Population Health Interventions

Brendan T. Smith

Abstract
Reducing health inequalities has become a major public international health priority. However, how best to achieve this goal is not well understood. Population health intervention research has the potential to address some of this knowledge gap. In this working paper, the utility of simulation studies to evaluate the effectiveness of population health interventions for reducing socioeconomic inequalities in health is examined. This topic is explored using the example of socioeconomic inequalities in coronary heart disease (CHD). The development, characteristics, and utility of simulation models for evaluating population health interventions are briefly outlined and contrasted with current methods in this field of research. In addition, the potential for simulation studies to produce unique evidence on the effectiveness of population health interventions to reduce socioeconomic inequalities in health is discussed. Specifically, simulation models can help estimate the effect of a number of “what-if” counterfactual scenarios, where the introduction of population health interventions could be tested for their capacity to both improve population health and promote health equity. In the CHD literature, this has been achieved in two ways: (1) modeling past trends to determine the degree to which changes in risk factors explain the observed rates in CHD; (2) evaluating the impact of population health interventions on changing future CHD rates. A significant gap in this literature was identified, as to date simulation models are not commonly used to estimate the effect of population health interventions on socioeconomic inequalities in health. Simulation models are a flexible, evidence-based research method with the capacity to inform public health policy-makers regarding the implementation of population health interventions to reduce socioeconomic inequalities in health.

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INTRODUCTION
Social inequalities in morbidity and mortality exist across a number of health outcomes (World Health Organization 2008), and reducing these inequalities is one of the most significant challenges facing public health today. To this effect, there have been a number of calls to action to reduce health inequalities, both in Canada (Public Health Agency of Canada 2008) and internationally (World Health Organization 2008). Most senior public health policy-makers agree that action and specific interventions are needed to reduce social inequalities in health (Public Health Agency of Canada 2008; Petticrew et al. 2004). However, which
interventions and preventive strategies will be most effective in reducing social inequalities in health is not well understood (Petticrew 2007).

Research on population health interventions has the potential to address some of this knowledge gap by providing evidence for decision-makers on how to improve health outcomes. Population health intervention research refers to efforts to examine the effects of policies, programs, and resource distribution strategies across all sectors that aim to improve population health and promote health equity (Hawe and Potvin 2009). This approach encourages a shift from descriptive and analytic studies of health problems and their determinants to a solutions-oriented research focus on interventions that realize the desired health goals (Hawe and Shiell 2007). To achieve this objective, a sound understanding of the complex causal pathways linking social and environmental determinants to health outcomes is required (Edwards and Di Ruggiero 2011). Appropriate research methods are necessary to derive this knowledge and to evaluate the effectiveness of population health interventions that aim to reduce social inequalities in health.

The use of mathematical simulation models to help understand complex systems is well established in a number of other fields of research. Two prominent examples include the modeling of global climate change and the forecasting of macro-economic conditions. Despite increasing calls for the integration of mathematical simulation models into chronic disease research, to date they remain an underutilized tool in this field of research (Galea, Riddle, and Kaplan 2010; Ness, Koopman, and Roberts 2007; Hammond 2009). Mathematical models are defined as “an analytical methodology that accounts for events over time and across populations based on data drawn from primary or secondary sources” (Weinstein et al. 2003, 10). These models have the potential to provide valuable insight into the effect of population health intervention research. By combining simulation with evidence on the effectiveness of population health interventions, these models can provide an opportunity to understand which causal factors should be targeted to reduce health inequalities. In addition, these models can help estimate the effects of a number of “what-if” scenarios, where the introduction of various interventions and policies alternatives could be tested for both improving population health and promoting health equity (Wolfson 1994). Mathematical models are commonly used for similar purposes in other fields of health research, such as economic evaluation (Petrou and Gray 2011) and infectious disease research (e.g., Hammond 2009).

In this paper, I discuss the typologies of interventions to reduce social inequalities in health and briefly review the most common population health intervention research methods. I argue that simulation modeling can add to this field of research by furthering our understanding of the impact of population health interventions on reducing social inequalities in health. To illustrate this point, simulation modeling is introduced along with a discussion of its strengths and weaknesses relevant to population health intervention research. Finally, I outline the types of population health research questions that can be answered using simulation modeling. Throughout the paper, the example of socioeconomic inequalities in coronary heart disease (CHD) is used to illustrate the potential of simulation models to contribute to population health intervention research. This is a relevant example, as the association between socioeconomic position (SEP; typically measured using education, occupation, and income) and CHD is well established (Harper, Lynch, and Smith 2011), and simulation studies have been applied to the study of this health outcome (Unal, Capewell, and Critchley 2006; Ford and Capewell 2011). I highlight CHD simulation studies to demonstrate how these research methods may be extended to provide evidence for efforts aimed at reducing social inequalities in health. Simulation studies can also be valuable tools for investigating the effect of population health interventions on other types of social inequalities in health (e.g., gender or racial/ethnic inequalities). However, for the sake of simplicity this paper focuses the example of SEP.

**BUILDING EVIDENCE TO REDUCE SOCIAL INEQUALITIES IN HEALTH: POPULATION HEALTH INTERVENTION RESEARCH**

Population health policies and interventions that address the underlying social and economic conditions essential for health have the potential to make a large impact on reducing social inequalities in health (Edwards and Di Ruggiero 2011). To date, epidemiologic research has focused on conducting descriptive and analytic studies to determine the extent to which social inequalities exist across health outcomes (Hawe
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The information from these studies has been invaluable in attempting to understand this phenomenon. For example, Harper et al. (2011) have provided a detailed review describing the emergence of social inequalities in cardiovascular diseases and their risk factors as well as the contribution of social determinants to the observed decline in cardiovascular diseases during recent decades.

However, evidence is often lacking on how to proceed to reduce social inequalities in health (Petticrew 2007). How do we move forward to build evidence regarding the impact of population health interventions on reducing social inequalities in health? A first step is to better understand what types of interventions can be introduced to reduce social inequalities in health. Further, it is appropriate to evaluate whether current research methods are adequate for producing evidence regarding the effectiveness of these different types of interventions.

**Typology of Interventions to Reduce Social Inequalities in Health**

There are several approaches to reducing social inequalities in health, ranging from intervening on micro (individual) to macro (societal) levels factors. Whitehead (2007) proposed four categories of interventions to reduce social inequalities in health. The first set is interventions that seek to strengthen individuals in disadvantaged circumstances. These interventions focus on building individual-level characteristics, for example, increasing health-related knowledge to reduce the risk of disease. A second class of interventions focuses on strengthening communities through improving social cohesion within members or between different social classes, for example, improving neighbourhoods to facilitate social interaction or improving access of a given community to resources and political participation. The goal of the third category of interventions is to improve overall living and working conditions present in society. For example, these interventions attempt to decrease social inequalities in health by decreasing exposure to disease risk factors and improving access to essential goods and health care both in the entire population (Anderson et al. 2005) and among low socioeconomic groups. The final group of interventions involves health-promoting macro-policies. These policies attempt to change the upstream determinants of health inequalities, focusing on the overarching social and economic conditions that cause health inequalities, for example, income inequality. A more elaborate discussion of this typology of interventions to tackle social inequalities in health can be found in Whitehead (2007). The proposed categories are broad, incorporating many possible interventions. Appropriate research methods are necessary to help guide policy decisions around which targets and types of interventions are likely to reduce social inequalities in health.

**RESEARCH METHODS FOR EVALUATING POPULATION HEALTH INTERVENTIONS**

A significant challenge in developing the evidence base around population health intervention research, particularly for those seeking to address social inequalities in health, has been the development of appropriate methods to answer the desired research questions (Petticrew 2007). The “gold standard” in this field of research is the randomized control trial. This fact reflects the prominence of the biomedical approach and is closely linked to experimental medicine (Hawe and Potvin 2009). The methodology is relatively simple when evaluating the impact of individual-level interventions (Galea, Riddle, and Kaplan 2010). In this study design, the intervention is randomized to one group of individuals, while a second control group receives either no intervention or usual care. The goal is then to determine whether individuals who received the intervention are more likely receive a health benefit than individuals in the control group. The application of this methodology is more challenging when applied to population-level interventions, as it is often the case for interventions that seek to modify social and environmental exposures. Many social exposures are not amenable to randomized control trials, as it would be impossible or unethical to randomize people to certain types of exposures or interventions. Moreover, large-scale randomized control trials are often logistically challenging (ibid.). They involve recruiting large numbers of groups (e.g., individuals, communities, cities) to participate, as social interventions tend to have diffuse effects, making it very costly to conduct these research studies. Additionally, study participants have to be tracked over a long period of time, as interventions on upstream determinants may take longer to impact the health of populations (ibid.). Evaluations using a short time window (e.g., within election cycles) may miss the mid-to-long-term impacts of a given population health intervention.
There are research methods available that overcome some of the limitations of randomized control trials for population health interventions. For example, quasi-experimental designs, such as “natural experiments,” interrupted time-series designs, regression discontinuity approaches, and comparative research between similar jurisdictions can often provide insight into what result we might expect with population-level changes in a given exposure. These research methods take advantage of quasi-experimental conditions, for example, a famine or the introduction of a new population health policy in one jurisdiction and not another. To determine effectiveness, estimates for both pre- and post-intervention are compared in communities with and without the proposed population health intervention. This method controls for both secular trends (pre- vs. post-intervention in each community) and time-invariant characteristics between the communities (communities with and without the intervention). Where appropriate, this method can help investigate the determinants of health inequalities and evaluate the impact of interventions that were implemented in real life, and not as part of an experiment (Petticrew et al. 2005).

A major limitation to these quasi-experimental designs is that researchers have no control over the interventions themselves, making it difficult to ascertain the effects of the timing, location, or dose of the intervention. In addition, the allocation of the intervention and control groups are not randomized (Petticrew et al. 2005). The intervention and control groups may not be comparable due to their dissimilar nature at baseline in ways that are related to the outcome. Therefore, the results from these interventions need to be treated with caution, as they are observational in nature. Moreover, quasi-experimental evaluations of population health policies and interventions are often complex with many interventions occurring simultaneously in one population, making it difficult to infer causality to the intervention itself (ibid.). This is in contrast to the intra-individual randomized control trials described above. Petticrew et al. (ibid.) provide a more complete discussion on the benefits and limitations of natural experiments for population health interventions of social inequalities in health.

From a research perspective, randomized control trials and quasi-experimental research designs can provide valuable information on the effectiveness of population health interventions. An increased use of these methodologies will help reduce the evidence gap on the effects of interventions on health inequalities (Petticrew 2007). However, even with this evidence, policy-makers may experience barriers to translating this information into decisions regarding the implementation of effective population health interventions (Petticrew et al. 2004). Policy-makers are tasked with answering a different question than researchers: not whether a given population health intervention is effective, but which intervention(s) will have the greatest impact on achieving the desired health goal. Challenges to answering this question arise from the limited availability of evidence from studies that have been conducted on a narrow set of population health interventions. Evidence on the cost-effectiveness and potential benefits of all interventions is often not available, making it difficult to reflect on an array of intervention options.

Therefore, from a decision-maker’s point of view, it is easy to see how researchers may often have the right answers to the wrong questions (Petticrew et al. 2004). Simulation modeling is one research method that can help fill this evidence gap. Simulation models are a platform for integrating the best available evidence from a range of studies, most prominently evidence produced from randomized control trials, natural experiments, and other observational studies. Using this information, simulation models attempt to replicate the complex reality responsible for population-level changes in the risk of disease. This platform can then be used to project the effects observed in study samples to effects estimated for a defined population. This feature of simulation models allows the investigation of counterfactual, or what-if, scenarios regarding the implementation of population health interventions, estimating the hypothesized impact of the intervention(s) on population health outcomes. By simulating multiple interventions, the effects of different interventions options can be forecasted and compared. This flexible, evidence-based research method produces the necessary evidence for policy-makers to make informed decisions regarding the implementation of population health interventions.

**SIMULATION MODELING**

Simulation models are an underutilized tool in chronic disease research (Galea, Riddle, and Kaplan 2010; Ness, Koopman, and Roberts 2007; Hammond 2009). These models combine information on the prevalence
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of exposure to risk factors, treatments, and estimates of the disease risk arising from a given exposure. These methods can be applied to simulate the impact of population health policies and interventions and estimate their effect on risk factors and health outcomes within a given population over time. For example, they can be used to measure the effectiveness of population health interventions that target the causes of social inequalities of health across chronic diseases, such as coronary heart disease.

Development of Simulation Models

The first steps in developing a simulation model are to define the scope of the problem and choose the type of model that is appropriate for the research question. Some options are presented below in the characteristics of simulation models section of this paper. The next step is to begin building the simulation model by mapping the relationships between a number of exposures and one or more outcomes. Mathematical equations are then used to model how these factors interact to cause an outcome (e.g., a new case of disease). To parameterize the mathematical equations in the model, one strategy is to use information from a number of data sources, prioritizing the highest level of evidence available. Alternatively, established predictive risk algorithms have been developed for a number of disease outcomes, for example, the Framingham Risk Score and the SCORE (Systematic Coronary Risk Evaluation) for cardiovascular disease (Wilson et al. 1998; Conroy et al. 2003). While these algorithms have been developed mainly for the prevention of disease in clinical populations, their relevance for assessing baseline risk in population settings has been illustrated (Manuel and Rosella 2009).

Once parameters are estimated, either from published sources or risk algorithms, models need to be calibrated (refinement of model parameters to reproduce expected or observed results) and validated using an external data source (Levy et al. 2011). Sensitivity analyses are also used to test the robustness of the different model parameters. This is accomplished by varying parameters using plausible values and observing whether the conclusions remain unchanged. Finally, it is possible to investigate the impact of a number of potential prevention efforts (e.g., different population health interventions) using the developed simulation model. These steps are discussed in more detail by Levy et al. (2011), with an example of the development of a simulation model for osteoarthritis described by Kopec et al. (2010).

Characteristics of Simulation Models

There are various types of simulation models. Selecting the appropriate characteristics for a simulation model is important to insure that the model adequately reflects the reality it is attempting to simulate. A brief overview of some of the different types of simulation models follows to help elucidate the potential of this technique to contribute to population health intervention research. A full review can be found elsewhere (Brennan, Chick, and Davies 2006; Levy et al. 2011).

Simulation models can take on a number of forms and vary in their complexity. More simple simulation models can be static, confined to looking at two points in time or at two different scenarios at one point in time (Levy et al. 2011). Alternatively, dynamic models consider longitudinal changes in an outcome variable over time (ibid.). A distinction can also be made between macro- and microsimulation models. Macrosimulation models focus on groups of the sample population, allocating separate risk parameters dependent on individual or sets of risk factors (e.g., mortality rate by age and sex). The number of observed outcomes in this type of simulation model is the product of proportion of the sample with a given risk set and the risk parameter for this group, summed across all risk sets (ibid.). Therefore, individual disease characteristics are not simulated in this type of simulation model. In contrast, microsimulation assigns the risk of outcome to each individual in the simulation based on individual characteristics (ibid.).

Additionally, simulation models can be distinguished by how individuals in the model transition from one state to another (e.g., age). In discrete models, this can take place only at specific time intervals (e.g., at the end of a calendar year), whereas in continuous models these transitions can occur at any time (ibid.). In more complex agent-based microsimulation models, transitions between states can be influenced by other “agents” or individuals. For example, likelihood of adherence to physical activity programs can be varied in the simulation model depending on the number of members of an individual’s social network who are
regularly physically active. Moreover, neighbourhood level influences, such as proximity and access to physical activity programs, can be included in these more complex simulation models.

Strengths and Limitations of Simulation Models
A major strength of simulation models is their ability to improve understanding of the complex pathways that influence the health of populations, and to synthesize evidence from multiple data sources. This method combines data from multiple studies as well as expertise from a range of scientific disciplines to model the social, behavioural, environmental, and genetic effects on health (Levy et al. 2011). The process of building a conceptual framework linking exposures and outcomes can be invaluable in identifying gaps in the evidence base, illustrated by the lack of evidence surrounding parameters to be included in the model (Ness, Koopman, and Roberts 2007). Simulation models can help overcome a number of limitations of empirical research approaches (e.g., randomized control trials or natural experiments). These study designs may only consider the effect of a single intervention, or lack the appropriate data or control to disentangle the complex factors necessary to determine the true effect of an exposure on a given health outcome. By combining these complex factors into a single model, a better understanding can be achieved of how they interact to influence health, for example, the complex interactions between the individual, community, and macro-policy level interventions available to reduce social inequalities in health (Whitehead 2007). It is important to note that I am not recommending simulation modeling as a replacement, but rather as a complement to traditional epidemiologic methods that examine the etiologic relationships between risk factors and disease.

Stemming from their ability to model complex systems of relationships, simulation models have a number of practical features that make them relevant to population health intervention research. They can provide useful information to policy-makers that speaks directly to making evidence-based decisions. For example, simulation models can help forecast future disease burden in a population (Ness, Koopman, and Roberts 2007). Moreover, the effects of multiple types of interventions, intervention strategies (e.g., targeting high-risk populations versus the whole population), as well as cost-benefit ratios can be estimated. In addition to predicting future events, simulation models can also be valuable in understanding the effect of past policies and interventions. Combined, this information can help policy-makers evaluate the potential health impact of implementing individual or combinations of population health interventions (Levy et al. 2011).

While there is real potential for simulation models to be a useful tool in population health intervention research, their quality is inevitably linked to that of the data, evidence, and assumptions specified in the model. Model validation and sensitivity analyses are performed to help identify potential biases included in the simulation model. Understanding the limitations associated with the selected parameters, and being transparent about these limitations, is important when communicating the results from the simulation models (ibid.). Another limitation of simulation modeling is the number of simplifying assumptions that need to be made when attempting to model reality. The degree to which these assumptions impact the overall conclusions should also be tested using sensitivity analyses.

WHAT TYPES OF QUESTIONS CAN WE ANSWER USING SIMULATION MODELING?
The complexity of the causal pathways leading to social inequalities in many health outcomes calls for appropriate methods to help elucidate which interventions are best suited to improve population health and health equity (Petticrew et al. 2004; Whitehead et al. 2004). Simulation models can help improve evidence regarding the potential effectiveness of population health interventions in two ways: modeling past risk factor and disease trends, and evaluating the impact of potential policies and intervention on the future burden of disease.

Modeling Past Trends in Coronary Heart Disease
Coronary heart disease (CHD) is a leading cause of mortality worldwide, despite a substantial decline in recent decades across a number of Westernized countries (Ford and Capewell 2011). Simulation studies have been applied to better understand what factors are contributing to this observed trend. For example, the IMPACT CHD mortality model seeks to evaluate the contribution of the two broad categories of causes attributed for the reduction in CHD mortality: changes in population health risk factors for CHD (e.g.,
attributed to the public health system) and to improvement of medical and surgical techniques (e.g., attributed to the medical system) (Ford et al. 2007). In general, applied across a number of Westernized countries, these studies found that risk factors explain between 44% and 76% of the decline in CHD mortality, and medical treatments explain from 23% to 47% (Ford and Capewell 2011). In addition to general estimates, these simulation models also provide estimates for individual risk factors and medical interventions. For example, approximately 12% of the decline in CHD mortality between 1980 and 2000 was attributed to the decline in smoking prevalence in the United States (Ford et al. 2007).

To date, simulation studies have not been extended to examine the impact of population health CHD risk factors and medical treatment on reducing the observed social inequalities in CHD (Ford and Capewell 2011). In Canada, differences in the prevalence of many CHD risk factors (Lee et al. 2009) and access to medical treatments for CHD (Alter et al. 1999) have been observed by socioeconomic groups. Evidence of whether there was a similar decline in CHD mortality across socioeconomic groups, and the degree to which risk factors and medical treatments are responsible for observed social inequalities in CHD mortality (Wilkins et al. 2008), is limited (Wilkins, Berthelot, and Ng 2002). It is possible to investigate the causes of these inequalities in health using simulation models. This type of information is valuable for policy-makers, as it helps provide evidence on which risk factors and medical treatments (both individually and as a group) have been most influential in creating and sustaining the observed social inequalities in CHD (Harper, Lynch, and Smith 2011). This can be important when making decisions about future resource allocation and which targets for population health interventions should be prioritized to reduce social inequalities in CHD.

**EVALUATING THE IMPACT OF INTERVENTIONS ON FUTURE TRENDS IN CORONARY HEART DISEASE**

In addition to explaining the contribution of factors to the reduction of CHD mortality, simulation models have also been useful in estimating future trends in CHD morbidity and mortality. For example, the American Heart Association projected that by 2030, 40.5% of the United States population will have some form of cardiovascular disease (Heidenreich et al. 2011). By estimating future burden of disease, simulation studies can help inform future health care needs and identify populations who will be at high-risk of CHD (Levy et al. 2011).

Moreover, projecting future disease burden of CHD can be useful when estimating the impact (both in terms of health and cost-effectiveness) of population health interventions to reduce CHD. Once a valid simulation model has been constructed, it is possible to manipulate different aspects of the model to determine what their impact would be on the future burden of CHD. For example, Bibbins-Domingo et al. (2010) estimated that a population-wide reduction in dietary salt by 3 grams per day over a one-year period would result in an annual reduction of between 60,000 and 120,000 new cases of CHD in the United States for each year the intervention is applied. Simulation studies provide a cost-effective and flexible option to test what-if intervention scenarios with respect to changes in CHD risk factors. In addition, simulation models can be used to estimate the differential effects of CHD interventions across different populations (e.g., men and women, low versus high socioeconomic groups). For example, Alvarado et al. (2009) examined different scenarios for how the proposed US Health People 2010 targets could be achieved and what the corresponding effect would be on population and inequalities in CHD. This study exemplifies how the effects of population health interventions can differ in the whole population compared to population subgroups.

**Intervention Theory: Who Should Be Targeted by the Proposed Population Health Intervention**

In addition to different interventions, simulation models can also distinguish between the effectiveness of various intervention strategies on CHD outcomes. For example, when examining social inequalities in health, a relevant question would be whether or not to address the whole population or simply target high-risk populations, for example, low-income individuals. The focus of this paper is not to debate the justification of either method, but rather to point out that this type of hypothesis can be tested using simulation models. A summary of these issues can be found elsewhere in the literature (Manuel and Rosella 2009; Rose 1985; McLaren, McIntyre, and Kirkpatrick 2009).
Simulation Modeling: Opportunities to Improve Evidence on the Effectiveness of Population Health Interventions to Reduce Social Inequalities in Health

To date, CHD simulation studies have focused on estimating the effects of population health interventions that target CHD risk factors. These studies have provided evidence both on the historical factors that have been most responsible for the declining trend in CHD mortality as well as the potential impact of future population interventions should they be implemented. However, despite strong evidence demonstrating an association between SEP and CHD, few simulation studies have attempted to investigate which interventions are most effective in reducing social inequalities in CHD. Simulation studies, both on historical and future effects of CHD, can be utilized to better understand the causes of social inequalities in CHD. Valuable information could be gained regarding which CHD risk factors, if targeted, would result in the greatest reduction in social inequalities in CHD. In addition, these models can be extended to include upstream determinants of health. However, doing so likely requires additional information on the impact of policies and interventions outside the field of health. Future studies are needed to test the extent to which policies and interventions aimed to improve the social environment (e.g., increasing education, income, or early life interventions) will affect future CHD outcomes. These studies will help add to the evidence base of which population health interventions will be most effective in reducing social inequalities in CHD. For example, simulation studies that include policy levers such as the price of commodities and advertising (e.g., cigarettes and food) have been conducted in the fields of smoking prevention (Main et al. 2008) and obesity research (Levy et al. 2011).

CONCLUSION

There is currently a gap in evidence between the descriptive and analytic evidence demonstrating social inequalities in health outcomes and the knowledge of which population health interventions are most likely to reduce the observed health inequalities. This mismatch of problems and solutions is not surprising, given the complexity of factors that are responsible for causing the observed social inequalities in health. These factors can interact in non-linear ways, may only manifest over long periods of time, and may change depending on the context and time period. To develop adequate population health interventions to reduce social inequalities in health, researchers need to use appropriate methods that elucidate the causal pathways linking the social environment to health outcomes.

Current methods used to evaluate the effectiveness of population health interventions include randomized control trials as well as quasi-experimental observation studies. In addition to these research methods, this paper argues that simulation models can provide valuable insight into which population interventions would have an optimal impact on reducing social inequalities in health. Specifically, simulation studies can estimate the historical contribution of risk factors to the observed trends in social inequalities in health. This information can be used to identify potential targets for population health interventions to reduce social inequalities in health. Moreover, simulation models can be used to forecast future trends in social inequalities in health, based on current estimates of a combination of data sources. This feature presents a powerful tool for policy-makers and researchers alike to evaluate what-if scenarios, estimating the effects of potential population health interventions on future health outcomes. These models can also be used to estimate which prevention strategies (e.g., whole population versus high-risk subgroups) will best reduce health inequalities. The proposed methodology is not unrealistic: it is currently being applied to chronic diseases that disproportionately affect low socioeconomic groups. A significant challenge in achieving health equity has been a poor understanding of the outcomes of population health interventions across socioeconomic groups. Simulation studies can help address this research gap by demonstrating cost-effective, timely research methods that provide decision- and policy-makers with evidence for action to reduce social inequalities in CHD.
References


