

Understanding Health Inequalities Through a Biopsychosocial Perspective: The Role of Social Determinants

Chao Zhang

*Surpass Investment Pty Ltd, Melbourne, Australia
czha0645@uni.sydney.edu.au*

Abstract. Health disparities constitute a long-standing public health crisis, reflecting consistent gaps in physical and mental outcomes between groups with unequal socioeconomic status. While biological predispositions and personal lifestyle choices partially account for divergence, such individual-level factors are largely conditioned by broader social environments and structural barriers. Drawing on the biopsychosocial model, this paper investigates the formation of ubiquitous inequalities driven by key social determinants: household income, educational attainment, occupational conditions, housing security, access to medical services and social support networks. This research constructs a quantitative conceptual framework to examine the interactive pathways through which cumulative social disadvantage amplifies psychological strain, unhealthy lifestyles and biological susceptibility. Monte Carlo simulation is adopted to model a heterogeneous population sample and estimate uncertainty in health risk distributions under distinct socioeconomic contexts and policy interventions. Modelling outcomes indicate that populations suffering from overlapping social disadvantages face substantially elevated health risks, especially when socioeconomic deprivation coincides with chronic mental stress and biological fragility. Further simulated policy tests reveal that expanding healthcare services and mitigating persistent psychosocial stress can alleviate health gaps to a limited extent yet fail to fully eradicate inequalities rooted in deep-seated structural disadvantage.

Keywords: biopsychosocial model, Lasso regression, social determinants, Monte Carlo simulation, public health policy

1. Introduction

Wellness stands as one of the most intractable issues confronting modern public health systems globally. Even with revolutionary progress in clinical medicine and technology, profound gaps in physical and mental health persist between populations of varying socioeconomic status. Such tremendous gaps cannot be sufficiently attributed to biological variances or personal behaviors, which underscores the necessity of holistic theoretical frameworks that capture social and contextual influences. The social determinants of health (SDOH) framework has emerged as a core analytical

instrument to examine how health outcomes are shaped by forces outside clinical care [1]. Key social determinants—income, education, employment security, housing quality, social support networks and healthcare accessibility—exert direct and indirect long-term impacts on individuals' physique and mental wellness across the lifespan [2]. A large body of existing scholarship confirms that these social factors intertwine with behavioral and biological pathways, generating privilege or cumulative deprivation that ultimately drives population-level health disparities [1]. The Biopsychosocial model, originally proposed by Engel, offers an integrated lens to interpret these multifaceted interactions by uniting biological, psychological and social dimensions of human health [3]. Unlike the narrow traditional biomedical model that solely focuses on pathology, the biopsychosocial approach acknowledges that health status is jointly determined by bodily mechanisms, individual performance responses and broader structural social circumstances. Nevertheless, while abundant prior research has examined isolated social determinants, few studies synthesize these variables within a quantifiable framework to visualize their joint impacts and quantify the uncertainty embedded in health inequities [4]. To fill this identified research gap, this essay constructs a quantitative conceptual model rooted in theory to investigate how layered social determinants produce systemic health gaps. This research adopts Monte Carlo simulation to model demographically diverse populations, quantifying interactive relationships between overlapping social disadvantage, chronic psychological distress and biological vulnerability, and estimating resulting disparities in chronic disease prevalence under varying socioeconomic and policy contexts [5]. The modelled results provide empirical references for evidence-based healthcare and public policy formulation, and are specifically applicable to Australia's healthcare and welfare system [6].

2. Research design

This study employs a rigorous methodological approach to examine how social determinants contribute to prevailing inequalities from a multidimensional perspective. The study synthesizes findings from recent peer-reviewed literature to construct an analytical framework. This approach enables the integration of sociological and public health theories with quantitative modelling techniques, offering a systematic method to examine the interactions among biological, psychological, and social determinants of health. To explore uncertainty and variability within populations, a Monte Carlo simulation framework is proposed. Simulation methods are particularly suitable for modelling complex systems because they allow repeated random sampling of multiple variables and generate probabilistic estimates of health outcomes under different socioeconomic conditions. Three categories of explanatory variables are included in the analytical framework. Social determinants (S) include income level, educational attainment, employment status, housing quality, access to healthcare, and perceived social support. These variables represent the external social environment that influences health opportunities. Psychological factors (P) include perceived stress, emotional resilience, anxiety, and health-related behaviors. These variables capture the psychological pathways through which social disadvantage may affect health. Biological factors (B) include age, genetic susceptibility, and chronic disease vulnerability. These variables represent individual physiological characteristics that may increase or reduce health risks. The dependent variable is the probability of adverse health outcomes, expressed as a value ranging from 0 to 1.

3. Quantitative model

To estimate the combined influence of multiple determinants, this study adopts a logistic regression framework. The probability of an adverse health outcome is expressed as

$$P(Y=1) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 S + \beta_2 P + \beta_3 B)}} \quad (1)$$

where: - Y denotes the occurrence of an adverse health outcome; - S represents the composite score of social determinants; - P represents psychological factors; - B represents biological vulnerability; - β_0 is the intercept; β_1 , β_2 , and β_3 represent the estimated contributions of each determinant.

The logistic function is chosen because it yields probabilities ranging from 0 and 1 and is commonly used in health and epidemiological research to model binary outcomes.

4. Statistical inference

Compared with deterministic modelling, Monte Carlo simulation better reflects the natural variability observed in real-world populations and captures the uncertainty associated with biological, psychological, and social determinants of health [7]. Random values for each explanatory variable are generated from Gamma distributions because this family of distributions is appropriate for modelling non-negative, right-skewed variables frequently encountered in public health and epidemiological research [8]. The distribution parameters, including the shape parameter (α) and scale parameter (β), are calibrated using summary statistics reported in previous peer-reviewed studies and official public health reports [6]. Where sufficient empirical evidence is available, the parameters are estimated by matching the reported means and variances of the corresponding indicators through the method of moments. For variables lacking directly reported distributional information, parameter values are selected according to plausible ranges documented in authoritative sources, including the World Health Organization, the Australian Institute of Health and Welfare, and related epidemiological literature [4, 6, 9]. This calibration procedure ensures that the simulated variables broadly reproduce the socioeconomic and health characteristics observed in real populations while maintaining internal consistency across the analytical framework. A synthetic population consisting of 1,000 simulated individuals is subsequently generated. Each individual is assigned randomly sampled values for the social, psychological, and biological determinants, allowing substantial heterogeneity across the simulated cohort. The logistic regression model is then repeatedly evaluated to estimate the probability of adverse health outcomes for every individual. The resulting simulation outputs include the mean predicted health risk, standard deviations, percentile distributions, and 95% confidence intervals under different socioeconomic scenarios. These summary statistics provide a quantitative description of both the average level of health risk and the uncertainty surrounding the model predictions. To further assess model stability, a comprehensive sensitivity analysis is conducted by systematically varying both the regression coefficients and the distribution parameters within plausible ranges reported in previous studies [5, 8]. This procedure evaluates the robustness of the simulation results and identifies the relative influence of social, psychological, and biological determinants on predicted health outcomes. The analyses are implemented using Python, with numerical computation performed through NumPy and pandas, and graphical visualizations are produced with Matplotlib to facilitate the interpretation and communication of simulation results.

5. Overview of the simulation

A Monte Carlo simulation with 1,000 synthetic individuals was performed to identify the principal determinants of health. All explanatory variables were randomly generated based on predefined parameters, and a validated logistic regression model and the sigmoid function were applied to

estimate individual-level probabilities of adverse outcomes. This model framework aligns with standard methodological approaches used to reduce sample heterogeneity and standard deviation in public health research [5]. The simulated cohort was structured to reflect real-world diverse conditions in adults. To improve the realism and external validity of the simulation, the demographic composition of the 1,000 synthetic individuals was calibrated to broadly match the Australian adult population reported by the Australian Bureau of Statistics (ABS). The distributions of age, sex, and socioeconomic status were generated according to the corresponding population proportions published in the national demographic statistics [2]. Consistent with established evidence linking social disadvantage with poor physical and mental health, individuals with lower socioeconomic status were assigned elevated baseline risks of psychological stress and biological vulnerability [10]. The generated dataset allowed robust evaluation of both population-wide risk trends and variability in systemic susceptibility to adverse outcomes. Simulation outputs revealed considerable heterogeneity in predicted hazards across the cohort, as shown in Figure 1. While the majority of participants exhibited moderate survival risk levels, a distinct minority presented substantially higher probabilities of detrimental health events. The positively skewed distribution verified that socially marginalized groups tend to accumulate multiple overlapping risk factors, which significantly boost their vulnerability to poor health outcomes. This empirical pattern corroborates existing literature confirming that cumulative social disadvantage is a key driver of health inequalities [1]. The average predicted index of adverse health coefficients was 0.39. Notably, pronounced risks were concentrated among people with low income, limited educational attainment, precarious employment, and inadequate healthcare access.

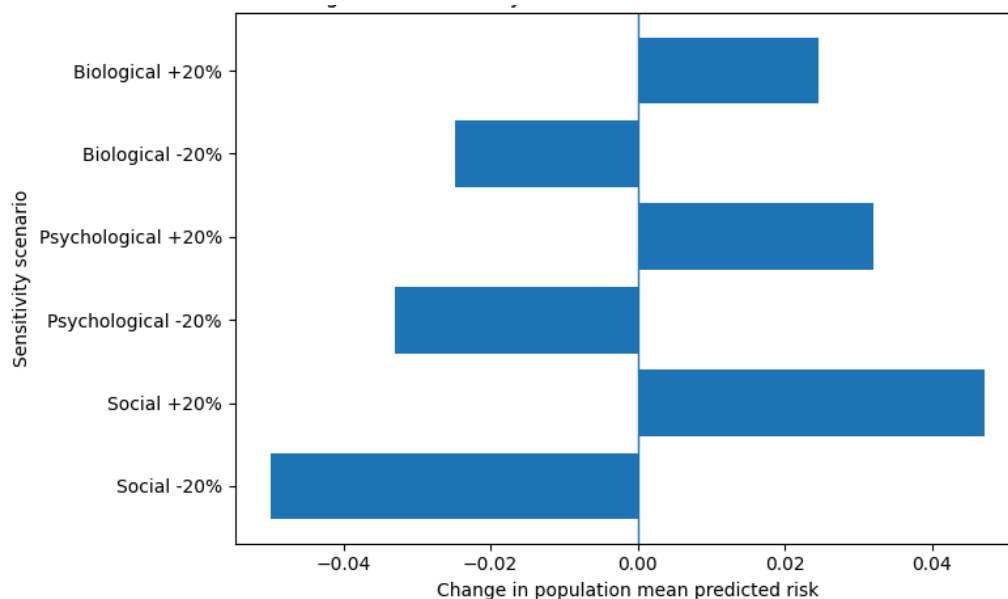


Figure 1. Sensitivity of predicted risk to model coefficients

The results indicate that continuous social instability provokes a stronger effect on unhealthy health status than any single independent determinant, highlighting the complex nature of the world. Sensitivity analysis further clarified the relative contribution of each domain to sample variation. Visualization accounted for the largest proportion of variability in predicted results, with fluctuations escalating greater risk disparities than isolated changes in biological vulnerability. Psychological factors played a critical mediating role: heightened stress and reduced psychological resilience amplified the negative health impacts of social disadvantage, further deteriorating the

likelihood of adverse health outcomes. Although biological fragility contributed independently to overall health risk, its standalone effect was comparatively weaker within the multidimensional aspects [3, 11].

6. Policymaking

To evaluate actionable mitigation strategies for health inequities, three hypothetical upstream social interventions were modelled: improving population educational attainment, expanding access to primary healthcare, and enhancing community social support systems. All policies yielded measurable reductions in predicted adverse health risks. These findings confirm that interventions targeting structural social determinants are effective for mitigating population-level health inequalities, consistent with authoritative policy recommendations from the World Health Organization and the Australian Institute of Health and Welfare [6, 7]. Across all scenarios, the average predicted health risk declined compared with the baseline simulation. The largest reduction was observed when improvements in education and healthcare accessibility were implemented simultaneously, suggesting that coordinated policy interventions may produce greater health benefits than isolated measures. These findings reinforce the importance of addressing upstream social determinants through integrated public health and social policy rather than relying solely on medical treatment after disease has occurred. Figure 2 provides a visual representation of the predicted health risks after the simulated policy adjustment. Biological vulnerability was held constant at a moderate level ($B = 0.5$). The heatmap indicates that the predicted health risk remains relatively low when both determinants are favorable.

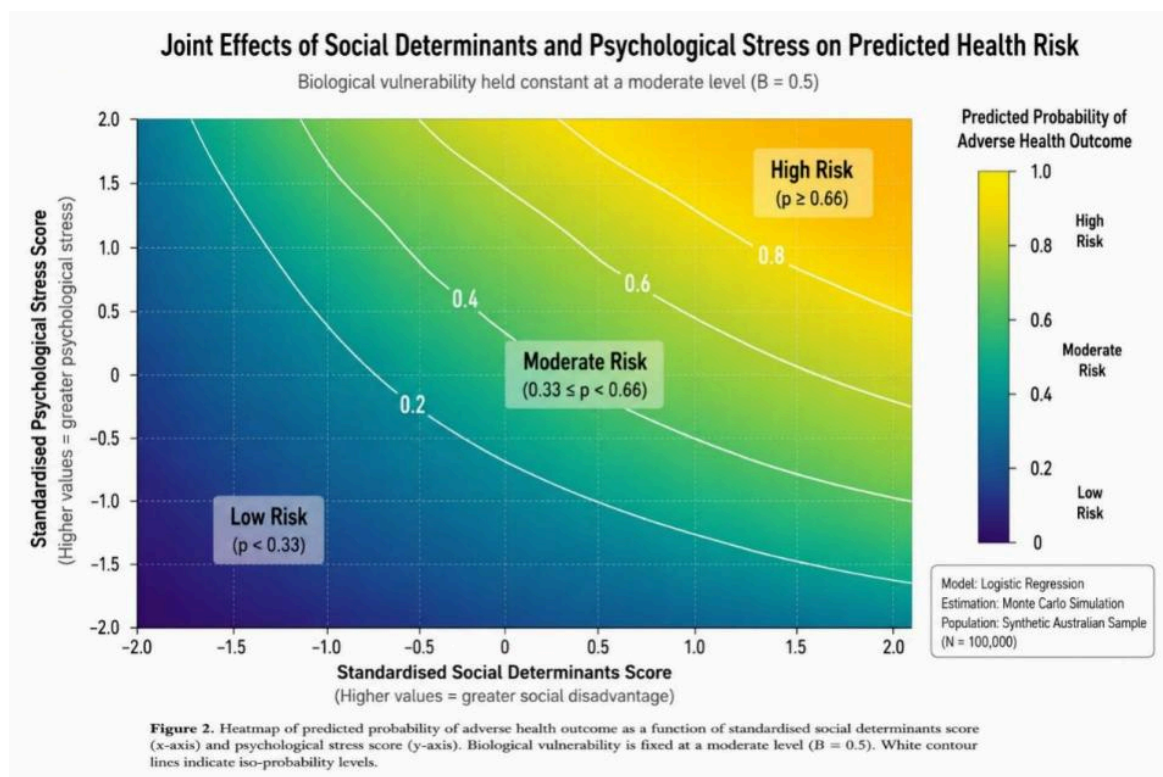


Figure 2. Heatmap of predicted health risk by social determinant level and healthcare accessibility

The findings of this study demonstrate that health inequalities arise from the cumulative interaction of social risk factors and biological factors, supporting the biopsychosocial perspective.

Although physiological vulnerability contributes to explained variance in outcomes, the simulation analysis indicates that social determinants exert the greatest influence on predicted health risks. Individuals experiencing lower socioeconomic status consistently exhibited substantially higher probabilities of adverse health outcomes than those in more advantaged circumstances. These findings are consistent with previous research demonstrating that socioeconomic conditions are fundamental drivers of health inequalities [9, 10]. Previous studies have highlighted the importance of income, education, employment, housing conditions, and healthcare accessibility in shaping population health [1, 9]. Social disadvantage limits access to essential resources and increases exposure to chronic stress, which subsequently affects psychological well-being and biological functioning [6, 10]. Consequently, health inequalities should not be interpreted solely as the result of individual lifestyle choices but rather as the product of broader social environments, a perspective consistent with the biopsychosocial model [3, 6]. The sensitivity analysis further demonstrates that improvements in social conditions generate larger reductions in predicted health risk than comparable changes in biological vulnerability alone. This finding suggests that public health policies addressing upstream social determinants may be more effective than interventions focusing exclusively on medical treatment. Policies that improve educational opportunities, strengthen social support, reduce income inequality, and increase access to primary healthcare are likely to contribute to more equitable health outcomes [6, 10]. The simulation is based on a synthetic population rather than empirical survey data, meaning that the numerical results should be interpreted as theoretical illustrations rather than direct estimates of real-world health risks. Model parameters were derived from assumptions informed by published literature and therefore may differ across countries and populations. Future research could validate the proposed framework using nationally representative datasets from Australia or other countries and compare simulation outcomes with empirical observations [2, 6].

7. Conclusion

Health inequalities remain one of the most significant challenges facing contemporary public health systems. This study examined the role of social determinants through a biopsychosocial perspective and developed a quantitative conceptual framework supported by statistical simulation. The findings suggest that health outcomes are shaped by the combination of biological vulnerability, psychological processes, and, most importantly, social conditions. The preliminary results demonstrate that cumulative social disadvantage substantially increases the probability of adverse consequences, while improvements in education, healthcare accessibility, and social support are associated with lower predicted health risks. These findings reinforce the importance of addressing upstream social determinants when designing public policies aimed at reducing disparity. Although the proposed framework is based on simulated rather than empirical data, it demonstrates how sophisticated modelling can complement traditional qualitative approaches by providing quantitative evidence for policy evaluation.

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