Applying ML for Mediation Analysis between Residential Segregation and Mortality Rates

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***Abstract*—Residential segregation is a key determinant of health disparities across racial and economic groups. Prior research has consistently shown a strong association between residential segregation and leading causes of death, with statistical analyses confirming that these relationships are unlikely due to chance. Evidence suggests that unhealthy behaviors and limited healthcare access may serve as mediators in this association. However, there remains a gap in quantifying the indirect effects of these mediators. In this study, we developed a machine learning–based model to estimate the proportion of effects attributable to unhealthy behaviors and healthcare access in the relationship between residential segregation and major causes of death. This study examined the mediation effects of unhealthy behaviors and healthcare access on the relationship between residential segregation and mortality at the county level in the United States. We compared the most deprived counties with the most privileged counties. Our findings indicate that both unhealthy behaviors and healthcare access partially explained the observed link between higher residential segregation and increased mortality. Unhealthy behaviors emerged as key mediators across multiple causes of death, while healthcare access also contributed to disparities between the most deprived and the most privileged counties. These results suggest that addressing unhealthy behaviors and improving healthcare access may reduce the mortality burden associated with residential segregation.**

***Index Terms*—Mediation Analysis, Mortality Rates, Residential Segregation, ML, Unhealthy behaviors, Healthcare access**

I. Introduction

Residential segregation refers to the systematic division of populations into distinct neighborhoods based on race and socioeconomic status [1]. In the United States, its origins can be traced to early 20th-century policies and practices that were not merely the outcome of individual choices but were reinforced by legal and institutional frameworks designed to preserve racial homogeneity and socioeconomic inequality [2], [3]. These entrenched structures have had lasting impacts on the demographic and socioeconomic composition of communities, contributing to persistent disparities in access to healthcare, education, employment, and other essential resources [4]. By shaping environments where marginalized groups face compounded disadvantages, residential segregation has long been recognized as a critical social determinant of health [5]. It reflects and reinforces historical and systemic inequities, creating conditions that perpetuate health disparities across populations. The resulting disparities have created persistent cycles of poverty and limited upward mobility for those living in historically marginalized neighborhoods [6]. Consequently, these structural inequalities have continued to impact health outcomes, economic stability, and social well-being, entrenching disparities across generations [7].

A substantial body of research has documented the strong association between residential segregation and a wide range of health outcomes, including mortality [8]–[10]. Gong demonstrated a strong association between residential racial and economic segregation and age-adjusted all-cause mortality, as well as the eleven leading causes of death across U.S. counties, with a clear decreasing trend observed across segregation quintiles. Mortality rates for all eleven leading causes of death declined significantly from the most deprived counties to the most privileged ones [8]. Income, race, and poverty level are key determinants of residential segregation [11]. Several measures have been developed to quantify this phenomenon, including the Dissimilarity Index, Interaction Index, and Isolation Index [12]. Among these measures, the Index of Concentration at the Extremes (ICE) is one of the most widely used, as it effectively captures both economic and racial aspects of segregation. Previous studies that compared the performance of different segregation indexes in examining the relationship between residential segregation and health disparities reflected in mortality rates found that ICE offers a more nuanced and reliable measure. Analyses based on ICE quintiles and other segregation metrics demonstrated its superior ability to reveal the association between segregation and mortality outcomes [13]. Since previous studies have repeatedly demonstrated the association between residential segregation—measured by ICE or other indexes—and mortality rates [8]–[13], evidence suggests that unhealthy behaviors and limited healthcare access may act as mediators in this relationship [14], [15]. However, the indirect effects of these mediating factors have not been well quantified. In this study, we developed a machine learning (ML)–based model to estimate the proportion of the association between residential segregation and major causes of death that can be explained by unhealthy behaviors and healthcare access. Smoking, drinking, physical inactivity, and obesity were selected as indicators of unhealthy behaviors, while the proportion of uninsured individuals and the availability of primary care physicians were used to represent healthcare access. Our findings indicate that both unhealthy behaviors and healthcare access partially explained the observed link between higher residential segregation and increased mortality. Unhealthy behaviors emerged as key mediators across multiple causes of death, while healthcare access also contributed to disparities between the most deprived and the most privileged counties.

The structure of this paper is organized as follows: Section II provides a review of related work; Section III describes the multiple datasets utilized; Section IV outlines the design of the proposed model; Section V presents the results and key findings from its application across all datasets; and Section VI concludes with final remarks.

II. Related Work

There are three forms of ICE: ICE for income, ICE for race, and ICE for income + race, which measure residential segregation based on income alone, race alone, or a combination of both factors [16]. Among them, ICE for income + race generally demonstrates stronger discriminatory power and explanatory performance because it captures the joint effects of economic and racial inequalities. Income and race often interact—communities with higher racial segregation frequently experience concentrated economic disadvantage, and vice versa. Therefore, considering both together provides a more realistic representation of social stratification and spatial inequality, making ICE for income + race a more comprehensive indicator of residential segregation [11]. Since poverty level is also a critical determinant of residential segregation [17], this study applies a ML approach to integrate income, race, and poverty level in developing the proposed model. Traditional segregation measures such as ICE or other commonly used indexes are typically limited to one or two dimensions and therefore cannot fully capture the combined effects of these three crucial factors. For instance, ICE for income or race alone overlooks the socioeconomic context of poverty, while ICE for income + race does not explicitly account for the spatial concentration of poverty that often amplifies segregation effects. To overcome these limitations, a machine learning approach was adopted to simultaneously incorporate income, race, and poverty, allowing for a more comprehensive and data-driven representation of residential segregation. Previous studies have demonstrated that clustering is an effective ML technique for grouping data, even when multiple dimensions are involved [18]. Liu et al. further demonstrated that by leveraging the strong correlation between ICE and poverty rate, balanced clustering could be implemented [19]. This study demonstrated that using ML methods can improve the definition of ICE quintiles and identify a stronger association between residential segregation and age-adjusted mortality rates. Other machine learning methods, including K-means clustering, decision trees, and regression trees, have also been applied to better capture both the extreme groups and the middle of the distribution [20], [21]. These approaches provide a more comprehensive understanding of the relationship between residential segregation and health outcomes [19]–[21].

In the healthcare field, many studies have applied mediation analysis to better understand causal relationships [22]. Traditional epidemiologic studies mainly examined the association between exposure and outcome. Recent advances now focus on identifying the intermediate processes that explain causal pathways [23]. Mediation analysis has become an important tool for uncovering these mechanisms, evolving from simple regression models to modern causal frameworks with clearer assumptions [24]. Unhealthy behaviors have been shown to mediate various relationships, such as those between shift work and perceived health [25] and between workplace demands or social support and depressive symptoms [26]. In addition, healthcare access can also act as an important mediator, influencing how social, occupational, or environmental factors translate into health outcomes [27]. Other potential mediators identified in previous studies include stress levels, lifestyle factors (such as diet, smoking, and physical activity), and socioeconomic conditions, all of which help explain the complex pathways linking exposure to disease or well-being [28]. In our study, based on the available datasets, we used smoking, drinking, physical inactivity, and obesity as indicators of unhealthy behaviors, while the proportion of uninsured individuals and the availability of primary care physicians were used to represent healthcare access.

III. Data Description

A. Dataset 1

We extracted county-level age-adjusted mortality rates (per 100,000 population) for leading causes of death in the United States for 2016–2020 from the CDC WONDER database [29]. To accompany these rates, we also downloaded each county's resident population counts for the same years from the CDC to ensure consistent denominators for analysis.

B. Dataset 2

County-level poverty data were obtained from the Small Area Income and Poverty Estimates (SAIPE) program of the U.S. Census Bureau [30]. This dataset provides annually updated model-based estimates of poverty rates for each county. For our analysis, we calculated the average proportion of the population living in poverty across the years 2016–2020 to represent the county-level poverty measure.

C. Dataset 3

We derived county-level Index of Concentration at the Extremes (ICE) measures using data from the U.S. Census Bureau's American Community Survey (ACS) 5-year estimates for 2016–2020 [31]. The ICE quantifies the degree of socioeconomic and racial polarization within a geographic area by comparing the proportions of privileged and deprived groups. For each county (i), we identified the number of White householders with annual incomes of $125,000 or higher ($A_i$), the number of Black householders with annual incomes of $25,000 or lower ($P_i$), and the total population with reported income (T_i). The ICE was then calculated as $(A_i - P_i)/T_i$, yielding values that range from -1 (maximum deprivation) to $+1$ (maximum privilege). Higher ICE values indicate greater concentration of advantaged populations, while lower values reflect greater concentration of disadvantaged populations.

D. Dataset 4

This study included unhealthy behaviors and healthcare access as mediators. Unhealthy behaviors were measured using county-level, age-adjusted averages from 2016–2020 for: smoking, obesity (BMI $\geq$ 30 kg/m²), physical inactivity (no leisure-time activity), and binge or heavy drinking. Healthcare access mediators included the percentage of adults under 65 without health insurance and the number of primary care physicians per 100,000 population, both averaged over the same period. County-level averages for unemployment rates, educational attainment (adults aged 25–44 with some post-secondary education), and all mediators were obtained from the County Health Rankings National Database [32].

IV. Methods

Missing values for residential segregation measures were generally below 5%. When the proportion of missing data for age-adjusted mortality of a specific disease was also less than 5%, we performed listwise deletion, which slightly reduced the sample size but did not materially affect the results. However, if the proportion of missing mortality data exceeded 5%, we applied multiple imputation to estimate the missing values. Similarly, if more than 5% of the residential segregation data were missing, multiple imputation was applied to both variables to ensure robustness and minimize potential bias. [21].

After addressing missing values and calculating ICE and poverty rates, we arranged the county-level values in ascending order to reflect the gradient from most deprived to most privileged areas. We then applied a balanced clustering approach to these ordered values to determine AIM [19].

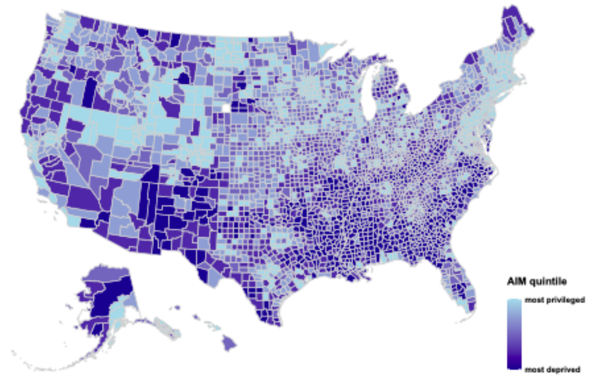


Fig. 1: The distribution of AIM quintiles.AIM quintiles range from the most deprived to the most privileged counties.

This method ensures that each cluster (or quintile) contains a nearly equal number of counties, allowing for fair comparison across socioeconomic levels. In this study, the first quintile (Q1) represents the most deprived counties, while the fifth quintile (Q5) represents the most privileged counties. Specifically, Q1 and Q5 each included 629 counties, and Q2, Q3, and Q4 each included 628 counties, for a total of 3,142 counties across the United States.

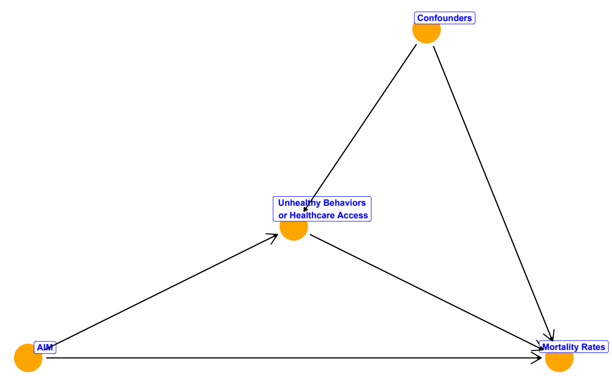


Fig. 2: Residential segregation was measured by AIM, with age-adjusted mortality rates at the county level serving as the outcome variable for both all-cause mortality and mortality from major causes of death. AIM had a direct effect on the outcome variable and indirect effects on the outcome through its influence on the mediators..

Based on the spatial distribution shown in Figure 1, clear geographic patterns were observed in the AIM quintiles across U.S. counties. The map reveals that the most deprived counties (darker shades) are largely concentrated in the Southeastern and South-Central regions, particularly across parts of Mississippi, Alabama, Louisiana, Arkansas, and Georgia, while the most privileged counties (lighter shades) are predominantly located in the Northeast, Midwest, and West Coast. These visible regional disparities suggest a strong geographic structure in the distribution of socioeconomic conditions. To account for this spatial dependence, we defined the U.S. Department of Health and Human Services (HHS) Regions 1–10 as analytical clusters in our model, ensuring that the analysis captures potential regional effects related to economic, demographic, and health system variations.

As illustrated in Figure 2, the mediators in this study included unhealthy behaviors (smoking, obesity, physical inactivity, and drinking) and healthcare access (percentage uninsured and primary care physician density). These mediators represent behavioral and structural pathways through which residential segregation, measured by AIM, may influence mortality outcomes. To ensure accurate estimation of these relationships, several confounding variables were included—namely, the average unemployment rate, urbanization status, the percentage of post education, and the proportions of non-Hispanic White and non-Hispanic Black populations from 2016 to 2020. The inclusion of these covariates was guided by the spatial patterns observed in Figure 1, which shows distinct regional clustering of AIM quintiles across the United States. Areas with higher deprivation (darker shades) are more common in the Southeastern and South-Central regions, where unemployment rates are higher, educational attainment is lower, and the population composition differs markedly by race compared with more privileged regions in the Northeast and West. These socioeconomic and demographic factors are closely linked to both AIM and mortality, and thus may confound the estimated relationships. Adjusting for them allows for a clearer understanding of the direct and indirect effects of residential segregation on health outcomes.

After constructing the AIM quintiles to represent levels of residential segregation, we selected the fifth quintile (most privileged counties) as the reference group. Using this reference, we estimated the mediation effects of unhealthy behaviors and healthcare access on the relationship between AIM and mortality outcomes. This approach allowed us to account for both fixed effects of county-level characteristics and random effects across HHS regions, capturing potential spatial dependencies observed in the AIM distribution. To further strengthen causal inference, we applied the Double/Debiased Machine Learning (DML) method in the causal mediation analysis. The DML framework reduces bias from high-dimensional covariates and model misspecification by using machine learning–based estimators to flexibly control for confounders. This method provided robust estimates of both direct and indirect (mediated) effects, along with their 95% confidence intervals (CIs). Applying these methods after deriving AIM enabled us to quantify how much of the observed association between residential segregation and mortality could be explained by behavioral and healthcare access pathways, rather than by differences in socioeconomic composition alone.

V. Experiments And Findings

Table I presents the characteristics of U.S. counties from 2016–2020, grouped into five quintiles based on the Area-based Inequality Measure (AIM). The quintiles divide counties into equal-sized groups, with the 1st quintile representing the most deprived and the 5th quintile the most privileged. The table summarizes key demographic, socioeconomic, and health-related characteristics across these groups. As AIM increases, several consistent trends emerge: the percentage of White residents rises, while the percentage of Black or African American residents declines; rural (non-metro) counties become less common, and urban (metro) counties increase. Economic and educational indicators also improve, with unemployment rates decreasing and the proportion of adults with post-secondary education increasing. In terms of health behaviors, the prevalence of smoking, physical inactivity, and obesity decreases across quintiles, whereas excessive drinking shows a modest increase. For healthcare access, the percentage of uninsured residents declines, and the number of primary care physicians per capita increases steadily from the lowest to the highest quintile.

Figure 3 illustrates mortality rate ratios for all-cause deaths, heart disease, and cancer across AIM quintiles. Mortality rates consistently decline as AIM increases, indicating that counties with greater privilege experience lower mortality. For instance, the all-cause mortality rate ratio decreases from 1.36 in the most deprived quintile to 1.12 in the most privileged, with heart disease showing a similar gradient. The decline for cancer mortality is present but slightly less steep, suggesting other contributing factors beyond socioeconomic disparity.

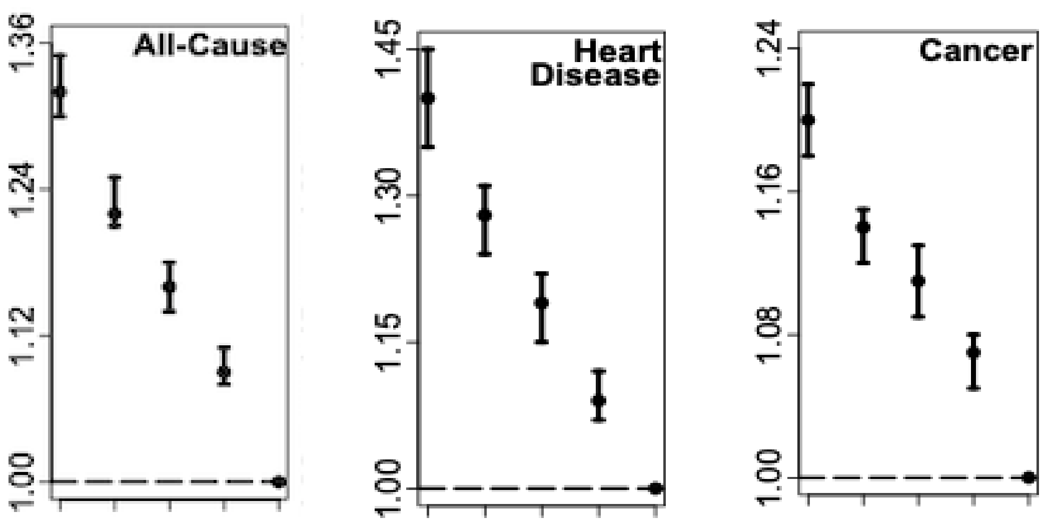
Table II further explores these associations through mediation analysis, identifying key pathways through which residential segregation affects mortality. Smoking and physical inactivity emerge as the strongest mediators for all three outcomes. For all-cause deaths, smoking accounts for 69.2% of the total effect and inactivity for 35.7%. For cancer mortality, the mediation effect of smoking is especially pronounced at 95.4%, implying that nearly all of the segregation-related differences in cancer mortality are explained by smoking behavior. Obesity and drinking show smaller but still notable contributions, mediating 16–18% and 2–8% of the total effects, respectively. Lack of health insurance has a minor positive mediating effect (up to 3.5% for cancer), while primary care availability exhibits a negative mediating effect, suggesting that better access to primary care may help offset the adverse health impacts of residential segregation.

VI. Conclusion

Using a machine learning-based mediation analysis, this study investigated how unhealthy behaviors and healthcare access mediate the link between residential segregation and

TABLE I: Characteristics of US counties by quintiles of AIM, 2016-2020.

	1^{st} quintile	2^{nd} quintile	3^{rd} quintile	4^{th} quintile	5^{th} quintile	p-value
% Male	50.00	50.41	50.05	50.07	50.02	0.007
% Age 65+	18.69	19.45	20.66	19.84	17.83	< 0.001
Race/Ethnicity						
% White	59.44	78.31	82.03	83.01	82.59	< 0.001
% Black or Africa American	26.90	5.30	7.04	4.03	4.47	< 0.001
% Urbanization status						
Non-Metro	76.60	73.92	70.70	58.35	34.71	< 0.001
Metro	23.40	26.08	29.30	41.65	65.29	< 0.001
% Unemployment	6.01	5.33	4.52	4.60	4.15	< 0.001
% Education	48.71	53.96	59.73	62.33	69.12	< 0.001
% Smoking	23.07	21.14	19.04	17.95	15.87	< 0.001
% Excessive drinking	15.46	17.47	18.87	19.75	20.63	< 0.001
% Physical inactivity	33.09	29.22	27.28	25.50	22.56	< 0.001
% Obesity	38.52	35.33	34.82	33.07	31.06	< 0.001
% Uninsured	14.00	12.84	11.11	10.69	8.74	< 0.001
Primary care physicians	42.77	50.84	50.74	58.08	69.42	< 0.001



(a) (b) (c)

Fig. 3: (a) Mortality Rate Ratio by AIM for age-adjusted all-coause of death; (b) Mortality Rate Ratio by AIM for Heart Disease; (c) Mortality Rate Ratio by AIM for Cancer.

TABLE II: Mediating effect of unhealthy behaviors and healthcare access on the association between residential segregation and mortality, examining all deaths, heart disease, and cancer. The analysis will compare the percentage of the effect that is mediated among the most deprived counties (1st quintile) versus the most privileged counties (5th quintile).

Cause	Smoking	Drinking	Inactivity	Obesity	Uninsured	Primary Care
All deaths	69.2 (62.4, 77.0)	6.1 (3.8, 9.0)	35.7 (31.3, 41.0)	16.3 (12.3, 20.0)	1.6 (0.5, 3.0)	-0.2 (-1.2, 1.0)
Heart Disease	46.1 (37.8, 56.0)	7.7 (5.0, 11.0)	41.3 (35.3, 48.0)	10.8 (7.8, 14.0)	1.9 (0.4, 4.0)	-1.4 (-3.0, 0.0)
Cancer	95.4 (81.8, 113.0)	1.9 (0.3, 4.0)	44.6 (36.8, 54.0)	18.4 (13.4, 24.0)	3.5 (0.7, 6.0)	-1.0 (-2.9, 0.0)

mortality. Key findings include: 1. Mortality rates for major causes of death, like all-cause, heart disease, and cancer, were consistently lower in more privileged counties and higher in more deprived counties. 2. Unhealthy behaviors, specifically smoking and physical inactivity, were found to be substantial mediators connecting segregation and mortality. 3. Healthcare access also played a mediating role, though its effect was smaller yet consistent.

Despite these insights, several limitations should be acknowledged. The study's limitations include using county-level aggregate data, which risks ecological bias by masking within-county variation, and employing a cross-sectional design, which prevents establishing causality . The reliability of machine learning results is also affected by data quality and missing information. Future research should use longitudinal data and finer-scale spatial data (e.g., census tracts) to improve precision and capture changes over time. Additionally, integrating social determinants such as income inequality, housing, and environmental factors can provide a more comprehensive understanding of health outcomes.

Our future work will focus on expanding the application of MLM to other types of cancer or chronic diseases.

REFERENCES

[1] E. E. Bruch, "How population structure shapes neighborhood segregation," American Journal of Sociology, vol. 119(5), pp.1221-1278, 2014.

[2] A. T. Erickson and A. R. Highsmith, "The neighborhood unit: Schools, segregation, and the shaping of the modern metropolitan landscape," Teachers College Record, vol. 120(3), pp.1-36, 2018.

[3] A. A. Dani and A. de Haan, "Social policy in a development context: structural inequalities and inclusive institutions," Inclusive States: Social policy and structural inequalities, pp.1-36, 2008.

[4] S. Amri and J. Sihotang, "Impact of Poverty Reduction Programs on Healthcare Access in Remote Ar-eas: Fostering Community Development for Sustainable Health," Law and Economics, vol. 17(3), pp.170-185, 2023.

[5] J. W. Faber and J. P. Drummond, "Still victimized in a thousand ways: segregation as a tool for exploitation in the twenty-first century," Annual Review of Sociology, pp.50, 2024.

[6] T. Riketty, "Theories of persistent inequality and intergenerational mobility," Handbook of income distribution, vol. 1, pp.429-476, 2000.

[7] K. S. Rahman, " Constructing and contesting structural inequality," Critical Analysis L., vol. 5, pp.99, 2018.

[8] R. Gong, " Relationship Between Residential Racial and Economic Segregation and Main Causes of Death in US Counties," J. Racial and Ethnic Health Disparities, pp.1-9, 2025.

[9] N. Breen, J. Andres, M. Fossett, M. M. Gomez, and E. Moy, " The Effects of Residential Segregation on Black and White Mortality in the United States," The Review of Black Political Economy, vol. 51(1), pp.79-120, 2025.

[10] M. Siegel, M. Rieders, H. Rieders, L. Dergham, and R. Iyer, " Association between changes in racial residential segregation and trends in racial disparities in early mortality in 220 metropolitan areas, 2001–2018," Journal of Racial and Ethnic Health Disparities, vol. 11(6), pp.3782-3793, 2024.

[11] T. D. Logan and J. M. Parman, " Racial residential segregation in the United States," Journal of Economic Literature, vol. 63(3), pp.964-1010, 2025.

[12] A. D. Williams, M. Wallace, C. Nobles, and P. Mendola, " Racial residential segregation and racial disparities in stillbirth in the United States," Health & place, vol. 51, pp.208-216, 2018.

[13] R. Gong, J. Liu, and M. Zhao, " Comparison of Segregation Indexes and Residential Segregation for Mortality Analysis," 2024 International Conference on Electrical and Computer Engineering Researches (ICECER), pp.1-6, 2024.

[14] Y. Zhu, L. lamosas-Falcón, W. C. Kerr, J. Rehm, and C. Probst, " Behavioral risk factors and socioeconomic inequalities in ischemic heart disease mortality in the United States: A causal mediation analysis using record linkage data," PLoS medicine, vol. 21(9), pp.e1004455, 2024.

[15] K. Flike, L. L. Hayman, T. Byrne, Q. Song, and T. Aronowitz, " The impact of patient-centred care on the relationship between access to care and subjective health outcomes amongst people experiencing homelessness: a mediation analysis," Health & Social Care in the Community, vol. 30(6), pp.e5755-e5764, 2022.

[16] A. Larrabee Sonderlund, M. Charifson, A. Schoenthaler, T. Carson, and N. J. Williams, " Racialized economic segregation and health outcomes: a systematic review of studies that use the Index of Concentration at the Extremes for race, income, and their interaction," PloS one, vol. 17(1), pp.e0262962, 2022.

[17] R. E. Dwyer, " Poverty, prosperity, and place: The shape of class segregation in the age of extremes," Social problems, vol. 57(1), pp.114-137, 2010.

[18] P. Hernández-León and M. A. Caro, " Cluster-based multidimensional scaling embedding tool for data visualization," Physica Scripta, vol. 99(6), pp.066004, 2024.

[19] J. Liu and R. Gong, " AIM: Using AI to Improve Residential Racial and Economic Segregation for Mortality Analysis," 2024 IEEE World Forum on Public Safety Technology (WFPST), pp.19-24, 2024.

[20] R. Gong, " Using Machine Learning to Improve Residential Segregation for Association Analysis," 2025 IEEE 15th Symposium on Computer Applications & Industrial Electronics (ISCAIE), pp.224-229, 2025.

[21] R. Gong and J. Liu, " MLM: Using ML to Handle Missing Values in Residential Segregation and Mortality Rates for Association Analysis," 2024 IEEE/ACM International Conference on Big Data Computing, Applications and Technologies (BDCAT), pp.36-41, 2024.

[22] S. J. Jung, " Introduction to mediation analysis and examples of its application to real-world data," Journal of Preventive Medicine and Public Health, vol. 54 (3), pp.166, 2021.

[23] N. Pearce, " Traditional epidemiology, modern epidemiology, and public health," American journal of public health, vol. 86 (5), pp.678-683, 1996.

[24] L. Keele, " Causal mediation analysis: warning! Assumptions ahead," American Journal of Evaluation, vol. 36 (4), pp.500-513, 2015.

[25] I. K. Proper et al., " The mediating role of unhealthy behavior in the relationship between shift work and perceived health," BMC Public Health, vol. 21 (1), pp.1300, 2021.

[26] L. L. Magnusson Hanson, P. Peristera, S. H. Chungkham, and H. Westerlund," Longitudinal mediation modeling of unhealthy behaviors as mediators between workplace demands/support and depressive symptoms," PLoS One, vol. 11 (12), pp.e0169276, 2016.

[27] K. Flike, L. L. Hayman, T. Byrne, Q. Song, and T. Aronowitz, " The impact of patient-centred care on the relationship between access to care and subjective health outcomes amongst people experiencing homelessness: a mediation analysis," Health & Social Care in the Community, vol. 30 (6), pp.e5755-e5764, 2022.

[28] J. S. Carroll, J. M. Dale, T. Niyonsenga, W. A. Taylor, and M. Daniel, " Associations between area socioeconomic status, individual mental health, physical activity, diet and change in cardiometabolic risk amongst a cohort of Australian adults: A longitudinal path analysis," PLoS One, vol. 15 (5), pp.e0233793, 2020.

[29] CDC Wide-ranging ONline Data for Epidemiologic Research (WONDER), " Underlying cause of death, 2016–2020 request," Atlanta, GA: Centers Dis Control Prev, 2024.

[30] Small Area Income and Poverty Estimates, " Small Area Income and Poverty Estimates (SAIPE) Program," U.S. Census Bureau, 2024.

[31] American Community Survey, "American Community Survey (ACS) 5-year estimates for 2016–2020," U.S. Census Bureau, 2025.

[32] University of Wisconsin Population Health Institute., "County Health Rankings & Roadmaps ," University of Wisconsin Population Health Institute, 2024.