# Big Data, Big Insights: Leveraging Data Analytics to Unravel Cardiovascular Exposome Complexities

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## **ABSTRACT**

The exposome encompasses the full range of environmental exposures throughout a person's lifetime and plays an important role in cardiovascular health. Interactions with the social, natural, and built components of the exposome significantly impact cardiovascular disease prevalence and mortality. Robust data analytics, including machine learning and geospatial analysis, have advanced our understanding of how these factors converge to influence cardiovascular disease risk. The integration of multiomics platforms and advanced computational approaches enhances our ability to characterize the exposome, leading to targeted public health interventions and innovative risk reduction strategies aimed at improving cardiovascular health globally. These multiomics platforms that integrate factors such as genomics, epigenomics, clinical data, social factors, environmental factors, and wearable technology will characterize the exposome in greater detail concerning cardiovascular health. In this review, we aimed to elucidate the components of the exposome and discuss recent literature regarding their relationship to cardiovascular health.

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**REVIEW**

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#### **INTRODUCTION**

Understanding the exposome is essential for advancing our knowledge of cardiovascular health. The exposome encompasses the full range of exposures a person encounters throughout their lifetime, including physical and chemical factors, living and working environments, occupation, and food security. Defining and understanding the impact of different components of the cardiovascular exposome ([Figure 1](#page-1-0)) has become an emerging field supported by robust data.<sup>1</sup> For example, studies have demonstrated the causal impact of various environmental factors such as air pollution, noise pollution, and light pollution on cardiovascular disease prevalence. Air pollution is recognized as one of the leading causes of morbidity and mortality worldwide, often indirectly through cardiovascular disease.<sup>[2,](#page-8-2)[3](#page-8-3)</sup> The Global Burden of Disease study revealed that these types of environmental exposures are responsible for the vast majority of cardiovascular disease burden in Africa and South Asia.<sup>[1,](#page-8-1)[2](#page-8-2)</sup>

The exposome refers to the totality of exposures individuals encounter and encompasses a wide range of internal and external factors. Historically, capturing the exposome has been challenging due to limited historical data. However, with growing recognition of the cardiovascular exposome's complex impact, we propose categorizing it into three distinct domains: social, natural, and built environments. The social environment component includes factors such as socioeconomic distress, vulnerability, environmental justice, and access to health care. The natural environment encompasses pollution of air, water, and land as well as extreme temperatures. Finally, the built environment consists of human-designed spaces where people live and engage in daily activities, highlighting aspects such as walkability, access to greenspace, and community design.

In this review, we outline important data sources for each exposome category and discuss findings of recent literature as to how this component of the exposome may affect cardiovascular health and disease. This paper also introduces the characterization of environmental exposures



<span id="page-1-0"></span>**Figure 1** Overview of the cardiovascular exposome and its components. SDI: social deprivation index; CVD: cardiovascular disease; NLP: natural language processing: PM2.5: fine particulate matter smaller than 2.5 micrometers in diameter

in relation to cardiovascular prevention, prevalence, and outcomes<sup>1</sup>

# **DATA ANALYTICS IN THE SOCIAL ENVIRONMENT**

The social environment significantly impacts cardiovascular health through factors such as systemic racism, marginalization, discrimination, economic status, and social deprivation. Recent studies have investigated various social quantification methods and their relationship to cardiovascular health ([Table 1\)](#page-3-0). These methods include the Social Vulnerability Index, Social Deprivation Index (SDI), and Area Deprivation Index, which have been explored across the wide cardiovascular health spectrum, from diagnosis and prevention to management and prognostic implications.<sup>4-15</sup> These indices quantify the magnitude of many social influences, such as household composition, transportation, financial status, and minority racial and ethnic status. Given the recognized importance of quantifying social influences in cardiovascular care, the updated risk prognostication scoring system, the Predicting Risk of Cardiovascular Disease Events (PREVENT) Score, has incorporated the SDI into its algorithm for predicting future cardiovascular events.[16](#page-9-2)

Data sources for studying social influences on the cardiovascular exposome include numerous registries. Census data, used for nationally representative samples, helps test complex social hypotheses and their impact on cardiovascular outcomes. The Centers for Disease Control and Prevention Population-Level Analysis and Community Estimates (PLACES) dataset, Surveillance, Epidemiology, and End Results (SEER) dataset, and electronic health records are valuable sources of such social influences. The Centers for Disease Control and Prevention's PLACES dataset utilizes data from the American Community Survey to obtain 5-year estimates of various social factors, which include housing crowding, internet access, housing costs, poverty rates, educational attainment, and unemployment rates[.17](#page-9-3) For example, one recent analysis found a higher rate of ischemic heart disease mortality in regions with a greater lack of health insurance.[18](#page-9-4) Additionally, the SEER dataset, introduced by the National Cancer Institute, provides data on cancer statistics, including incidence rates, survival, and mortality-related outcomes. A multitude of studies have investigated cardiovascular outcomes in relation to patients with malignancies using the SEER dataset.<sup>19-[23](#page-9-6)</sup>

The Environmental Justice Index (EJI) is another quantification method that incorporates many social variables, such as the Social Vulnerability Index, and includes various environmental factors obtained from the US Census Bureau, the US Mine Safety and Health Administration, and the US Environmental Protection Agency.<sup>24</sup> A recent study aggregated prevalence rates of cardiovascular diseases within census tracts into quartiles of the EJI and compared the prevalence of cardiovascular diseases through risk ratios by multivariable Poisson regression models.<sup>25</sup> This study found a greater prevalence of cardiovascular disease burden in US regions with a higher EJI. Another method to quantify the impact of social influences on cardiovascular health includes historical redlining, a practice that previously classified neighborhoods for mortgage risk primarily driven by racial segregation. One recent analysis evaluated the impact of historical redlining on out-of-hospital cardiac arrest bystander involvement. Using data from the Cardiac Arrest Registry to Enhance Survival, the study found that historical segregation practices led to reduced rates of bystander cardiopulmonary resuscitation.[26](#page-9-9)

Furthermore, since 2015, efforts have led to the integration of social determinants coding within the International Classification of Diseases system through Z-codes within ICD-10-CM, classified as Z55 to Z65[.27](#page-9-10) These codes represent psychosocial and socioeconomic factors, with the goal of identifying health risks associated with a patient's social context. Z-coding domains include housing situation, economic circumstances, educational attainment, occupational exposures, employment status, and physical and social environments. Although Z-coding has been significantly underutilized, studies revealed an association between Z-coding documentation and increased prevalence of hypertension, greater comorbidity burden, and increased pharmaceutical costs.<sup>[28,](#page-10-0)[29](#page-10-1)</sup>

Analytic approaches to exploring social influences on the cardiovascular exposome include structural equation modeling and multiple regression, which are frequently used in ecological studies. However, many studies in this area are cross-sectional or retrospective, showing numerous associations without establishing causality, thus limiting the interpretability of the results. Regression modeling with appropriate control for confounding variables is crucial for identifying the independent effects of social factors on cardiovascular health; however, it continues to have limitations. Future efforts directed at cohort studies are therefore vital for understanding how social determinants directly impact cardiovascular health and tracking changes over time to establish causal relationships.

Geospatial analysis is also an important tool for exploring the spatial distribution of social determinants of cardiovascular health. One study used a geographic information system analysis of a multisite and multiyear cohort investigating out-of-hospital cardiac arrest outcome disparities, revealing significant racial and socioeconomic disparities in out-of-hospital cardiac arrest



<span id="page-3-0"></span>**Table 1** Studies investigating the association between the social environment and cardiovascular outcomes. CDC: Centers for Disease Control and Prevention; ATSDR: Agency for Toxic Substances and Disease Registry; CMS: Centers for Medicare and Medicaid Services; SVI: Social Vulnerability Index; CVD: cardiovascular disease; AMI: acute myocardial infarction; HF: heart failure; IHD: ischemic heart disease; CPR: cardiopulmonary resuscitation

outcomes, particularly impacting Black populations in the US.[30](#page-10-2) Furthermore, it also revealed that university hospital settings, as opposed to safety net hospitals that primarily serve Black populations with lower socioeconomic status, had higher income commercially and the lowest odds of death among Medicare-insured patients. Through the integration of geographic information systems with population health data, it becomes easier to visualize and analyze geographical patterns that correlate social determinants with cardiovascular health. This approach can identify higher-risk areas to enable targeted public health interventions and appropriate resource allocation, ultimately guiding policymakers to implement effective strategies that promote healthcare equity. For example, although social vulnerability has been associated with higher overall Medicare expenditures, $31$  there is no robust evaluation about whether cardiovascular care-related expenditures are affected by social vulnerability.

Finally, advancements in innovative analytic techniques such as machine learning algorithms and natural language processing (NLP) have significantly enhanced our ability to handle large and complex datasets, allowing for nuanced hypothesis testing.[32](#page-10-4) For example, NLP approaches can extract meaningful and prognostically relevant information from unstructured data sources, providing valuable insights into social factors. NLP methods can include rule-based algorithms, deep-learning techniques, and supervised machine learning. Among the various types of NLP, one study revealed that machine-learning approaches are commonly applied to social factors, including substance use and homelessness, rule-based methods for housing and transportation factors, and deep-learning for cardiovascular risk factors utilizing complex datasets.[32](#page-10-4)[–37](#page-10-5) One study in 2021 assessed rehospitalization risk in populations with acute myocardial infarction using NLP methods, particularly evaluating the impact of various social factors including social support systems and housing.<sup>38</sup> Similarly, one study used the opensource Canary NLP system to explore the capability of this algorithm to detect multiple cardiovascular comorbidities including stroke, hypertension, dyslipidemia, diabetes, and coronary artery disease, resulting in an accurate and predictive model[.39](#page-10-7)

# **DATA ANALYTICS IN THE NATURAL ENVIRONMENT**

The natural environment influences cardiovascular health, particularly through factors such as air pollution, water and land pollution, and extreme temperatures [\(Table 2\)](#page-5-0). [40–](#page-10-8)[42](#page-10-9) For example, recent studies have investigated the impact of

environmental factors within the exposome on increased atrial fibrillation risk,<sup>43</sup> an underrecognized phenomenon. Additionally, numerous studies have established a strong association between air pollution and cardiovascular disease.[2](#page-8-2) The Global Burden of Disease study, for instance, identified air pollution as a leading environmental health risk[.2](#page-8-2) Specifically, fine particulate matter smaller than 2.5 micrometers in diameter, known as  $PM_{2.5}$ , is a major component of air pollution.<sup>44</sup> The relationship between  $PM_{2.5}$  and cardiovascular diseases is well-documented. While chronic exposures to  $PM_{25}$  have shown a significant impact on cardiovascular health outcomes,<sup>45</sup> acute and shorter-term exposures can also lead to a considerable increase in cardiovascular morbidity.<sup>46[,47](#page-10-14)</sup> For instance, a Canadian study found that for each 1 µg/m3 increase in  $PM_{2.5}$ , there was a 25% increase in the 10-year hazard ratio for cardiovascular mortality.[48](#page-10-15) Among the cardiovascular disorders, cerebrovascular disease morbidity and mortality also play a prominent role as being significantly influenced by PM<sub>2.5</sub> exposure.<sup>49</sup> One study exploring a US veteran cohort that has undergone coronary artery bypass grafting found that patients living in regions with higher ambient PM<sub>25</sub> were associated with higher rates of 10-year cardiovascular events[.50](#page-10-17) Furthermore, high blood pressure has also been identified in US regions with air pollution that has exceeded the World Health Organization guidelines.<sup>51</sup>

Ozone, another independent risk predictor of cardiovascular mortality, has been shown to affect cardiometabolic health in both short- and long-term exposures[.52](#page-11-1)–[54](#page-11-2) The combined presence of ozone with other air pollutants can amplify adverse health effects through changes in chemical half-life, potentially disrupting the blood-brain barrier and causing endothelial dysfunction.<sup>48</sup> Furthermore, toxic metals such as arsenic, mercury, lead, and cadmium also play a major role in the natural environment's impact on cardiovascular health.<sup>55</sup> These metals have been linked to various cardiometabolic diseases. For example, lead exposure, which remains particularly high in middle- to low-income countries, significantly increases blood pressure and is associated with cardiovascular mortality.<sup>[56](#page-11-4)[,57](#page-11-5)</sup> Lead, mercury, cadmium, and arsenic exposure have also been linked to an increase in cardiovascular disease-related mortality[.58](#page-11-6)–[60](#page-11-7) Lastly, extreme temperatures, whether below or above the optimal range, have been widely associated with increased cardiovascular morbidity and mortality[.2](#page-8-2)

Despite current knowledge about the impact of the natural environment on the cardiovascular exposome, significant gaps remain in this area of research. While many of the studies have revealed the individualistic effects of pollutants, there is minimal understanding of the synergistic or potentially antagonistic effects when



<span id="page-5-0"></span>**Table 2** Studies investigating the association between the natural environment and cardiovascular (CV) outcomes. CDC: Centers for Disease Control and Prevention; ATSDR: Agency for Toxic Substances and Disease Registry; CABG: coronary artery bypass graft

multiple pollutants are presented at various levels. This is supported by one study that revealed the synergistic impact of noise pollution combined with air pollution, as both of these factors converge at the vascular level to promote oxidative stress and inflammation, thus

contributing to the cardiovascular risk factor burden.<sup>61</sup> Furthermore, mechanistic understandings regarding genetic predispositions and their respective interaction with environmental factors are important to effectively identify vulnerable populations. These populations, including

those with existing health conditions and economically disadvantaged groups, may be more susceptible to increasing hazardous exposure. Additionally, while most of the studies investigating the impact of the natural exposome on cardiovascular health are retrospective and cross-sectional, more longitudinal studies that track environmental exposures over an entire life course may yield detailed insights regarding exposome-related early-life, adolescence, and adult-related outcomes.<sup>[62](#page-11-9)</sup> Longitudinal studies would also facilitate dose-response modeling that may quantify the relationship between exposure levels and health outcomes more precisely over a prolonged period of time.

A recent study used data from the China Health and Retirement Longitudinal Study to explore the impact of artificial light exposure, obtained from satellite image data, on incident cardiovascular disease.<sup>63</sup> They found that both low and high outdoor artificial light exposure were associated with greater rates of cardiovascular disease. This study emphasizes the crucial role of remote sensing technologies in monitoring environmental exposures. Satellite data can provide detailed information on air quality, temperature variations, and land use changes over time. By integrating this data with health records, longitudinal studies become feasible.[63](#page-11-10) This integration may also enable increasingly accurate predictive modeling techniques, aiding future predictions of cardiovascular events based on environmental data. These models can potentially simulate various scenarios, such as changes in pollution levels due to policy interventions, and predict their impact on cardiovascular health.

Machine learning and artificial intelligence algorithms could enhance our understanding of the relationship between the natural environment and cardiovascular health. One study evaluated the performance of multiple artificial intelligence models using nitrogen dioxide levels from ground-based monitoring systems and found that these models accurately forecasted nitrogen dioxide levels, potentially impacting future monitoring system approaches.[64](#page-11-11) Furthermore, unsupervised learning techniques like clustering can group similar exposure profiles to determine their respective impact on cardiovascular health. Ultimately, while many cardiovascular outcomes have shown an association with poor natural exposome environments, the implementation of science and translation into effective public health policies remain poorly understood.

# **DATA ANALYTICS IN THE BUILT ENVIRONMENT**

The built environment, encompassing human-designed spaces where people live and engage in daily activities, is increasingly recognized as a significant factor that impacts cardiometabolic health ([Table 3\)](#page-7-0). [65](#page-11-12) The built environment significantly influences cardiovascular health by shaping behavioral risk factors associated with cardiovascular disease. Key attributes, such as promoting active lifestyles, providing access to recreational spaces and greenspace, encouraging walkability, and ensuring food security, all play a crucial role in this relationship.

Key elements of the built environment include walkability, access to greenspace, and community design. For example, using data from the Houston Methodist Learning Health System Outpatient Registry, the relationship between cardiovascular risk factors and neighborhood walkability were explored.<sup>66</sup> Using a cross-sectional design, this study identified that patients who resided in the most walkable regions had the least prevalence of cardiovascular risk factors—including hypertension, obesity, diabetes, and dyslipidemia—regardless of the presence of clinical atherosclerotic coronary disease.<sup>[66](#page-11-13)</sup> Furthermore, a crosssectional study using data from the Cardiovascular Health in Ambulatory Care Research Team (CANHEART) cohort investigated the relationship between neighborhood walkability and cardiovascular disease risk factors<sup>67</sup> and found that lower walkability was also associated with higher rates of hypertension and diabetes.<sup>67</sup> This reflects that actively targeting factors associated with improved cardiovascular health, well-being, and quality of life should be encouraged within the exposome framework, a concept recently coined as the "benignome," in contrast to the "pollutome" which relates to chemical and physical pollutants[.68](#page-11-15)

Access to greenspaces—areas with shrubs, grass, trees, or other vegetation—offers cardiovascular protection through encouraging physical activity and social interaction while also mitigating noise and air pollution exposure. For example, increased residential greenery correlated with increased protection against both high and low blood pressure<sup>[69](#page-11-16)</sup> and reduced cardiovascular mortality[.70](#page-11-17) Another aspect of the built environment impacting cardiovascular health is food insecurity, characterized by limited access to sufficient and nutritious food. Over 10% of American adults experience food insecurity, which is linked to poor cardiometabolic health.[71](#page-11-18) Moreover, one study investigated the impact of food insecurity on 27,188 individuals who participated in the US National Health and Nutrition Examination Survey.<sup>[72](#page-11-19)</sup> It found that participants with low food security had higher rates of all-cause and cardiovascular disease-related mortality compared to participants with higher food security, regardless of adjustment for other demographic and socioeconomic variables[.72](#page-11-19) Another retrospective analysis examined the impact of the food environment index, a measure of food insecurity and



<span id="page-7-0"></span>**Table 3** Studies investigating the association between the built environment and cardiovascular outcomes.

food deserts, on cardiovascular mortality $73$  and found that a lower food environment index was associated with higher cardiovascular mortality, with the most pronounced effect in counties with greater income inequality and a predominantly African-American population. A corroborating retrospective cohort analysis revealed that food deserts were associated with a higher proportion of residing US veterans with established atherosclerotic cardiovascular disease and subsequently higher risks of all-cause mortality and cardiac events.<sup>[74](#page-11-21)</sup>

Mechanisms related to food insecurity and cardiovascular health are likely multifactorial. Populations with a lower socioeconomic status may have a greater tendency to consume cheaper, calorie-dense foods, which may lead to insulin resistance and adipose tissue deposition, along with the emotional and physiological stress associated with food insecurity. Additionally, the financial burden from healthcare costs can negatively affect financial security, potentially leading individuals to opt for more affordable food choices. Similarly, the consumption of ultra processed foods, which are industrially produced and often energy-dense, has surged in both middle- and high-income countries.<sup>75</sup> Ultra processed foods are linked to poor cardiovascular health outcomes, contributing to the development of diabetes, obesity, hypertension, and hyperlipidemia.[76](#page-12-1)

Advancements in artificial intelligence, similar to those in the social and natural components of the exposome, have progressed considerably in recent years. For example, a recent study used satellite imagery of different US cities to investigate its predictive capabilities regarding the prevalence of chronic kidney disease, cerebrovascular disease, and coronary heart diseases.[77](#page-12-2) This study built a model that accurately estimated the census-level burden of cardiometabolic disease prevalence by utilizing a deep learning network consisting of Google Street View features. Subsequently, machine learning models were used for prevalence prediction, resulting in appropriately predictive models.[77](#page-12-2)Another cross-sectional study used Google Street View images to create a machine vision-based model of the built environment in order to estimate the prevalence of coronary heart disease at a census-tract level.<sup>78</sup> Using activation maps, convolutional neural networks, and linear mixed-effects models, these deep-learning algorithms predicted 63% of the coronary heart disease prevalence independent of census-tract level population demographics.

Ultimately, the research paradigm related to evaluating the impact of the built environment on the cardiovascular exposome has shown promising advancements. Machine- and deep-learning algorithms can provide valuable information about healthier living

conditions, focusing on city planning initiatives that promote cardiovascular health. Longitudinal approaches are still lacking, which could differentiate the impact of short- and long-term walkability on cardiovascular disease. Additionally, the analysis of cardiovascular risk factor prevalence before and after modifications to the built environment, such as bike lanes, new parks, and other features, has been less investigated. These studies could be conducted using time-series analyses or timed pre- and post-intervention studies.

#### **CONCLUSION**

Increased use of computational approaches in medical data-driven analyses has advanced our understanding of the exposome, revealing a myriad of important components. Recent advancements in understanding the cardiovascular exposome have revealed significant, independent associations with the prevalence and management of cardiovascular disease. Despite these promising developments, there is still a gap in the creation of platforms that utilize poly-social and exposomal variables for risk assessment as well as in the formulation of updated health-related policies. Such a platform will improve our understanding of the details that encompass various exposome facilitators, developing fingerprints related to CVD prevention, prevalence, and treatments categorized through spatiotemporal neighborhoods. Datadriven multiomics platforms that integrate factors such as genomics, epigenomics, clinical data, social factors, environmental factors, radiologic data, and wearable technology will characterize the exposome in greater detail concerning cardiovascular health. Such an approach would enable targeted public health interventions and early intervention in vulnerable regions, thereby fostering innovation in risk reduction strategies.

## **KEY POINTS**

- **•**  Exposome Impact: Emphasizes the comprehensive impact of environmental and socioeconomic factors on cardiovascular health.
- **•**  Data Analytics Role: Highlights the essential role of advanced data analytics in understanding and managing cardiovascular disease risks.
- **•**  Public Health Strategies: Supports the development of targeted public health interventions to reduce cardiovascular disease prevalence based on exposome insights.

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The authors have no competing interests to declare.

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