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RESEARCH ARTICLE

Economic Inequality and Cardiovascular disease in the United Kingdom: A new benchmark and a web dashboard

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Abstract

This paper examines the disparities in heart disease prevalence among different income groups in the United Kingdom, highlighting significant inequalities that persist within the healthcare system. Utilising a specialised Gini index tailored for health inequality, we quantify the extent of these disparities, providing a robust statistical framework for understanding the relationship between socioeconomic status and heart disease outcomes. Our analysis reveals that lower-income groups experience a disproportionately higher burden of heart disease, underscoring the urgent need for targeted public health interventions. To enhance public awareness and accessibility of health equity data, we developed an interactive web dashboard that visualises the prevalence of heart disease across income brackets, allowing users to explore and comprehend the health inequities affecting their communities. This dashboard serves as a vital tool for policymakers, healthcare providers, and the general public, fostering informed discussions and driving efforts toward reducing health inequalities in the UK. Through this work, we aim to contribute to the ongoing dialogue around health equity and advocate for policies that address the root causes of health disparities.

Keywords: *Cardiovascular disease*; *Inequality*; *Gini health coefficients*

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Inequality is a pervasive issue that affects various aspects of health and well-being, with heart disease serving as a prominent example. As one of the leading causes of morbidity and mortality, heart disease not only reflects individual health outcomes but also mirrors the broader socio-economic disparities present in society (Marmot, 2010). The relationship between socio-economic status and heart disease is complex, influenced by a myriad of factors including access to healthcare, lifestyle choices, environmental conditions, and social determinants of health (Lynch et al., 2000). In the UK, significant disparities in heart disease prevalence and outcomes have been observed across different demographic groups. Research indicates that individuals from less affluent socio-economic backgrounds are at a higher risk of developing heart disease, with contributing factors such as poor diet, lack of physical activity, and limited access to healthcare services (NHS Digital, 2021). Furthermore, these inequalities are often compounded by geographical variations, with certain regions experiencing higher rates of heart disease due to socio-economic deprivation, lifestyle factors, and healthcare access (Public Health England, 2025).

This paper aims to advance quantitative studies of the relationship between inequality and heart disease in the UK. A benchmark, the Gini coefficient for disease, is formulated for selected cardiovascular conditions in UK cities. This index makes disparities in terms of income and health readily apparent. Some preliminary results of how this measure varies by outcome and city are presented, along with a study on how health inequality depends on the wealth of the city. A second aim is to present a first version of a web geographical dashboard where the user can select from a number of illnesses, ascertain the locations of assessment centres in the graphical j5tnbnbmaps and visualise the distribution of disease based on income levels. Such a health equality web dashboard allows easy examination of geographical trends in health inequality.

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Materials and Methods

Data

A total of 3235 observations from 17 assessment centres in the UK Biobank were used for the analyses. Vascular heart problems assessed were angina, heart attack, high blood pressure and stroke.

Gini coefficient and lowest to highest ratio

The Gini coefficient for each disease was derived from the distribution of income in the five Income Groups (g): less than £18,000; 18,000-31,000; 31,000-52,000; 52,000-100,000, and greater than £100,000. The basic benchmarks are shown in Table 1. The Gini index measures inequality, but it does so based on the relative distribution of wealth among a population.

The cumulative quantity Cumulative Group Disease Prevalence (CDP_g) is then derived from:

$$CPD_g = \sum_{i=1}^{g} DP_i$$

Where DP_i is the proportion of the population in an individual group. Similarly the Cumulative Group Population (CP_g):

$$CP_g = \sum_{i=1}^{g} P_i$$

Based on a total number of groups n (in this case 5), these are then normalized as a) the Cumulative Disease Frequency (CDF_g) = CPD_g / CPD_n and Cumulative Population Frequency (CPF_g) = CP_g / CP_n, respectively. The final step is then the Gini coefficient for health (GCH):

$$GCH = \frac{1}{n}\sum_{i=1}^{n} \frac{\left(CDF_i - CP_i\right)}{CP_i}$$

Based on a sorting of the income groups from lowest to highest, the lowest to highest ratio measures the ratio between the prevalence in the lowest and the highest income group:

$$LTH = \frac{DF_1}{DF_n}$$

Table 1. Income prevalence concepts

Entity	Notation	Interpretation
Group Disease Prevalence	DP_g	Number of observations in an income group having the condition
Group Population	P_g	Total number of people in the group
Group Disease Frequency	DF_g	Share of population in an income group having the condition

The association between health inequality measures and various socio-economic quantities was ascertained with a Spearman's rank correlation test.

Web Dashboard Framework

The primary framework used to build the application was React.js, which provided an efficient way to render UI components and manage state. React follows a virtual DOM (Document Object Model) approach, which optimises rendering performance by updating only the components that have changed rather than reloading the entire page. React's unidirectional data flow and state management ensure predictable UI updates, making it particularly effective for complex, interactive applications such as data-driven dashboards. In this application, an interactive map visually represents disease prevalence across different geographic areas, dynamically adjusting as users apply filters. The app was tested thoroughly for responsiveness, interactivity, and data accuracy.

The interactive mapping (Figure 1) was implemented using Leaflet.js, with React-Leaflet serving as a React wrapper of seamlessly integrate Leaflet's powerful mapping features into React components. By leveraging React's state-based reactivity, the application can dynamically update the map in response to user interactions. CSV data containing location or property information was parsed using Papa Parse, enabling the app to display relevant markers and interactive pop-ups associated with detailed information. For data visualisation, D3.js was employed to scale and colour elements based on geospatial data, enhancing the user experience with a clear visual representation of locations and user interactions. For simpler charting needs, the application also utilises Chart.js. In this application, Chart.js is particularly useful for maintaining an orderly bar chart of visualise income levels and disease prevalence. Regarding the user interface, it was styled with CSS3 and Tailwind CSS, enabling a responsive, modern, and flexible design.

React.js was used as the primary framework for building the user interface, providing an efficient way to render UI components and manage state interactions. The mapping functionality was implemented using Leaflet.js, a widely used mapping library, with React-Leaflet as a React wrapper for seamless integration. This allowed the map to dynamically update with markers and pop-ups. To handle and parse CSV data containing location or property information, Papa Parse was utilised, enabling the app to display relevant markers based on the data. Styling was achieved with custom CSS3 and Tailwind CSS, ensuring a responsive, modern design. For data visualisation, D3.js was employed to scale and colour elements based on geospatial data, enhancing the user experience with a clear visual representation of locations and user interactions. The map was created with Leaflet.

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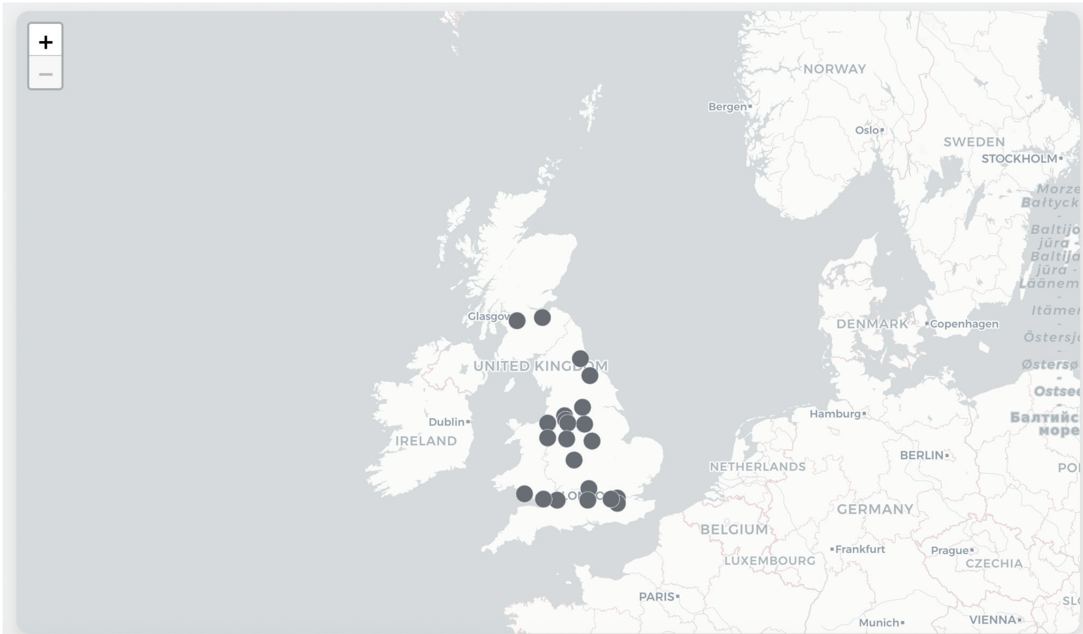

Fig. 1. Interactive map of the UK.

js and React-Leaflet, allowing for dynamic rendering of markers based on parsed CSV data. Each marker was associated with detailed information, displayed through interactive pop-ups when clicked. Papa Parse handled parsing of CSV data, which was used to update the map dynamically. D3.js enabled the application of visual effects, such as scaling and colouring, based on specific data attributes. The user interface was styled with custom CSS3, enabling a responsive, flexible design. The app was thoroughly tested for responsiveness, interactivity, and data accuracy.

The application is built using React.js (https://react.dev/), a widely adopted JavaScript library for building declarative, component-based user interfaces (UIs). React follows a virtual DOM (Document Object Model) approach, which optimises rendering performance by updating only the components that have changed rather than reloading the entire page. React's unidirectional data flow and state management ensure predictable UI updates, making it particularly effective for complex, interactive applications such as data-driven dashboards.

The interactive map (Figure 1) is implemented using React-Leaflet (https://react-leaflet.js.org/), a React wrapper for Leaflet.js (https://leafletjs.com/). Leaflet is a lightweight, open-source JavaScript library for interactive maps, designed with simplicity and performance in mind. Unlike bulkier mapping frameworks like Google Maps API, Leaflet is optimised for speed, making it ideal for real-time, interactive visualisations. React-Leaflet enables seamless integration of Leaflet's powerful mapping features into React components, leveraging React's state-based reactivity to dynamically update the map in response to user interactions. In this application, the map visually represents disease prevalence across different geographic areas, dynamically adjusting as users apply filters.

The application's styling is written in CSS, Level 3 (CSS3), which provides enhanced styling capabilities such as flexbox, grid layouts, and animations. By separating styling from component logic, the application maintains clean, modular code, ensuring scalability and maintainability. The graphs (Figure 2) are created using D3.js (https://d3js.org/), a powerful JavaScript library for data-driven document manipulation. D3.js allows for the creation of scalable, dynamic visualisations by binding data to SVG elements and applying transformations based on that data. Unlike traditional charting libraries, D3.js offers complete control over the visualisation, enabling customised interactions and transitions. It is particularly well-suited for complex, interactive data visualisations such as those in this application. For simpler charting needs, the application also utilises Chart.js (https://www.chartjs.org/), a lightweight yet powerful charting library designed for quick, flexible graph integration in web applications. react-chartjs-2, a React wrapper for Chart.js, is used to facilitate seamless integration of Chart.js within React components. Unlike D3.js, which provides low-level control over visualisation elements, Chart.js offers a more intuitive API for generating common chart types such as bar, line, and pie charts. In this application, Chart.js is particularly useful for maintaining an orderly bar chart visualisation

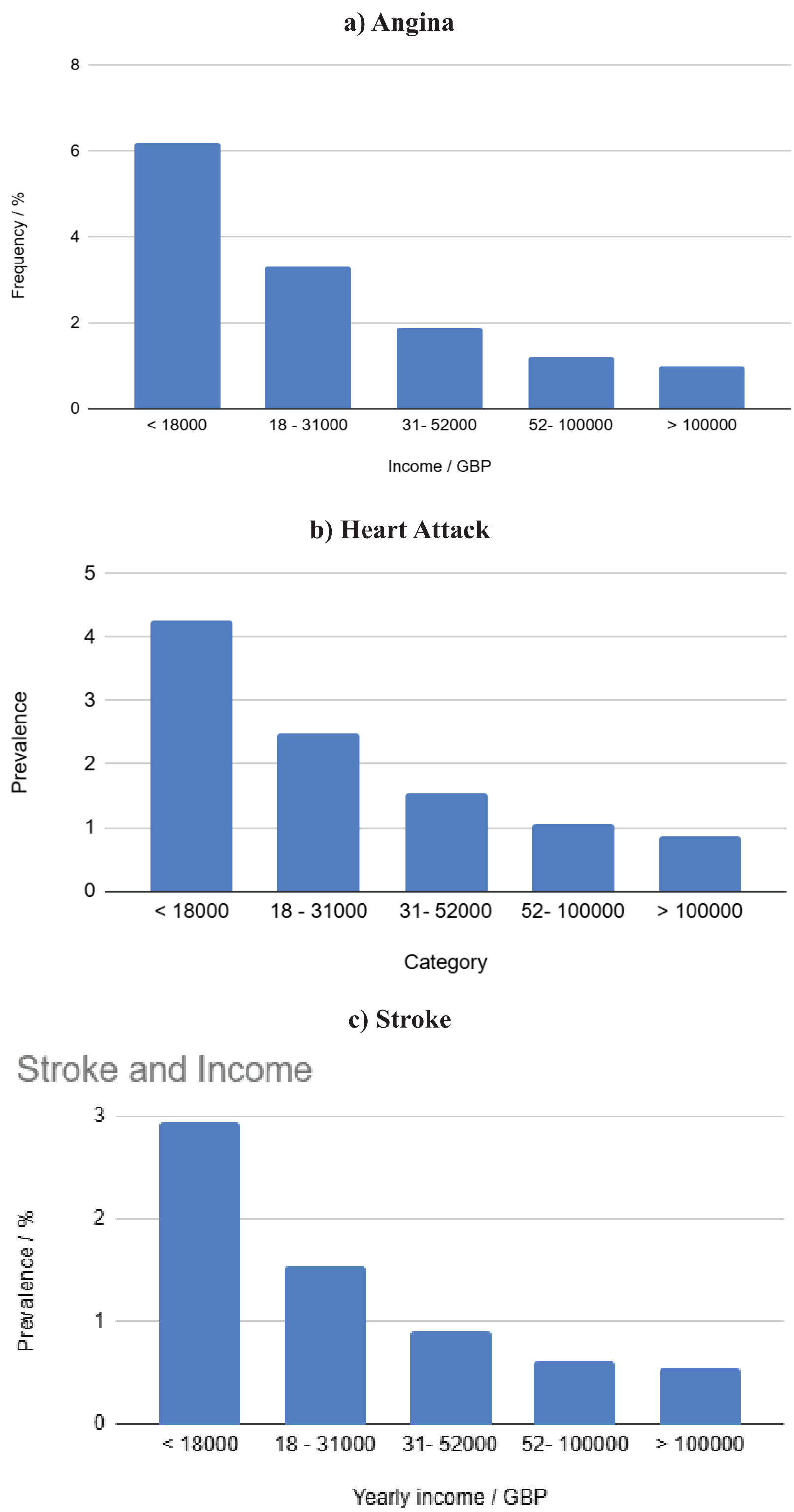

Fig. 2. Prevalence by income category for a) Angina, b) Heart Attack and c) Stroke based on the entire country.

of income levels and disease prevalence. The data is stored in CSV (Comma-Separated Values) files and parsed using Papa Parse (https://www.papaparse.com/), a fast and efficient client-side CSV parser for JavaScript. Papa Parse is optimised for handling large datasets with streaming capabilities and error detection, making it particularly well-suited for applications dealing with extensive health and demographic data.

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Theory

Inequality and health

The Social Determinants of Health (SDH) framework posits that health outcomes are significantly affected by the conditions in which people are born, grow, live, work, and age (Dean et al., 2013). It emphasises that socio-economic status, education, and access to healthcare are critical determinants of health. Research has demonstrated that individuals in lower socio-economic strata often experience higher rates of heart disease, attributed to factors such as limited access to healthy food, inadequate healthcare, and increased stress levels (Kuh, 2000).

Another relevant theory is the Health Belief Model (HBM), which suggests that individual health behaviours are influenced by personal beliefs about health risks and the benefits of taking action (Rosenstock, 1974). This model can help explain why individuals from disadvantaged backgrounds may engage in behaviours that increase their risk of heart disease, such as smoking or poor dietary choices, often due to a lack of awareness or perceived barriers to healthier options (Champion & Skinner, 2008). The Life Course Perspective also plays a crucial role in understanding health disparities. This theory posits that health outcomes are the result of cumulative exposures and experiences throughout an individual's life (Elder, 1994). Factors such as childhood poverty, education, and social networks can have long-lasting effects on cardiovascular health, highlighting the importance of early interventions to address inequalities (Ben-Shlomo & Kuh, 2002). In addition, the Ecological Model provides a comprehensive approach by considering the interplay between individual, relationship, community, and societal factors. This model emphasises that health behaviours and outcomes are influenced not only by individual choices but also by broader social and environmental contexts (McLeroy et al., 1988). For heart disease, this means that community resources, social support networks, and policies can significantly impact health outcomes and help mitigate inequalities.

Benchmarks of inequality

Economic and social differences are measured using fixed points that allow us to compare groups over time and across populations. These numbers reveal gaps in income, wealth, access to healthcare, and education. The Gini coefficient is a statistical dispersion measure used to represent income inequality within a population (De Maio et al., 2007). Perfect equality is represented by a coefficient of 0 and absolute inequality by a coefficient of 1 (Charles, Gherman, and Paliza, 2022). A larger gap between the rich and the poor is indicated by a higher Gini coefficient (Sitthiyot & Holasut, 2020). The numeric calculation of the value as the area in a Lorenz curve is visualised in Figure 3.

Affluence and inequality

Research consistently demonstrates that socioeconomic status significantly influences health outcomes. Interrelated factors such as poverty, employment opportunities, access to healthcare, and education levels impact health. For example, lower-income households purchase fewer fruits and vegetables while consuming higher amounts of sugar-sweetened beverages (French, et al., 2019), contributing to an increased risk of diet-related diseases such as obesity, type 2 diabetes, and cardiovascular conditions. Wealthier individuals typically benefit from faster, more comprehensive medical care. A 2024 study found that young people aged 15 to 17 from more affluent areas of the UK have significantly better access to outpatient care, including mental health and dental services, compared to those in less affluent regions (Martínez-Jiménez, Hollingsworth, & Zucchelli, 2024). This disparity can have long-term consequences, as early intervention and preventive care are crucial to maintaining overall well-being. Undiagnosed and untreated conditions exacerbate health inequalities over time.

Web mapping frameworks

Web mapping frameworks provide powerful tools to display and interact with geographic data in web applications. These frameworks enable developers to integrate interactive maps, handle geospatial data, and create dynamic, user-friendly experiences. One of the most widely used web mapping frameworks is Leaflet. Leaflet is an open-source JavaScript library known for its simplicity, performance, and flexibility. It allows for easy integration of interactive maps into web applications.

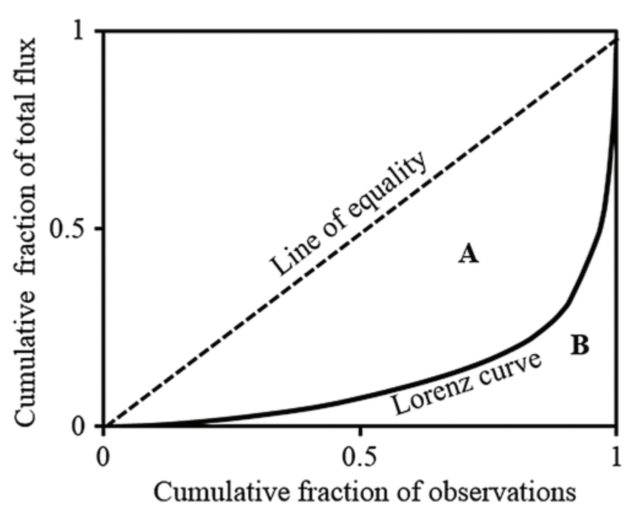

Fig. 3. Visual explanation of Gini coefficient (Saha et al., 2018).

With Leaflet, developers can add features such as zoom controls, custom markers, pop-ups, and various map layers, all while maintaining a lightweight and responsive experience. Its support for numerous map tile providers, including OpenStreetMap and Google Maps, and its compatibility with various plugins make it an ideal choice for creating custom, data-driven maps.

Leaflet's versatility extends to both mobile and desktop environments, ensuring a smooth experience regardless of platform. Its ability to handle geo-spatial data and display it in a user-friendly manner is a key advantage, especially when combined with data-driven layers like heatmaps, choropleth maps, and real-time data visualisation. For more complex needs, Leaflet can be extended with plugins that add functionality such as routing, clustering, and geolocation. In summary, Leaflet is a powerful web mapping framework that provides essential tools for integrating interactive maps into web applications, making it an excellent choice for developers looking to present geospatial data in an intuitive and engaging way.

UK Biobank

The UK Biobank is one of the largest and most comprehensive health databases in the world, established to support scientific research into the causes of a wide range of diseases and to improve public health (Sudlow et al., 2015). The Biobank includes genetic, lifestyle, and health information from over 500,000 participants across the United Kingdom, providing a rich dataset for understanding how genetics, environment, and behaviour interact to influence health outcomes. Participants in the UK Biobank provided detailed information on their lifestyle choices, including physical activity, diet, smoking, and alcohol consumption, as well as their medical history. Additionally, the database includes genetic data, offering insights into how genes may predispose individuals to certain diseases or conditions. This vast amount of data is used by researchers to identify patterns and risk factors for chronic diseases such as cardiovascular conditions, diabetes, cancer, and mental health disorders. The recruitment process is described in Figure 4.

Results

Nationwide

The distribution of people between income groups is shown in Figure 5.

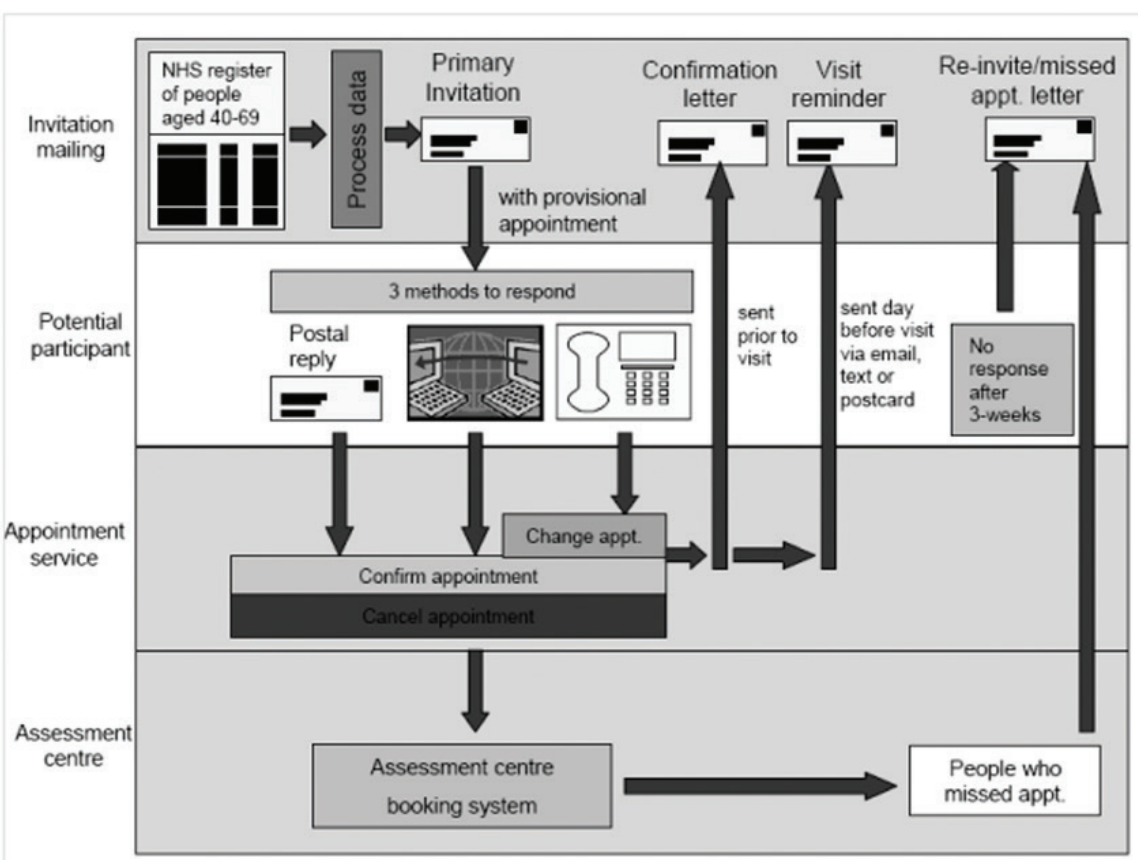

Fig. 4. UK Biobank recruitment (Smith et al., 2013).

The prevalence of angina, heart attack (myocardial infarction), and stroke, in each income group nationally, is presented in Figure 2. Angina tended to be the most unequal of the conditions, both in terms of the lowest to highest ratio and the Gini coefficient Table 2. For comparison, the overall Gini coefficient for income for the total population studied was 0.29.

By City

The mean Gini coefficients (mean of the values for the three studied conditions) and ratios of prevalence, lowest income to highest, for each city are shown in Table 3. The correlation between health inequality measures and various socio-economic quantities was ascertained. The Gini coefficent was strongly correlated to mean income ($rs = 0.71$, $p < 0.001$), implying that higher affluence led to more inequality. The correlation between Gini Income and Gini Health was -0.83, but it was not significant.

The Health Equality Dashboard

The app showcases correlations between heart disease and economic inequality in the UK. With an interactive interface (Figure 6), users can choose between specific cities and heart conditions, like angina, stroke, high blood pressure and heart attack. As shown in Figure 6, the sidebar displays the overall prevalence alongside a graph showing prevalence for each economic group.

This dashboard provides an easy-to-understand resource that presents information on health inequalities in cardiovascular conditions. Although other cardiovascular health dashboards exist, they typically focus on disease prevalence or mortality rates. The dashboard presented here differs in that, rather than simply showing outcomes, it provides some insight into the underlying factors accounting for patterns in disease occurrence seen.

Prevalence

When a specific data center and condition are selected, a segment in the sidebar displays the percentage prevalence of that disease in the given area (Figure 7).

Statistics

A Bar chart using React ChartJS-2 shows the correlation between income levels and the chosen disease. It also shows the Gini coefficient, a statistic measuring income inequality, and the discrepancy in prevalence across income groups (e.g., lowest, lower-middle, upper-middle, and highest). The visibility of the income graph is dependent on whether income data is available for the selected center and disease.

Discussion

All studied conditions show a clear trend: individuals with incomes below 18,000 GBP have the highest prevalence, while the most affluent have much lower rates. The Gini coefficient was strongly correlated with mean income, suggesting that greater affluence was associated with greater inequality. This indicates that as income increases, the prevalence of these diseases declines, highlighting the underlying negative correlation between

Table 2. Heart disease statistics for the United Kingdom

Condition	LTH ratio	Overall prevalence	Gini coefficient
Angina	6,17	3,05	0,36
Heart Attack	4,83	2,23	0,31
Stroke	5,36	1,48	0,35

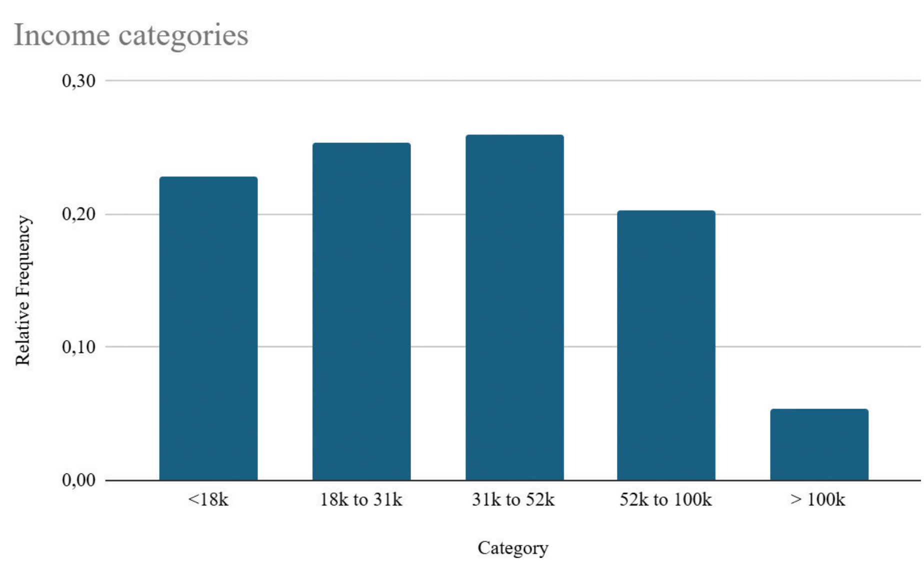

Fig. 5. Income categories and relative frequencies.

Table 3. Summary of mean Gini and Gini coefficient for UK cities

Centre	Mean Gini Health	Mean Income / (GBP per week)	Gini coefficient income
Birmingham	0.26	652	0.35
Bristol	0.35	709	0.30
Bury	0.25	618	0.35
Cardiff	0.37	676	0.32
Croydon	0.29	772	0.30
Edinburgh	0.43	746	0.30
Glasgow	0.38	750	0.34
Hounslow	0.36	724	0.30
Leeds	0.31	665	0.33
Liverpool	0.26	671	0.35
Manchester	0.32	707	0.34
Middlesbrough	0.26	591	0.34
Newcastle	0.29	640	0.35
Nottingham	0.30	592	0.34
Oxford	0.48	755	0.28
Reading	0.40	784	0.27
Sheffield	0.30	638	0.34

Oxford has the highest amount of health inequality and Edinburgh second, while Bury is the most egalitarian center followed by Birmingham, Middlesbrough and Liverpool.

them. This finding is in line with earlier studies (Kuh, 2000; NHS Digital, 2021) that have shown a relationship between chronic health conditions and socioeconomic status. Angina tended to be the least equal of the three, which calls for further research.

By city

There was a very distinct association between health inequality and mean income, with richer communities exhibiting a less egalitarian distribution of cardiovascular disease. While cities can be more diverse and offer a wide range of opportunities to improve residents' health, they often have high concentrations of deprivation and poverty. Because these deprived and poor areas are often very close to affluent areas, the health effects of deprivation are particularly evident (Chief Medical Officer, 2024). Therefore, wealthier cities might highlight a more significant disparity between people living in affluent and impoverished areas.

National

In addition, recent data published in December 2024 by the Office for National Statistics (ONS) of the UK have revealed that health inequalities have increased over the past decade in England and Wales. The ONS measures Health Life Expectancy (HLE), defined as the years an individual is expected to live in "good" general health. Between the highest- and lowest-ranked areas in England, in the periods from 2011 to 2013 and from 2021 to 2023, the

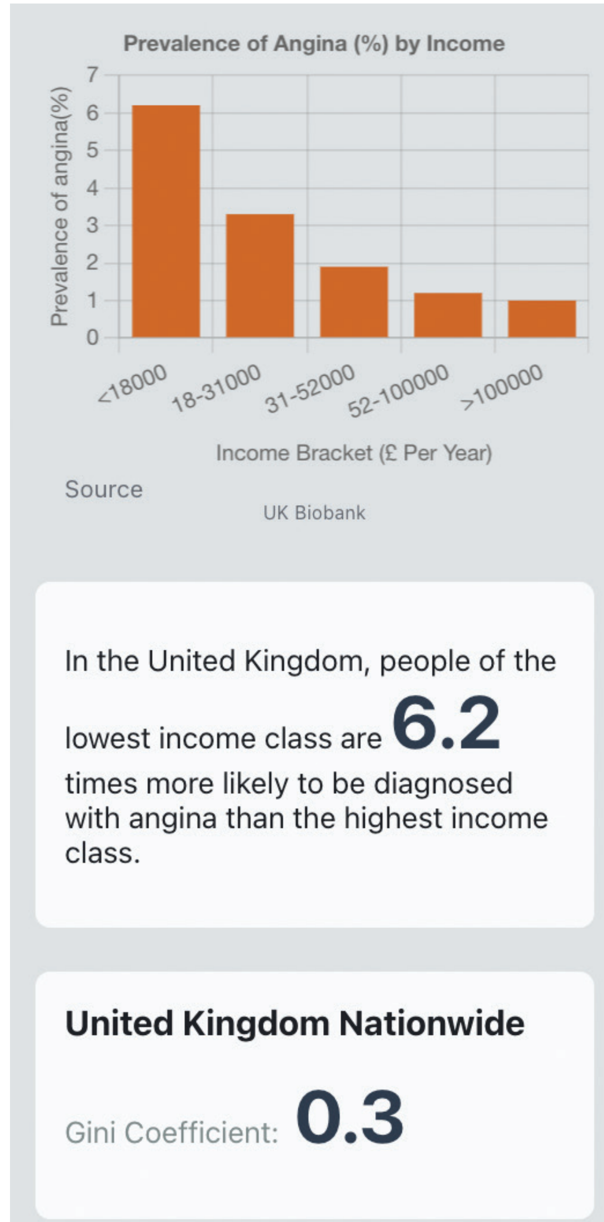

Fig. 6. Economic Data Visualisation.

Fig. 7. Prevalence widget.

difference in HLE was huge. For males, this gap grew by 22% from 2011 to 2013, reaching a difference of 17.9 years. For females, the gap was 18.2 years, with a growth of 17.1%

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from 2011 to 2013. Regarding the region of Wales, the difference in HLE was lower: 11.0 years for males, and 12.6 years for females. Even though the difference is smaller than in England, the gap increased significantly from 2011 to 2013, by 13.3% and 16.5% for men and women, respectively (ONS, 2024). In conclusion, individuals living in more affluent areas of the UK can expect to live more years in good health than those living in less affluent areas.

Implications

The main takeaways from our study are that a) heart disease is highly unequally distributed among the income echelons, with the least affluent groups being up to 10 times more likely to be struck by one of the main conditions, b) modern front-end frameworks and geographical packages make it possible to present data on prevalence and inequality to the general public. This helps enlighten the public and form the basis of a discussion on inequality in health outcomes.

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