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Understanding and Predicting Health across the London Region: Developing an Index of Accessibility to Healthy Environments

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Abstract

Attributed to widening health inequalities and deterioration of health across the United Kingdom, how accessibility to physical environmental features may be implicated in neighbourhood-level health has become a central concern for policy-makers in designing healthy neighbourhoods. However, the dominant explanation of health inequality and outcomes has centred around understanding demographic and socio-economic factors. Therefore, this work looks to develop an over-arching framework to quantify accessibility in order to identify inequalities in access to healthy environments and how this may be useful for understanding/predicting health. Using points of interest data for 8 health-related facilities/services, this work uses network analysis in the creation of a multidimensional accessibility index. The work further uses correlational and regression analysis to establish associations between the index, demographic and socio-economic factors, and health in London. The work identifies a clear urban-rural divide in accessibility, with those in urban areas benefitting from greater access to healthy environments. However, no associations were identified between accessibility and health measures, thus, accessibility does not emerge as a useful predictor of health across London. Instead, age, skill level, and education arise as the key explanatory factors of health variation in London.

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Chapter 1: Introduction

1.1: Research Context

Accessibility, defined as the 'distance of an individual or object to a dimension or feature of interest' (Green at al., 2018), is a key platform for spatial development. The concept of accessibility has long been used in a human and urban geography context, in the analysis of land use, analysing facility and service distribution, and identifying optimal routes for overcoming distances between locations (Ingram, 1971). The analysis of accessibility continues to provide a central perspective for urban, regional, and national research endeavours across the wider geographical literature, recently within the realm of health geography.

Despite advancements in healthcare quality and treatment, the prevalence and size of health inequality has increased, unabated, over the last 10-15 years. Marmot et al. (2020) have highlighted how across England, health inequalities are 'worrying' and 'unjust', with health deteriorating and health inequalities widening nationwide since their review of health a decade ago; this includes greater inequalities between life expectancy, infant mortality rates, and physical health outcomes. While it has been theorised that this pattern of widening health inequality can be attributed to social and economic platforms, the question arises regarding the influence accessibility to healthy environments may have on such an issue. Subsequently, attributed to the significant advancements in geospatial analysis and geographic information systems (GIS), as anticipated by (Guagliardo, 2004), accessibility has, in the last 4 decades, come to the forefront as a key approach for identifying and understanding the geographical or spatial dimension of health (Páez et al., 2010). This has motivated researchers to attempt to understand how living close to a health-related features of the environment may influence the risk of ill-health. However, ensuring equity in accessibility is a considerable challenge for local councils and policy-makers given there is a lack of quantifiable research surrounding this topic. Green et al. (2018) are among few researchers who have endeavoured to explore this highlighting apparent spatial inequalities in access to healthy environments. Such research provides beneficial resources for policy makers in being able to identify areas facing inequality, aiding policy-making decisions when aiming to target areas facing the greatest inequality to health-related environments (Richardson et al., 2010).

However, what appears to be an ostensibly obvious relationship between health and accessibility may not really be what it seems. With lifestyles becoming increasingly sedentary and health provision not meeting the needs of the population in all areas, those unable to access healthy environments may be most at risk of living in poor health (Williams et al., 2020). Previous research assumes that those facing greatest inequality regarding access to healthy environments will inevitably have reduced health outcomes and face greatest health inequalities. However, the understanding behind such claims is complex, with few pieces of research reliably drawing associations between accessibility and health outcomes. Scholars have reached varied conclusions, based on quantitative and qualitative analysis, on what they believe to be the main determinants of health (WHO, 2008; McKeown, 2016). 'Classical' research emphasises the role of aspatial factors as key predictors and platforms for understanding health with complex interaction between socio-economic and demographic factors providing undeniable associations with health outcomes and health inequality (White-Williams et al., 2020). Hence, with health data in England demonstrating rising numbers of poor health (Newton and Fitzpatrick, 2018), understanding whether geographical accessibility has an implicating role in health outcomes, alongside demographics and socio-economics, has become of vital importance to limit expansion of health inequality and to allow for positioned, area-targeted changes to health policies.

1.2: Research Aims, Questions and Objectives

Given the need to ensure health inequalities do not continue to expand and health outcomes improve, the overarching aim of this investigation is:

"To use GIS and spatial data to identify inequalities in accessibility to healthy environments and understand the extent to which this can be used to understand and predict health variation across London Lower Super Output Areas (LSOAs) when combined with a number of known impacts on population health"

To achieve the aim, this dissertation will seek to answer three primary research questions, each associated with a set of objectives:

- **How can the geographical dimension of health be used to understand health inequality across London?**
    - *Use points of interest (POI) data to develop a multidimensional index to quantify accessibility to health-related environments.*
    - *Using ArcGIS Pro, identify the spatial distribution of accessibility (the geographical dimension of health) to understand spatial inequalities in access to healthy environments across London LSOAs.*
- **Do any patterns to accessibility exist beyond distance?**
    - *Ascertain associations across London LSOAs between the overall accessibility index and its constituent domains with a series of demographic and socio-economic area characteristics using the SPSS statistical programme.*

- **To what extent can accessibility be used to predict general health of London's population?**
    - *Using SPSS, develop a multivariate linear regression model to synthesise accessibility, socio-economic and demographic data and measure their influence on London's health.*

This work will critically investigate whether understanding accessibility provides a valuable platform for policy-makers when aiming to target areas with poor health outcomes or facing the greatest health inequalities. Although determinants of health have been comprehensively researched, it is important to build on existing work, expanding knowledge, and contributing to the literature information regarding how accessibility may be implicated in health. Based on previous findings, it is expected that results will develop a spatial understanding of accessibility inequalities, with access likely unevenly distributed across London, as noted by Green et al. (2018). It is expected that associations between accessibility and area characteristics will be identified with low-access areas likely having stronger associations with poor self-reported health and deprivation, as found by Green et al. (2018). Finally, it is hypothesised that accessibility will likely have some ability to predict health, although demographics and socio-economics will still emerge as key predictors of health (Diez-Roux, 2001).

1.3: Document Structure

This research has been divided into 7 chapters, as below:

- Chapter 2: Literature Review
- Chapter 3: Data
- Chapter 4: The Geographical Dimension of Health
- Chapter 5: Using Accessibility to Predict Health
- Chapter 6: Research Limitation
- Chapter 7: Conclusion

Chapter 2: Literature Review

This chapter analyses the major academic work relevant to the topic of this dissertation. The chapter's analysis is mainly focused on identifying the key concepts and domains for understanding accessibility as a determinant of health, providing background knowledge essential to achieve the aim of this thesis. This chapter will also seek to engage with more traditional research regarding aspatial determinants of health. The chapter will assess suitable methodologies before identifying areas of accessibility and health geography literature that require further insight, which will form the basis for ensuing chapters.

2.1: Aspatial Determinants of Health

Demographic and social determinants of health are arguably the most comprehensively researched influences of health inequality and health outcomes, establishing a basis for a myriad of health research within the social sciences domain (Varbanova and Beutels, 2020). Both demographic and socio-economic factors are implicated in ill-health alongside healthcare-seeking behaviours and attitudes toward healthcare treatment (Bourne, 2009; Ibok, 2012, Jindrová and Labudová, 2020). Understandably, both factors have, therefore, become focal points within research, intervention, and policy-making environments when tackling health inequalities.

2.1.1: Demographics

Embedded in health is demographics, not least age, and ethnicity, both of which have been heavily researched regarding their impacts on health outcomes and how they aid understanding of health inequality (Hanefeld and Fischer, 2021). The works of Singh and Misra (2009) and O'Rourke et al. (2018) concur that as an individual ages, physical deterioration is inevitable. Alongside this, they highlight increased risk of social isolation and loneliness as a consequence of living alone, limited close family ties or loss of friendship networks that are more difficult to build and maintain in older age, all of which have been strongly associated with reduced mental wellbeing. Additionally, elderly individuals exhibit reduced mobility, potentially limiting the range and frequency of out-of-home activities including socialisation opportunities and medical visits (Páez et al., 2010), consolidating the notion of poorer health with older age. Nonetheless, other scholars argue a diverging perspective identifying a subset of the population that have reduced tendency to seek medical care or uptake medical treatments such as vaccinations (Taber et al. 2015; LGA 2021). Typically, this behaviour has been presented among young to middle-aged adults who perceive that their generally good physical health will allow their illnesses to improve over time without assistance, subsequently raising concern surrounding their health outcomes. Nonetheless, there is minimal evidence to suggest this is having a negative impact on health of this age group and therefore the key research focus relates to the foremost statement.

The literature further attempts to understand relationships between demographics and health from an ethnicity perspective, with a general understanding that those identifying as ethnic minorities are more likely to face health inequality (Egede, 2006). Although different behaviours and beliefs of minority groups may result in the reduced acceptance of medical advice (Patel et al., 2020), the need to respect cultural diversity has, in the past, posed daunting challenges to healthcare ethics with evidence that ethnic minorities tend to receive lower quality care, regardless of clinical needs, accessibility, or preferences (Egede, 2006). This has been explained by Brannigan (2000) in terms of ethnic relativism *(a reactionary use of cultural, racial, and/or ethnic beliefs as a reasonable passage for providing inadequate service)* and has subsequently been linked to reduced health outcomes among minority groups, highlighting potential incompatibilities between the healthcare system and ethnic minorities. Public Health England (2013) provide evidence for this across London with higher infant mortality rates among afro-Caribbean mothers, lower vaccination uptake within Black and Minority Ethnic (BAME) groups and higher cardiovascular/respiratory disease and cancer mortality rates among ethnic minorities. Chauhan et al. (2020) also recognises a multitude of factors that may contribute to health inequity among minority populations including limited social support, lower socioeconomic status, and a sense of disempowerment. Thus, existing research indicates a strong association between health and ethnicity, allowing a myriad of reasons surrounding how ethnicity is implicated in health inequality to be identified across literature (LaVeist and Isaac, 2010; Chase et al., 2020).

2.1.2: Socio-economics

Health inequalities have been widely linked to socio-economics, with research identifying a social gradient between those living in a higher social or economic position and health. This association between health and socio-economic status has been comprehensively researched, thus is well-established (Assari, 2015; MacDonald et al., 2018); the Marmot review published in 2010 substantiates that the lower a person's social position, the worse their health (Marmot et al., 2010).

The rudimentary principle for socio-economic and health research builds on work completed by Marmot et al. (2010) who highlighted that health inequalities related to socioeconomic status are a consequence of inequalities in material circumstances, particularly income. For example, Assari (2014) theorises that the protective effect of a higher socio-economic position on health can be strongly attributed to superior access to financial and material resources. This corresponds with Marmot et al. (2010) and Moradpour and Hollis (2020) who agree that those in better economic and social positions are able to access goods and services that may maintain or improve health, such as fitness memberships, health supplements, and healthy, organic produce, while those in lesser circumstances may be forced to purchase goods and services with associated health risks, for example fast-food. Public Health England (2013) further support this finding with those in the most socio-economically deprived wards in London more likely to report poor health, with greater inclinations to consume an unhealthy diet and lower vaccination uptake (immunisation uptake, ranging from 98.0% in Camden to 78.6% in Enfield). Similarly, NHS England (2013) further report extreme differences in life expectancy, and infant mortality rates between the most and least economically deprived London boroughs.

However, a systematic review of findings obtained by Marmot et al. (2010) highlights additional factors that may implicate socio-economic status and ultimately health. These include education, housing type, quality, and composition, access to transport, and work status, all of which have found a basis within literature, highlighting that health inequality does not only exist between the most and least affluent but across all aspects of the social gradient (Anderson et al., 2020). Several empirical studies have focused on these factors; Case and Deaton (2017) noted that unemployment and consequent loss of socialisation opportunity are strongly associated with increased despair-related deaths; Fitzpatrick et al. (2015) emphasised that housing insecurity and quality can be used to predict high health service usage; and NHS England (2013) noted that GCSE attainment across London varied between 74.4% (Kensington and Chelsea) and 51.3% (Lewisham) which was attributed to mental health problems in later life. Consequently, this demonstrates how socio-economic characteristics are consistently related to health outcomes and inequalities, but also displays a complex relationship between socio-economic status and health, extending far beyond just income (Anderson et al., 2020).

However, demographics and socio-economic factors may no longer be an adequate platform for obtaining a thorough understanding of health, thus findings of previous research may be less generalisable to the current environment. There is consistent evidence that health is influenced by not only demographics and socio-economics but also accessibility (Marmot et al, 2010; Ibok, 2012). It is therefore in the interest of this dissertation to develop a measure accounting for the interaction between individuals and their environment to assess the extent to which this may be useful for identifying health inequality and predicting health. This may provide practical applications in designing health indicators (Green et al., 2018) alongside aiding policy-making decisions aiming to target areas exhibiting unhealthy environments (Richardson et al., 2010).

2.2: Accessibility as a Determinant of Health

2.2.1: Understanding Accessibility

The concept of accessibility as a mechanism for understanding the geography of health, has recently become one of the foremost research topics within health geography, motivated by the idea that the supply of goods and services an individual has access to may shape behaviour (Cummins et al., 2007). It can be important to demonstrate how greater exposure to services and facilities may influence ill health (Green et al., 2018), and how differing neighbourhood characteristics can be associated with various levels of exposure (Mair et al., 2008). This conceptualisation of accessibility within health geography, Green et al. (2018) argues, can be best understood across three domains: *access to health services, access to retail environments, and access to recreational environments*, forming the basis for several academic pieces (Daras et al., 2019).

Despite the theoretical rationale that access to healthy environments impacts health behaviours, understanding surrounding this topic is still somewhat uncertain. Few researchers have endeavoured to explore accessibility to health-related environments and its impact on general population health; research has explored the impact of accessibility on mental health (Murray et al., 2004), physical health (Norredam, 2011), and specific health issues such as obesity (Fraser and Edwards, 2010), typically within one domain, making results less generalisable to the whole environment. This is possibly surprising given the effort that policy makers have gone through to elucidate why the location an individual lives may influence overall health and promote health inequalities (Green et al., 2018). Consequently, the concept of accessibility has rarely been translated into quantifiable measures by which policy-makers can make practical changes (Handy and Niemeier, 1997; Mercer and Watt, 2007), with few researchers quantifiably seeking to understand accessibility as the geographical dimension of health and whether inequalities in accessibility may explain variations in overall health. This leaves a gap in the literature to develop an understanding of the extent to which accessibility can be used understand spatial health inequality and predict general population health, and whether this provides a platform for aiding policy-making decisions.

Despite this, researchers have suggested, *de facto*, that service availability is a limited measure for assessing accessibility. Individuals residing nearby services may have perceived access yet may be unable to utilise the services (Oliver and Mossialos, 2004); in other words, access is more than the presence of or distance to a facility but is better represented by a continuum in which acceptability, contact, and service effectiveness are incorporated (Hongvivatana, 1984; Moscelli et al., 2018).

However, whether physical accessibility alone may still provide a useful pathway for understanding health is crucial for policy-making and area-targeting.

2.2.2: Access to Health Services

The role of accessibility in utilisation of healthcare services forms the basis for understanding the geographical dimension of health. In the last twenty years, researchers have pursued this topic concluding that those living at greater distance from health services have a reduced tendency to use them (Jones et al., 2010; Green et al., 2018; Daras et al., 2019) and perhaps poorer health outcomes (Lovett et al., 2002). Consequently, an extensive theoretical literature exists regarding the equity of healthcare access and health outcomes. The inequity in health services is generally understood through the 'inverse care law', hypothesising that health services are located where need for them is lower (Hart, 1971); for example, in city centre areas where health is generally greater due to a traditionally more youthful population. Thus, Marmot (2018) identifies those living in areas where the inverse care law operates as more likely to suffer negative health consequences.

Although this is deemed a rudimentary perspective for analysing healthcare access, its general principle holds true; Sibley and Weiner (2011) identified a clear urban-rural gradient in healthcare access. They found that across rural areas in Canada, where greater average age suggests an increased need for health services, uptake of medical care including vaccinations, use of specialist physicians' services, and regular doctor visits is considerably lower than demographically comparable urban areas as a result of inadequate access. However, they stop short of developing a powerful argument, merely identifying these disparities in healthcare without elaborating at any length the ultimate effect this has on health outcomes, an issue apparent in other similar work (Douthit et al., 2015; Zhang et al., 2017). Similarly, research often assumes geographical inaccessibility to health services to be a rural problem, thus the primary focus tends to centre around the differences in access across the urban-rural gradient (Jordan et al., 2004). Recognising these shortcomings, this thesis will seek to understand not only disparities in access but whether these disparities to all aspects of the health-related environment may influence health outcomes, within a single urban area.

2.2.3: Access to Retail Environments

As part of the broader health geography literature, researchers have sought to explore how the expression of poor mental and physical wellbeing is somewhat shaped by the underlying spatial distribution of retail outlets. This interest has been driven by theoretical discussions suggesting that beyond known determinants of health, various aspects of local retail environments may be crucial factors in shaping health-related behaviours (Shortt et al., 2016).

Traditional retail accessibility research provides contextual explanation for distributions of diet-related morbidity, attributed to differential locational access to unhealthy food products within neighbourhoods (Pearce et al., 2008; MacDonald et al., 2018; Widener, 2018). In doing so, research reveals that environments are becoming increasingly obesogenic meaning individuals are living in closer proximity to fast-food, increasing an individual's opportunity to make unhealthy choices, contributing to weight gain in children and adults (Fraser and Edwards, 2010). More recently, a clear retail accessibility divide between rural and urban areas has been noted, acknowledging the complex psychosocial and environmental factors influencing health-related behaviours instigated by aspects of retail environments within cities (Ahalya et al., 2017). In relation, researchers have attributed greater levels of alcoholism and definitive increases in alcohol-related harms to greater retail access, explained in terms of the "single distribution theory" (Kehoe et al., 2012). This is where areas with higher concentrations of off-trade alcohol outlets, typically across inner-city locations, have higher average consumption rates across all consumption groups. Similarly, researchers have explored how neighbourhoods located closer to gambling outlets record higher levels of problem gambling behaviour (Pearce et al., 2008), associated with lower general wellbeing, intimate partner violence, psychiatric disorders, and suicides (Wardle et al., 2019). This is supplemented by the findings of NHS England (2013) where it was recognised that across inner-London, levels of addictive behaviours including binge drinking and gambling, were considerably greater than in outer-London areas. Each of these examples agree with the wider literature, supporting theoretical evidence that those living in closer proximity to such retail environments suffer poorer health.

2.2.4: Access to Recreational Environments

There is a rapidly expanding body of research, examining the relationship between recreational environments and wellbeing (McCormick, 2017). A wealth of research, pointing to the beneficial effects of residing in an area with good recreational access, provides an extensive grounding for this topic within health geography research.

It is increasingly recognised that levels of physical activity are associated with the distribution of recreational opportunities across neighbourhoods (Gidlow et al., 2019). Researchers believe that neighbourhoods with optimal recreational accessibility are best placed for reducing physical inactivity among the population (Gianfredi et al., 2021). Twohig-Bennett and Jones (2018) identified a clear link between access to recreation and health, observing those nearby recreational green space as more motivated to participate in physical exercise, subsequently recording reduced incidence of stroke, asthma, and coronary heart disease. Such research has shown consistency across the UK, where it was found that those living across inner-London wards, where indoor leisure services and outdoor recreational areas are more prevalent, obesity levels were substantially lower (NHS England, 2013).

In addition to supporting the beneficial role that access to recreational environments has on physical health, literature provides convincing evidence surrounding the mental benefits. A growing body of research indicates that spending time in environments that allow for recreational activities contributes to positive psychological outcomes (Zulyniak et al., 2020). Mitchell and Popham (2008) reveal that those with access to recreational environments may conceivably have protection from the effects of stress, anxiety, and depressive symptoms, reducing mortality rates and improving health outcomes relative to those with poorer access to such facilities. Subsequently, in neighbourhoods where there is an optimal accessibility pathway for which recreational environments may wield influence over an individual's behaviour, the presence of health inequality should be less pronounced. However, such a theory is underexplored within urban contexts, thus, whether these results hold true in an urban setting, is a key interest of this thesis.

2.3: Study Methodologies

Despite interest in the 'spatial dimension of health', until recently, relatively little research had been undertaken to understand its relationship with health (Guagliardo, 2004). Nonetheless, given increased availability, functioning, and affordability of GIS software and the increasing abundance of digital data (Luo and Wang, 2003), accessibility literature has expanded, contributing to advance methods suitable to measure geographical accessibility (Páez et al., 2010).

2.3.1: Measuring Accessibility

It is largely accepted that understanding accessibility is crucial for understanding health inequality, although measuring accessibility is a "slippery notion" (Lei and Church, 2010). As accessibility means different things to different people, whether that be distance, time, cost, or attractiveness, measuring this on a quantitative basis is complicated (Ingram, 1971). In turn, several contrasting methods for quantifying accessibility have been developed each producing different results (Pirie, 1979).

When evaluating spatial access to healthy environments, a measure that accurately captures physical accessibility is desired. Gravity measures, one of the most well-researched methods for measuring accessibility, couple straight-line distances with a measure of opportunity or attractiveness at each point of interest (Hansen, 1959; Pirie, 1979). These explicitly measure total accessibility to all opportunities and have been utilised across numerous accessibility studies, although typically where an individual has a choice of multiple service options, commonly in retail contexts (Saghapour et al., 2017; López et al., 2019). These authors highlighted how such methods allow factors such as attractiveness and willingness to travel, which cannot be incorporated easily into other measures, to be quantified, although noted that when aiming to establish accessibility to services where individuals likely only have one viable option, usability is limited.

One of the most traditional methods for measuring accessibility is that of distance measures which consider straight-line, physical separation between two places (Pirie, 1979). Many researchers have explored geographical accessibility using the shortest Euclidean distance including Rahman et al. (2020) who aimed to establish overall accessibility to health facilities in Bangladesh. However, as such an approach ignores transport, traveller, and temporal components of accessibility, the method was criticised for its rudimentary, simplistic approach to measuring accessibility. Consequently, as an expansion on simple distance methods, network analysis has emerged as a popular approach. As a method utilising networks of paths and roads to locate the shortest distance between an origin and destination point (Tonner, 2020), sources claim that network analysis provides a realistic measure of accessibility, and accurate estimations of physical distances (Nicholls, 2001; Ahmed et al., 2017). As such, GIS-based network analysis is used frequently when assessing accessibility in a variety of contexts; Green et al. (2018) applied network analysis to calculate physical road distance between postcodes and their nearest service; and Tonner (2020) utilised network analysis to assess accessibility to green space in Stockholm, Sweden. Through a systematic review of the literature, findings demonstrate that methods utilising spatial separation measured by existing networks, rather than straight-line or gravity measures, provide greater accuracy and communication of accessibility flows across an area, providing a simpler method for interpretation (Yenisetty and Bahadure, 2020).

2.3.2: Modelling Accessibility

What is needed is an approach to translate and combine accessibility into a quantifiable measure. A framework for transforming accessibility data into a single accessibility measure could provide policymakers with a commanding tool for determining health intervention and policies across neighbourhoods (Zao and Cheng, 2019).

Despite increasing quantities of openly-available data, heavy data processing required for developing an accessibility measure means few researchers have endeavoured to explore the spatial context of health on a multivariate level; for instance, Rekha et al. (2017) explored accessibility to a single dimension of the health-related environment in terms of healthcare facilities while Texier et al. (2018) created a univariate accessibility index to capture variations in urban green space accessibility. Although such research provides an insight into individual dimensions of health, it fails to account for the complexities undermining health in the geographical context. It is therefore necessary to develop accessibility measures that capture the diversity of healthy environments to better understand geographical dimensions of health.

Composite indicators, those that mathematically combine a series of indicators into a single index, have become a popular approach used by scholars across wider human geography academia. While there are limited examples of how these approaches can be used regarding health, they have been used in other fields, providing an overview of a particular problem. Exemplar attempts to capture multiple dimensions of a problem are demonstrated through the Carstairs index of deprivation (Morgan and Baker, 2006), Townsend index of deprivation (Morse and Vogiatzakis, 2014), and the UKs index of multiple deprivation (Smith et al., 2015), all of which use an additive method to encapsulate social, economic, health and accessibility dimensions within a single measure. Scholars highlight how adopting such an approach succinctly captures the existing state of a problem at the spatial level (Bhat et al., 2000), making them useful in making policy or intervention decisions. There are fewer attempts to apply such an approach to accessibility and health-related research despite known the known existence of multiple dimensions to health. Green et al. (2018) provide the paramount example within health geography, whose work, synonymous with this thesis, developed a multidimensional accessibility index to understand national access to healthy assets and hazards and how this was associated to health outcomes. Green et al. (2014) also developed a multidimensional model to understand mortality, although in this case used a K-Means classification method. Classification methods have, however, been criticised due to their tendency to be over-generalised. This argument centres around the ecological fallacy problem *(when interpretations about an individual are extrapolated from interpretations about the group to which they belong (Steel and Holt, 1996))* which reduces the productive output of the models. Although an index may pose such an issue, Burns (2017) suggests classifications further exacerbate this. It should be further noted that the use of multiplicative methods, where indicators are multiplied together as opposed to summated, may also provide a suitable method for modelling accessibility. However, Green et al. (2018) suggests that aggregate health is the accumulation of multiple factors; in other words, numerous factors added together make up the key determinants of health. Given this, creation of an additive composite indicator was selected as an appropriate method in this investigation.

2.4: Conclusion

The aim of this chapter was to analyse the academic work regarding the topic of this thesis. As demonstrated, there is a wide expanse of research available on the determinants of health, including demographics, socio-economics, and accessibility. This chapter evidences health as a multi-level problem that needs to be understood from several diverging perspectives. Although aspatial factors must be considered when aiming to understand health, research makes it clear that accessibility may be an important variable that needs to be considered. Research indicates an obvious spatial dimension to health which, although is becoming an increasingly researched topic in health geography, requires further insight. This chapter demonstrates that a sufficient body of academic literature available in the realm of accessibility and health with most work specifically examining individual domains or specific health problems. However, very few pieces of academic work have sought to develop an all-encompassing understanding of access to health-related environments and used this to address health from a broader perspective which may prove to be an important and powerful tool for understanding area-level health. It is, therefore, important for this dissertation to develop an over-arching framework to understand the inequalities and patterns in the spatial dimension of health before assessing the relationships this may have with overall population health.

Chapter 3: Data

3.1: Study Area

3.1.1: Geographical Scope

The region of London, located in South-East England, United Kingdom, comprising 4,835 Lower Super Output Areas (LSOAs) and covering the City of London, Inner London, Outer London, and Greater London areas *(Figure 1)*, forms the geographical basis for this dissertation. With an aim to understand the spatial dimension of health, LSOAs were selected as an appropriate geographical scale. LSOAs, characterised by 1000 to 3000 people or 400 to 1200 households, are one of the smallest scales for which census data is available in the UK, and the general scale routinely used by policy makers when making health system decisions (Green et al. 2018). Therefore, LSOAs provided a suitable practical level for understanding the spatial dimension of health, enabling the accessibility index to be compared with a range of census variables.

3.1.2: Why London?

London has the potential to become one of the world's healthiest cities with overall health and wellbeing of Londoners showing improvements; London has seen reductions in early deaths from cancers and lung, heart, and circulatory diseases alongside improvements in life expectancy and physical activity levels (Healthy London, 2018). Despite these improvements London still exhibits the widest intragenerational health inequalities within the UK:

- Healthy life expectancy (HLE)- *the average number of years an individual would expect to live in good health*- varies, ranging 15.7 years for women and 16.1 years for men (Public Health England, 2013).
- Overall life expectancy ranges from 82.4 to 86.2 years among women and 77.5 to 82.6 years for men (NHS England, 2013).
- There is a difference of 3.4% between the lowest and highest infant mortality rate- *the number of children who do not live past the age of 1* (Public Health England, 2013).

Consequently, understanding determinants of health inequality across London and the potential spatial dimension to these inequalities is crucial. This research formulated an accessibility index for London to be able to see whether existing health inequalities could be understood in the spatial context before analysing how accessibility may be implicated in health outcomes.

Figure 1: study area scope, including London LSOAs and Boroughs. Borough names labelled here will be referred to throughout this investigation

3.2: Data

The key focal point of this research was the development and application of an accessibility index for London. The inclusion of index variables was informed by a review of work conducted by Green et al. (2018) who identified each of these services to have a discernible relationship with health and wellbeing, providing a strong grounding for their inclusion in the index. Data were compiled into three domains as identified in the literature review: access to health services, access to retail environments and access to recreational environments. Each indicator was included as it was deemed to capture a specific dimension of health within its domain; within the health domain, GPs captured general care services (Claessen et al., 2013), pharmacies captured medicine availability, and hospitals captured emergency care services (Athey et al., 2001); retail indicators captured three distinctive negative-health behaviours, unhealthy food consumption, alcohol consumption and gambling; recreational domain indicators captured both indoor and outdoor recreation opportunities (Green et al., 2018).

Table 1: health-related services/features used in the accessibility index

Domain	Service/Feature	Number of Features
Access to Health Services	General Practitioners (GPs)	1,347
	Pharmacies	1,899
	Hospitals	162
Access to Retail Environments	Fast Food and Takeaway Outlets	8,454
	Bookmakers	1,426
	Off-Licences	1,337
Access to Recreational Environments	Green Space	3,734
	Leisure Centres, Sports Halls and Gymnasiums	1,822

The location of these features, except for green space locations, for each domain, were downloaded as a single file geodatabase containing points of interest, each of which were provided with a national grid coordinate to allow for visualisation, and relevant documentation from Digimap (2021a), which provided the most up-to-date account of facility location across London. Relevant points of interest *(Table 1),* were extracted from the geodatabase using the 'Select by Attributes' function in ArcGIS Pro. All resulting layers were clipped to the boundary extent of the London region shapefile. Green space data was the only feature for which data was not available on Digimap. This data was downloaded as a polygon shapefile, provided by Ordnance Survey (2021). From this, all publicly accessible green spaces, including public parks and gardens, play spaces, and cemeteries, were extracted using the 'Select by Attributes' tool; subsequently golf courses, sports facilities, tennis courts, bowling greens, religious grounds, and allotments, which may not be openly accessible for all members of the public, were discarded. Greenspace data were then refined by joining polygons that shared borders or corners, before converting polygons to points in line with other indicators and clipping to the London region extent.

In addition, as part of this thesis, statistical analysis was undertaken to establish relationships between the accessibility index and various socio-economic and demographic variables to understand whether accessibility may be a predictor of health. These variables, recognised as aspatial determinants of health, were obtained from the 2011 Census, and downloaded from the UK Data Service (2011) for all London LSOAs. Although the 2011 Census data is becoming increasingly outdated, it has the major benefit of providing more detail, by capturing 100% of the population, than other large-scale surveys conducted at the LSOA scale (OCSI, 2021). The census remains the only robust source of information regarding certain themes at an LSOA level, including health variables which are crucial for this investigation. The specific variables used to assess the relationship between the index and health are detailed in *Chapter 5*.

Chapter 4: The Geographical Dimension of Health

*This chapter will present the methodologies utilised to uncover the answer to the first research question: **"how can the geographical dimension of health be used to understand health inequality across London?"** The chapter will then present, analyse, and discuss the findings relating to the geographical dimension of health, investigating the accessibility index.*

4.1: Methodology

4.1.1: Network Analysis

Given greater accuracy and realism, as outlined in *section 2.3.1*, it was decided to measure physical accessibility from each London LSOA to its closest service or facility using network analysis. Origin-Destination (OD) cost matrix analysis, built into the 'Network Analyst' toolbox in ArcGIS Pro, provided an exemplar method for analysis in this dissertation. This measured the least-cost path along a network from pre-defined origin locations to pre-defined destinations (ESRI, 2021). Given the scale at which this thesis aimed to understand accessibility and the fact that other researchers have used the same approach in a synonymous way (Green et al. 2018; Daras et al. 2019), by adopting this methodology it was believed that valuable insight into accessibility to healthy environments could be provided.

To establish network distances to services across London LSOAs, it was first necessary to create a road network. To do so, a feature dataset was created in ArcGIS Pro, within which a roads shapefile, downloaded from Digimap (2021b) containing line data of all roads within the London region was added as a feature class. As the ArcGIS Pro software did not recognise that individual line segments in the roads feature class were connected to one another, it was necessary to convert the feature class to a network dataset using the 'Create Network Dataset' tool, before building the final road network.

With a road network established, it was possible to determine physical accessibility. Points of interest (POI) data, as outlined in *section 3.2*, and LSOA population-weighted centroids, points representing LSOA centres based on population density, were downloaded from ONS (2011) and inputted into ArcGIS Pro alongside the roads network. Using the 'Network Analyst' tool, an OD cost matrix analysis layer was created which provided access to a suite of tools which could then be used to calculate distance to the nearest feature across the road network. Within the OD cost matrix layer, origin locations, the 4,835 LSOA centroids, were inputted, defining the starting location for calculating distance across the network, with POI subsequently imported as destination locations. As this dissertation was only concerned with identifying physical accessibility between each LSOA to its nearest feature, the number of destinations was defined as '1' to inform the software to only calculate network distance from each LSOA centroid to its closest health-related feature. Network analysis was then performed, generating network distance, in kilometres, from each LSOA to its nearest feature. These distance values were used to create the accessibility index. This process was completed eight times, once for each service type.

4.1.2: Accessibility Index

As identified in *section 2.3.2*, a composite index provided the most appropriate and justified method for gathering multiple dimensions of a problem into a single measure, providing a reliable and quantifiable approach to modelling access across London.

Network analysis data had to be standardised so all values could be analysed on a comparable scale (0-100); variables were standardised from most healthy (value 0) to least healthy (value 100) in Microsoft Excel. Indicators in the health and recreational domains could be defined as health-promoting suggesting living close to such services may promote healthier behaviours (Green et al., 2018). Therefore, lower distance values were assigned lower standardised values and vice versa. This was computed using Equation A *(see below)*. Conversely, as the retail domain could be considered health-negating suggesting closer proximity to such facilities may promote unhealthy behaviours, larger distance values were given lower standardised values. This was calculated using Equation B *(see below)*.

$$\textbf{Equation A: } z_i = (x_i - \min(x)) / (\max(x) - \min(x)) * Q$$

$$\textbf{Equation B: } z_i = (x_i - \max(x)) / (\min(x) - \max(x)) * Q$$

'Z_i' standardised value; 'x_i' distance value being standardised; 'min(x)/max(x)' minimum/maximum distance values recorded across LSOAs for the given indicator; 'Q' maximum standardised value, in this case 100.

Given standardised variables displayed contrasting distributions, each variable was further transformed in SPSS to establish a normal, consistent distribution. Variables were transformed by calculating z-scores, beneficially enabling comparison between indicators for each LSOA on a continuous scale, quantifying extreme values (Wang and Chen, 2012). Calculation of z-scores found the mean values of each standardised indicator and assigned this a value of 0. All other values were distributed around this with negative values indicating values below the mean (health-promoting) and positive values indicating values above the mean (health-negating). All Z-scores were summated in SPSS to create an overall accessibility score for each LSOA. Z-scores were also combined to establish accessibility scores for each LSOA within the three domains: health services, retail environments, and recreational environments. Indicators were equally weighted when combined since there was no discernible rationale within literature suggesting weightings were necessary (Green et al., 2018). These accessibility scores formed the index of accessibility with lower scores representing areas with better health-related environments, thus representing areas located nearby health services and recreational environments but further from retail environments, and vice versa.

For visual representation, the overall accessibility index and accessibility scores for each domain were individually placed into quintiles (statistical data sets that representing 20% of the data) by ranking cases in SPSS, with the lowest 20% of scores placed into Quintile 1 and highest placed into Quintile 5. Quintiles were only used for mapping purposes to allow clearer and easier-to-understand spatial representation as it was acknowledged that such a technique potentially removes some of the detail within the data (Vogt and Johnson, 2011). Raw accessibility scores were used in further analysis (*Chapter 5)*.

4.2: Analysis

4.2.1: Network Analysis

The results from network analysis provided interesting insights into the patterns and distributions of health-related facilities within the London region. *Table 2* displays a summary of physical accessibility across LSOAs for each indicator, highlighting variations in access within domains and individual indicators.

Table 2: summary of physical accessibility across London LSOAs

Domain	Indicator	Mean Distance (km)	Range (km)
Health Services	Access to GP Surgeries	0.65	3.87 (0.01-3.88)
	Access to Pharmacies	0.57	3.799 (0.002-3.80)
	Access to Hospitals	2.49	9.344 (0.196-9.54)
Retail Environment	Access to Fast-Food, Takeaway Outlets	0.47	2.079 (0.001-2.08)
	Access to Bookmakers	0.73	7.3 (0.02-7.32)
	Access to Off-Licences	0.77	5.756 (0.004-5.76)
Recreational Environment	Access to Green Space	0.51	2.247 (0.003-2.25)
	Access to Leisure Centres, Sports Halls, Gymnasiums	0.80	7.79 (0.03-7.82)

The most accessible feature, located closest to each LSOA centroid, is fast food/takeaway outlets, with an average distance of 0.47km. Such services are closer than any health service or recreational feature that can be deemed health-promoting. Correspondingly, this indicator shows the smallest range between minimum and maximum distances. This implies a more equitable distribution of fast-food/takeaway outlets across London LSOAs, given it represents less variation in accessibility to these facilities. This supports the theory proposed by Fraser and Edwards (2010) who highlighted that neighbourhoods are becoming increasingly obesogenic, promoting the consumption of unhealthy products across all areas (Jia, 2021). Other indicators in the retail environment domain display higher average distances (0.73km and 0.77km for bookmakers and off-licences, respectively), suggesting lower physical accessibility levels, better for health. These indicators also display larger variations in distance across London, indicating unequal distribution of these facilities across London LSOAs.

Accessibility to both GP surgeries and pharmacies appears relatively good (0.65km and 0.57km, respectively) located within closer proximity than both bookmakers and off-licence facilities which are considered health-negating. Given a relatively small range of values for these services, it suggests a slightly more equitable distribution of such services, particularly in comparison to hospitals, the other indicator analysed within the health services domain. With the greatest average distance (2.49km) and largest range (9.344km), hospitals appear to be the least accessible feature, with average distance 5x greater than the most-accessible indicator, likely reflecting lower presence of hospitals across the region and indicating greater levels of inequality in access to this service. It should be noted, however, in comparison to the rest of the UK, where average distance to hospitals is 6.2km and ranges up to 18.6km (Nuffield Trust, 2014), access to hospital care in London, even though physical accessibility is the poorest, is still relatively good, which is beneficial for health.

Green space is one of the most accessible features being investigated with greater average physical accessibility (0.51km) than all facilities in the health services domain and greater access than both bookmakers and off-licences. The small range between minimum and maximum distances, indicates a more equitable distribution of green space across London LSOAs, in comparison to other facilities and services. Contrastingly, leisure centres, sports halls, and gymnasiums are somewhat less accessible than other features, displaying highest average distance (0.80km) and largest range (7.79km) behind hospital accessibility. Such a finding is likely telling of higher inequality regarding access to these features across London LSOAs.

4.2.2: Accessibility to Health Services

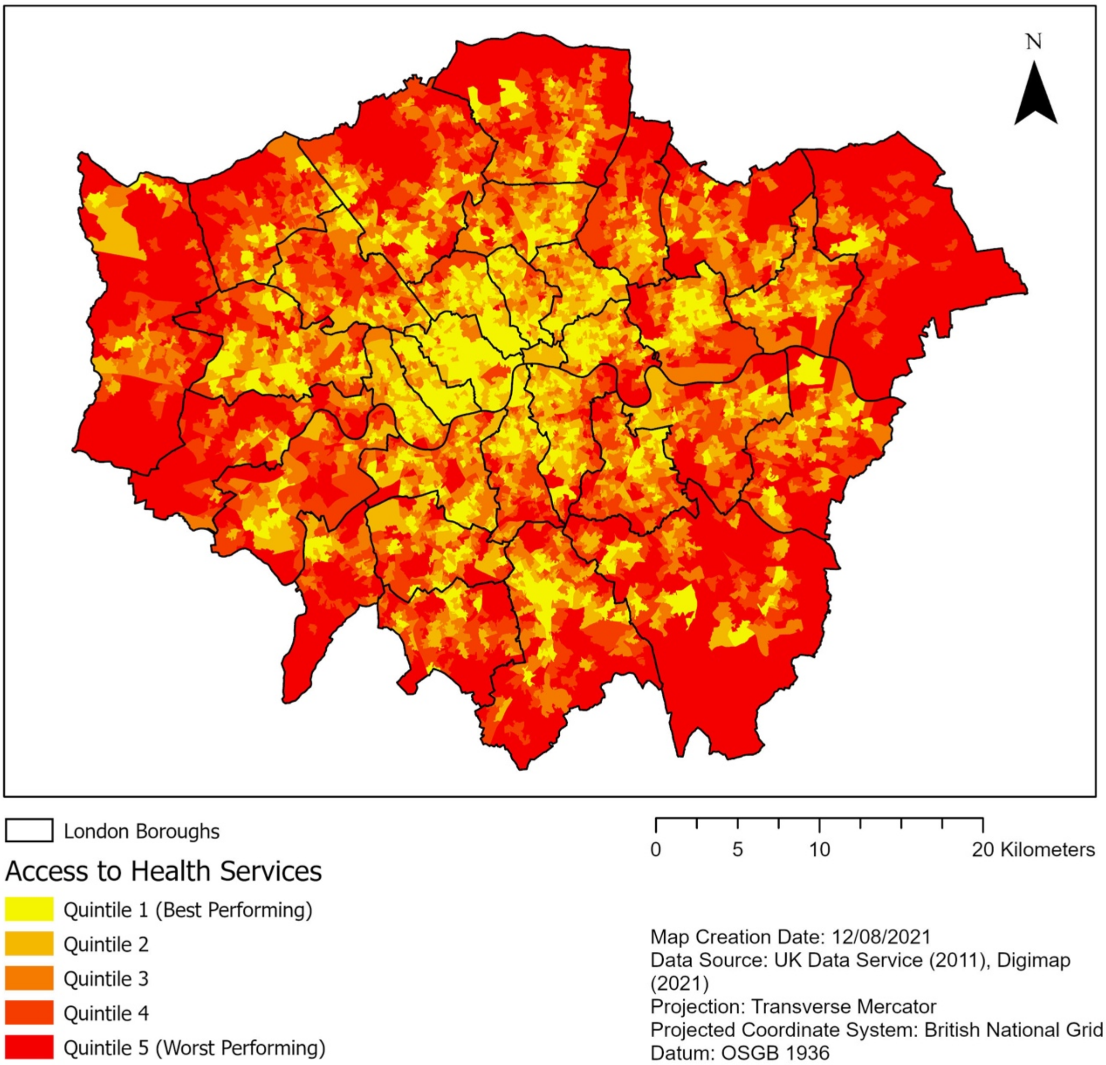

Figure 2: index of accessibility to health services

The combination of indicators within the health services domain, to understand accessibility to healthcare, exhibits clear variations. *Figure 2* demonstrates highest levels of accessibility across inner-city LSOAs, particularly those located across Westminster, and Kensington and Chelsea, in sharp contrast to LSOAs on the outskirts of the London region, notably in Bromley, Havering and Hillingdon, where LSOAs consistently fall within Quintiles 4 or 5. This indicates a healthier environment in terms of healthcare access in central LSOAs, reflecting the relative isolation of outer-London areas from GPs, pharmacies, and hospitals, demonstrating that those living in outer London face greater disparities in terms of health service availability. Such a finding is consistent with Hart (1971) and Marmot (2018) who noted that those in inner city regions will have greatest access to all types of healthcare, irrespective of demand, which has implications on healthcare-seeking behaviours. In relation to this, Public Health England (2013) noted apparent differences in vaccine uptake between areas in the inner-city (Camden, with the highest vaccine uptake) in comparison to outer-London areas (Enfield, with the lowest vaccine uptake), attributed to the differing socio-economic statuses between these areas. However, based on the results of this investigation, it is possible that these differences in healthcare uptake may also reflect accessibility as well as socio-economics with LSOAs in Camden showing greatest accessibility, generally in Quintiles 1 or 2, while LSOAs in Enfield show poor accessibility, generally in Quintiles 3 to 5. It should be further noted, that despite the clear pattern in accessibility to health services, variation is evident across some central-London locations, particularly LSOAs East of the City of London borough (Lewisham, Newham, Waltham Forest) where there does not appear to be a uniform pattern to accessibility across LSOAs; accessibility ranges from Quintile 1 to Quintile 5. This demonstrates that even across areas where health provision is considered high, there are still inequalities in accessibility to health services when looking at small-area geographies.

4.2.3: Accessibility to Retail Environments

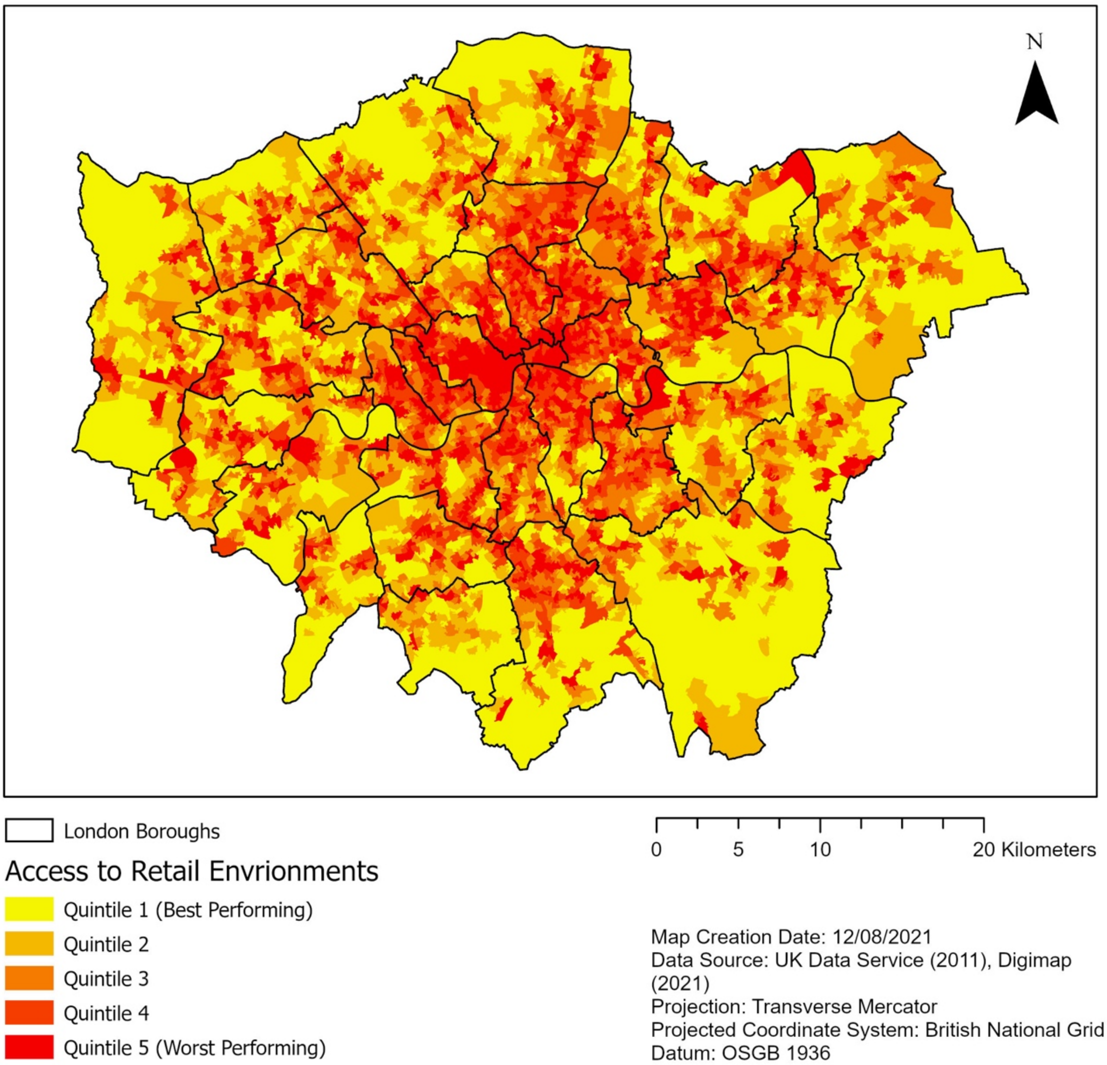

Figure 3: index of accessibility to retail environments

The summation of indicators to understand accessibility within the retail environment domain exhibits those LSOAs located in outer-London areas to have the best health-related retail environment (*Figure 3*). Boroughs on the outskirts of the London region, particularly those in the South have the greatest proportion of LSOAs assigned to Quintile 1 (Bromley, Sutton, Barnet), while boroughs in central London (City of London, Westminster, Islington, Hackney) have the greatest proportion of LSOAs assigned to Quintiles 4 or 5. This reflects higher accessibility to retail outlets across central areas, indicating that LSOAs located in this region face inequality regarding their accessibility to healthy retail environments. Such a finding is consistent with several academic reports, including Widener (2018) who recognised that retail access was like a continuum, with greatest access in inner-city areas, declining as distance from the centre increases. Nonetheless, it is apparent that higher levels of access to retail environments is not only restricted to these areas, with pockets of greatest accessibility levels apparent across the entire London region. Specifically, across City of London, Westminster and Tower Hamlets boroughs, access is not too dissimilar to access displayed across some LSOAs in Waltham Forest, Brent, and Haringey in outer-London areas; thus, while NHS England (2013) attributed higher addictive behaviours, specifically alcohol abuse, and gambling problems, in central areas to greater accessibility, given that other less central areas display similar patterns of access, it may be that these higher levels of addictive behaviours are rooted deeper than exclusively accessibility.

4.2.4: Accessibility to Recreational Environments

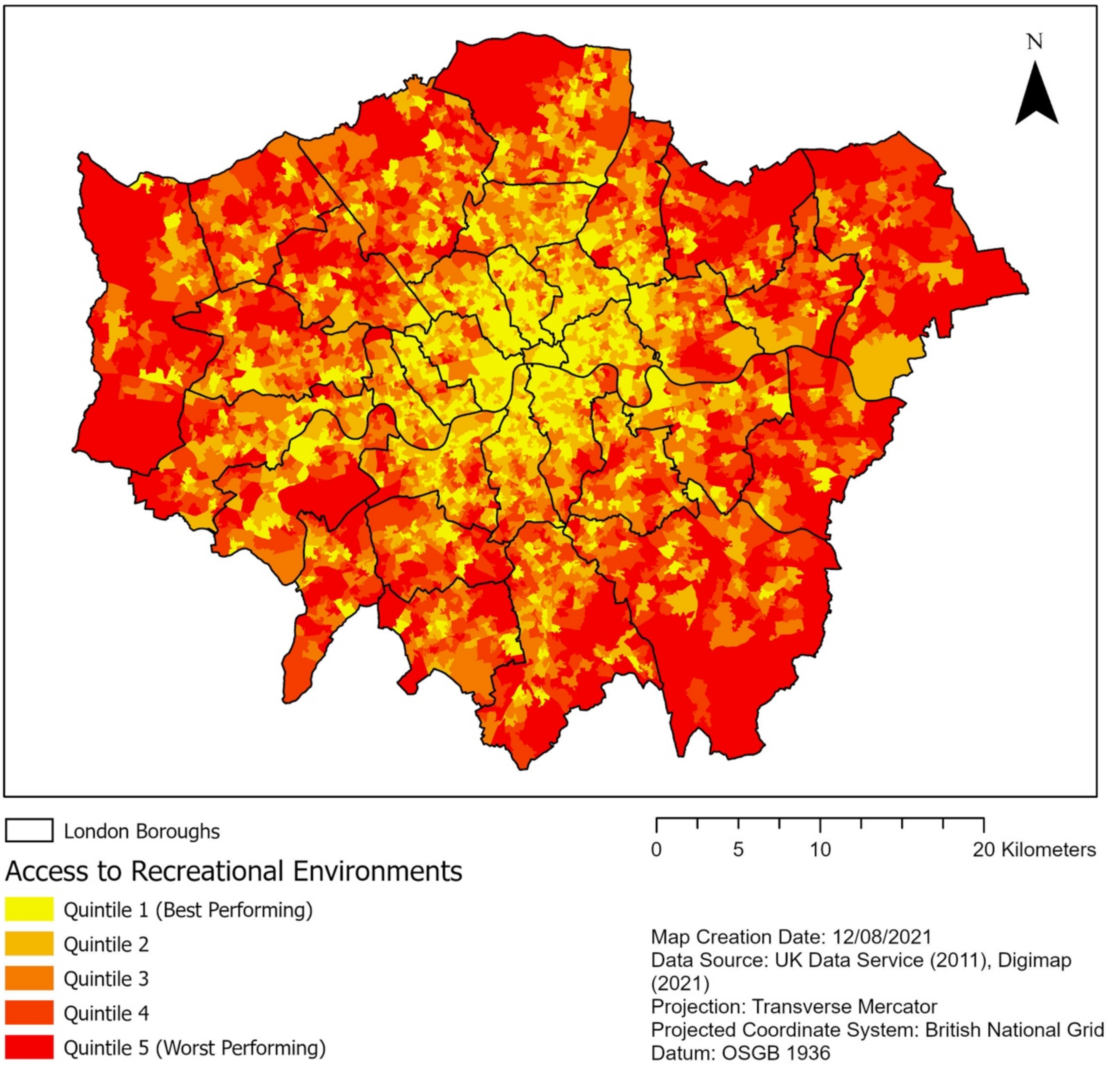

Figure 4: index of accessibility to recreational environments

Looking at overall accessibility within the recreational environment domain, it is evident that, similar to the health services domain, there is substantially greater accessibility levels among inner-city LSOAs (across City of London, Islington, and Westminster) in comparison to adjacent areas, particularly those LSOAs on the outskirts of the London region where Quintiles 4 and 5 dominate. This suggests that, in general, LSOAs located in central areas have access to healthier recreational environments, reflecting the isolation of outer-London LSOAs from green space and leisure facilities. From this, it can be inferred that, in line with Gianfredi et al. (2021) and Zulyniak et al. (2020), whom both quantified the impact of recreational accessibility on health, mental wellbeing and physical health among these central LSOAs should be enhanced. However, aside from this obvious spatial pattern in recreational access, across Northerly and Easterly LSOAs, the pattern of accessibility shows a lack of uniformity. There appears to be a high degree of variation in accessibility across outer-London LSOAs across these regions, including in Haringey, Ealing, and Hounslow, where, although general accessibility levels are poorer, they display areas of greater accessibility, thus have a number of LSOAs assigned to Quintiles 1 and 2. This likely reflects the more equitable distribution of green space, as identified in *Table 2*, capturing the small-scale variation in accessibility, demonstrating the effectiveness of utilising this method to measure accessibility. Nonetheless, *Figure 4* displays clear disparities in access between areas, showing LSOAs in outer-London face greatest inequalities in access to recreational environments.

4.2.5: Index of Accessibility to Healthy Environments

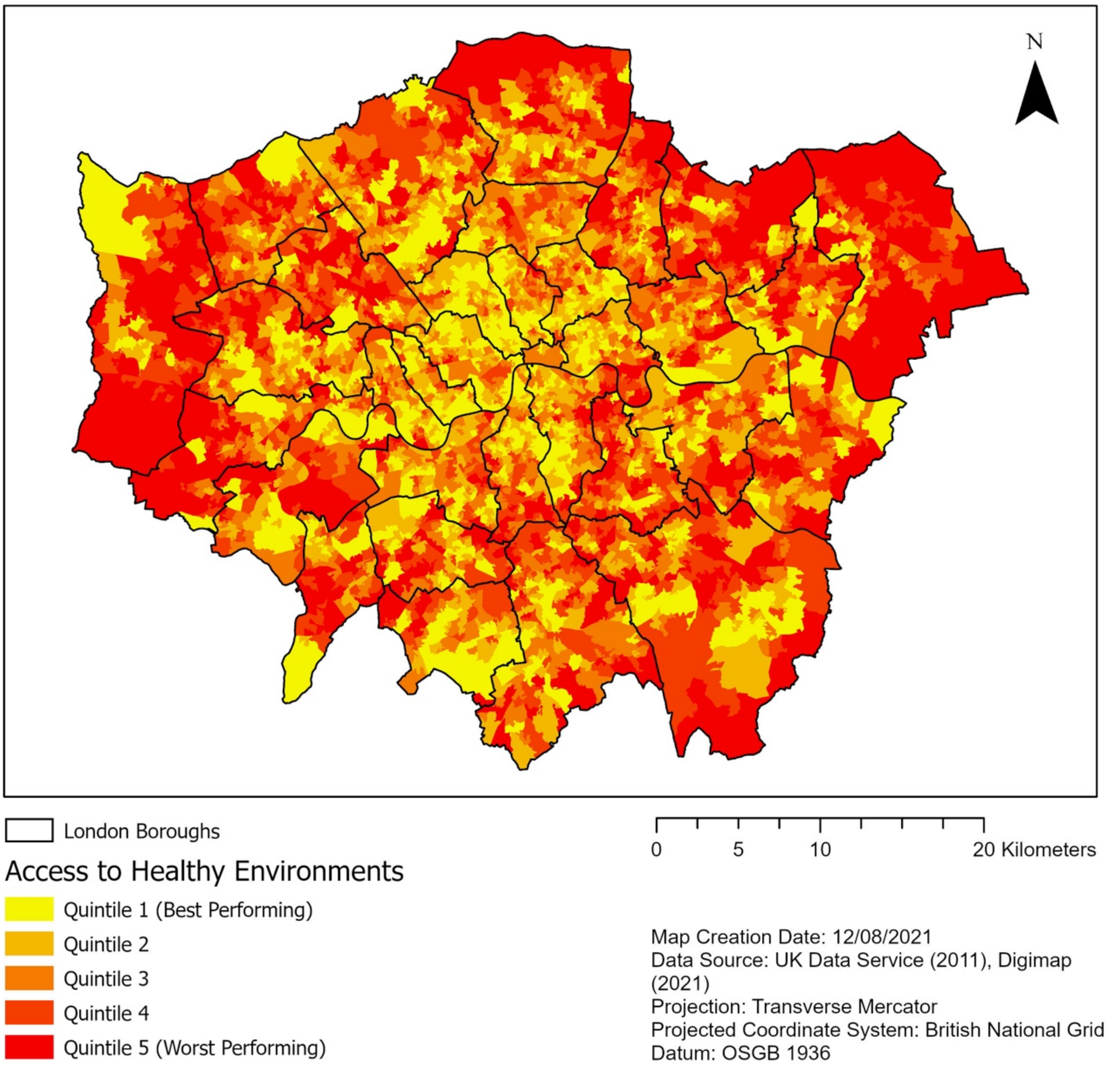

Figure 5: overall index of accessibility to healthy environments

Figure 5 presents the spatial distribution of the overall index of access to healthy environments. There is a distinguished inner-outer-London divide, with central LSOAs generally performing the best, typically dominated by Quintiles 1 to 2, despite their proximity to retail environments. The poorer performance of outer-London LSOAs is reflective of their relative isolation from both health services and recreational environments, hence the domination of Quintiles 3 to 5. This division does not mean that outer-London areas always perform poorly. A high number of LSOAs in certain boroughs, in particular Sutton, Ealing and Barnet show high performance, driven by inaccessibility to unhealthy retail environments and good accessibility to health services, particularly across LSOAs in Ealing.

The greatest levels of variation can be found across LSOAs in boroughs surrounding the inner-city, typically those in Lewisham, Greenwich, Newham, Merton, and Brent, where accessibility ranges from Quintiles 1 to 5, although generally showing average performance (Quintile 3). This is driven by closer proximity of these LSOAs to health services and recreational environments, combined with closer proximity of these areas to unhealthy retail environments. This variation extends, somewhat, into inner-city locations, effectively capturing the variations evident in the individual domains. This demonstrates that even within individual London boroughs, there are still access inequalities, revealing the fine resolution that can be captured looking at access across LSOAs using the method adopted in this investigation.

Nevertheless, looking at the overall pattern of the accessibility to healthy environments index, it is evident that LSOAs in outer-London, particularly those in the North and North-East (Enfield, Redbridge, Waltham Forest, Havering and Barking and Dagenham), are the most deprived in terms of accessibility, facing the largest inequalities in access to healthy-environments. These areas, except for Havering, are not only deprived in terms of accessibility but also contain areas within the 5% most economically deprived areas in England (EEBL, 2016). It is their socio-economic status that has been attributed to low levels of mental and physical wellbeing across these boroughs (Hoffman, 2014), although, given the pattern of accessibility obtained from this index, it can be suggested that, in agreement with Jones et al. (2010), Shortt et al. (2016) and McCormick (2017) poor access of such areas to healthy environments may also be contributing to low life satisfaction. It can therefore be assumed, in line with the primary aim of this investigation, that the spatial distribution of health-related services can be used to aid understanding of inequalities and identify areas where health inequalities may be prevalent across London. Thus, it provides a useful framework for policy-makers to identify which areas require targeting in approaches to ensure access to healthy environments is more equitable.

Chapter 5: Using Accessibility to Predict Health

Having developed an understanding of how accessibility can be used to understand health inequalities, this chapter expands the understanding of accessibility to answer the research questions ***"do any patterns to accessibility exist beyond distance"*** *and* ***"to what extent can accessibility be used to predict general health of London's population?"*** *This chapter will describe, analyse, and discuss the methods and subsequent findings used and acquired to assess this.*

5.1: Methodology

5.1.1: Correlational Analysis

Few researchers have endeavoured to study how aspatial factors may be associated to accessibility, often providing reductionist insight into accessibility and health. To contextualise what the accessibility index represented and develop an understanding of what low and high accessibility scores implied beyond merely distance, correlational analyses were undertaken.

Six variables were used in analysis *(Table 3)* to assess whether the index and domains were associated with health, population, deprivation, age, or ethnicity. All variables, except for the index of multiple deprivation (IMD), were downloaded from the 2011 Census as discussed in *Chapter 3*. IMD data were downloaded from the London Datastore (2019) as this contained most recent IMD scores for each London LSOA. As all census data were continuous, raw accessibility scores and raw IMD scores were used, opposed to quintiles or ranks, to ensure a consistent approach. Consequently, given all data were on continuous scales and normally distributed, Pearson's correlation was an appropriate method (Janse et al., 2021). Before analysis, data were imported and prepared, checking for outliers by visually presenting data distributions in boxplots using SPSS (Glass and Hopkins, 1996). Subsequently, using bivariate correlation functions, Pearson's correlation analysis was conducted.

Table 3: variables used in correlational analysis

Variable	Reason for inclusion
Percentage of persons reporting poor health *Whether an individual perceives their health/wellbeing to be fair, poor, or very poor*	Has proven associations with actual health status and increased health service usage (Williams et al., 2017)
Percentage of persons with limiting long-term health problems (LLHP) *Whether an individual's day-to-day life is limited by physical/mental health*	Has utility for identifying chronic illness and pockets of health deprivation (Moon et al., 2017)
Population density *Number of individuals per* km^2	To examine if accessibility is associated with a suburban-urban pattern, similar to the rural-urban pattern identified by Green et al. (2018)
IMD scores *Multidimensional measure of neighbourhood inequalities across social, economic, and environmental domains*	Has proven associations with health outcomes and access to healthy environments (MHCLG, 2019), capturing dimensions to deprivation that other measures do not acknowledge (Deas et al., 2003)
Percentage of persons aged 65+ *Age 65 was used as this is approximate healthy life expectancy within London*	Has long been associated with health outcomes but shows association with the inverse care law - reduced service provision and access across ageing neighbourhoods (Yam et al., 2009)
Percentage of persons identifying as minority ethnicities *Whether an individual identifies as Black, south-Asian, or Chinese background*	BAME groups been suggested to face greatest access inequality of all demographic groups due to deprivation and location of residence (Vissandjée et al., 2001)

5.1.2: Regression Analysis

To account for causation between the index and health, multivariate linear regression analysis was conducted. Linear regression provides an easy-to-interpret approach to tackling quantitative problems, thus has long been used across quantitative academic fields (Molnar, 2021), including in health geography and accessibility research (Dai, 2011; Green et al. 2018). Therefore, it was deemed an appropriate approach for identifying predictors of health within London.

For regression analysis the percentage of persons reporting poor health was used as the dependent/outcome variable, given its proven relationship with actual health status and widespread use within literature (Dunstan et al., 2013). Alongside overall accessibility index scores (opposed to domain scores), several independent variables reflecting aspatial determinants of health were obtained from the 2011 Census (*Table 4*) and incorporated into the regression models. To avoid subjectivity, variable selection was drawn from evidence within literature, specifically work by Marmot et al. (2010) who identified demographics, education, household quality/composition, transport, and work status to be implicated in health and work by Burns (2017) who incorporated many variables used in this investigation within his health classification.

Prior to regression analysis, variables were tested for multicollinearity *(linear relationships between two or more independent variables)*, as this can result in misleading regression coefficients owing to variable redundancy, resulting in some variables contributing no influence on model outcomes (Allen, 1997; Alin, 2010). Pearson's correlation was conducted in SPSS with the presence of extreme multicollinearity identified if correlations were between -0.8 to -1 or 0.8 to 1, in line with Jhangiani et al. (2015). Although some variables showed high correlation, no variables displayed multicollinearity based on thresholds defined in this investigation *(Appendix A)*, so all were included in the model.

Table 4: independent variables used in regression analysis

Variable	Reason for inclusion
Percentage of persons aged 65+	As an individual ages, alongside physical deterioration reducing physical health, social isolation and loneliness can contribute to reduced mental wellbeing (O'Rourke et al., 2018)
Percentage of persons identifying as minority ethnicities	Limited social support, lower socioeconomic status and ethnic relativism have been deemed to contribute to generally reduced mental and physical health outcomes among BAME groups (Chauhan et al., 2020).
IMD scores	Researchers have established a causal link between neighbourhood deprivation and increased risk of poor general health (Stafford and Marmot, 2003)
Percentage of persons in elementary occupations	Low-skilled workers have lower income/reduced job security (Milner et al., 2013), associated with reduced wellbeing and above-average suicide risk (ONS, 2017)
Percentage of persons with no qualifications	Lower educational attainment is attributed to lower income/long-term unemployment, with proven links to alcoholism, and reduced wellbeing (Ross and Wu, 1995)
Percentage of persons unemployed	Proven relationship with economic hardship associated with long-term physiological health issues including depression and anxiety (Wilson and Finch, 2021)
Percentage of households with no car	Limited transport options associated with reduced accessibility to healthcare, services, and employment opportunities, and greater social isolation, consequently linked to reduced general wellbeing (Lucas et al., 2019)
Percentage of households with no central heating	Living in cold homes present a longstanding causal relationship with adverse health including respiratory/cardiovascular illnesses (WHO, 2018a)
Percentage of households with less bedrooms than required	Overcrowded household conditions have a proven link with infection transmission, sleep disturbance, and fatigue, consequently associated with reduced health outcomes (WHO, 2018b)

Four linear regression models were conducted in SPSS, each adding to the understanding of health through the addition of independent variables. The first model accounted for accessibility to understand the extent to which this influenced health, independent of other variables, with subsequent models accounting for demographics, socio-economics, and household variables. Models were analysed at each stage of the process to develop an understanding of which factors demonstrated the greatest influence on health in London.

The equation used to understand multiple linear regression models was:

$$\mathbf{Y_i = \alpha + \beta_1 x_1 + \beta_2 x_2 + \ldots.\ \beta_n x_n}$$

'Y_i' estimate of the dependent variable; 'α' constant coefficient; 'β' unstandardised b-coefficients of independent variables; 'x' independent variables.

5.2: Analysis

5.2.1: Correlational Analysis

Table 5: Pearson's correlational analysis of the association between the index and its domain and aspatial factors

	Overall Index	Health Domain	Retail Domain	Recreational Domain
Poor self-reported health	0.025	0.15	0.16	-0.11
LLHP	0.023	0.10	0.09	-0.03*
Population Density	-0.18	-0.35	0.34	-0.29
IMD Score	-0.08*	-0.03*	-0.04*	-0.02*
Over 65	0.11	0.27	-0.36	0.34
Minority Groups	-0.04	-0.22	0.27	-0.17

** $p > 0.05$*

Analysis of the overall association between the index and its domains with a variety of aspatial factors produced insightful results (*Table 5)*. Overall index scores showed little association to either population health measure, indicating no relationship between access to healthy environments and health outcomes across London LSOAs. Disaggregating the overall index into its constituent domains, makes this result easier to understand. Each domain shows clearer associations to health measures with both health and retail domains showing significant, albeit weak, positive correlations, indicating that as accessibility scores increase, the percentage of persons with poorer health slightly increases. This confirms findings obtained by Lovett et al. (2002) and Myran et al. (2019) who stated those living further from health services or close to retail environments face greater inequality regarding potential health outcomes. Consequently, given correlational analysis corroborates their findings, it adds validity to the construction of domains. Contrastingly, there is weak negative correlation between the recreational domain and health variables, albeit insignificant for the LLHP measure, implying that those living further from recreational environments were slightly more likely to have positive health outcomes. Generally, recreational access has demonstrated agreement within literature, thus, it is surprising to note that this result contrasts the hypothesised direction of association identified in previous work. NHS England (2013) noted proximity to recreation to be associated with significantly better levels of physical health within London, while both Mitchell and Popham (2008) and Twohig-Bennett and Jones (2018) identified those with greater access to recreation within the UK to have significantly greater physical and mental wellbeing. This is one of the areas where this thesis falls short of developing a convincing argument as, although this relationship can be determined, why this is the case and why it differs from wider research is uncertain.

The overall index shows a negative association with population density indicating those areas that showed poorer access to healthy environments displayed lower population density. This validates *Figure 5*, which showed outer-London areas to face greatest inequalities regarding accessibility. Both health and recreational domains presented negative associations with population density (-0.35 and -0.29, respectively), demonstrating greater accessibility of inner-London areas to such facilities. The retail domain score was positively associated with population density (0.34), highlighting how higher population density was associated with greater retail access, reflective of higher retail concentration across inner-London. This holds similarities with work by Green et al. (2018) whose work displayed similar pattens to accessibility across urban-rural areas. However, his work noted considerably stronger associations in each domain, 0.65 and -0.56 for retail and health domains respectively, suggesting this pattern to accessibility is more extreme across urban-rural areas.

In contrast to what was expected, correlational analysis showed no association between the index or domains and deprivation levels, highlighting no linear relationship between the variables and accessibility. This is perhaps surprising given the large amount of research suggesting those living in social and economic hardship, as measured through IMD, typically face largest inequalities regarding access to healthy environments (Marmot et al., 2010). This offers potential for future analyses to further investigate associations between deprivation and accessibility, to establish whether any of the domains that constitute IMD may provide an indication of the association that has been suggested to exist between deprivation and accessibility.

The final two variables aimed to capture associations between accessibility and demographic characteristics. There was little association found between the overall index scores and both variables, although interesting associations were found within constituent domains. The 'Over 65' variable showed significant positive associations with both health and recreational domains and a significant negative association with retail environments, suggestive of higher proportions of elderly in areas with poorer access to healthy environments, typically in outer-London areas, as demonstrated in *Figures 2, 3, and 4*. The ethnicity variable showed a significant negative association with health and recreational domains, but a positive association with the retail domain indicating higher proportions of ethnic minorities in areas with greater access, revealing of ethnic minorities residing in inner-city locations. Such findings are substantiated by the spatial, demographic structure of London in terms of inner-city locations being dominated by youthful, multi-cultural populations and outer-city areas being dominated by ageing, predominantly white populations (Thomas et al., 2015). Within the health domain, results show consistency with research conducted in both Hong Kong and Canada where a mismatch between supply and demand of healthcare in areas comprising a high percentage of elderly was apparent (Yam et al., 2009; Sibley and Weiner, 2011). This highlights how the method adopted in this research may have practical applications for identifying where inverse care law operates. As such, this provides practical benefits for policy-makers to identify areas where healthcare supply needs to be adjusted to fulfil demand of the underlying population demographic.

Correlation findings supplement previous research emphasising differing neighbourhood characteristics are associated with differing accessibility levels (Mair et al., 2008). This suggests that the index, beyond understanding inequalities in distance from healthy environments, may be useful for understanding area characteristics associated with poor accessibility which will have major utility when making neighbourhood-level policy decisions. However, results highlight how individual domains are better platforms for understanding associations as they reflect environmental features that become less pronounced when combined into an overall index. This highlights future work and policy-making decisions may benefit from focussing on individual domains as these provide a more precise insight into characteristics of healthy neighbourhoods.

5.2.2: Regression Analysis

Model 1:

Table 6: regression analysis examining the association between the overall accessibility index and the percentage of persons reporting poor health

	Unstandardised Beta Coefficients	Confidence Levels	
	β	Lower Bound	Upper Bound
Constant	16.16**	16.04	16.27
Overall Index	0.07*	0.01	0.09
R^2 = 0.01			
Adjusted R^2 = 0.01			

** $p < 0.05$, ** $p < 0.01$*

The final part of this investigation was to establish whether the accessibility index could be used to predict variations in general health across London LSOAs. *Table 6* demonstrates that the overall index, consistent with correlational analysis, has no association with health. The β-coefficient suggests that for every 1-unit increase in the accessibility score, the number of people reporting poor health increases marginally by 0.07%, suggesting that as accessibility worsens, there is virtually no change in health outcomes. This supports the findings obtained by Diez-Roux (2001) who indicated that it would be unlikely for health to be affected by current environmental characteristics, but more likely how these change over time, showing further consistency with Green et al. (2018) who conducted a multivariate regression model and found no associations between their accessibility index and three health measures across the UK. It should be noted that in their investigation the relationship with self-reported health was considerably weaker (0.0002), which implies slightly greater utility of the index created in this investigation. Nonetheless, the relationship here is very weak suggesting the index does not provide a useful platform for explaining geographical variations in poor self-reported health across the London region. The overall model fit supplements this (Adjusted R^2=0.01) suggesting the index only accounts for 1% of the variation in health across London.

Model 2:

Table 7: regression analysis examining the association between the overall accessibility index and demographics with the percentage of persons reporting poor health

	Unstandardised Beta Coefficients	Confidence Levels	
	β	Lower Bound	Upper Bound
Constant	6.64**	6.24	7.04
Overall Index	0.04*	0.01	0.08
Over 65	0.44**	0.41	0.46
Minority Groups	0.13**	0.12	0.14
R^2 = 0.33 **Adjusted R^2 = 0.32**			

**p < 0.05, ** p < 0.01*

The addition of demographic variables into the regression model provides further insight into the geographical variation in self-reported health across London (*Table 7*). The variables included in this model result in a β-coefficient reduction of the accessibility index (0.07 to 0.04), indicating accessibility has a lesser effect on the model. In line with this, for every 1% increase in the percentage of people aged over 65 and identifying as ethnic minorities, the percentage of people reporting poor health increases by 0.44% and 0.13%, respectively. This highlights how variation in health is better accounted for by differences in demographic variables rather than differences in accessibility scores. The increase in overall model fit (Adjusted R^2=0.32), is reasonable, accounting for 32% of the variation in London health, reiterating that demographic variables greater explain variation in the dependent variable, thus may be better predictors of health across London. This finding follows the abundance of previous research that has indicated how the demographic characteristics of neighbourhoods have been associated with both mental and physical wellbeing of areas; O'Rourke et al. (2018) identified old age as a key explanatory factor of reduced physical and mental health and Chauhan et al. (2020) recognises how ethnic minorities face inequities in the healthcare system, thus are at increased risk of suffering reduced health outcomes. Although the results of their work are not directly comparable due to differences in age brackets used and their use of a broader range of ethnicities, it somewhat supplements the findings of this investigation, supporting the higher influence of demographics on health, as opposed to accessibility, across London.

Model 3:

Table 8: regression analysis examining the association between the overall accessibility index, demographics, and socio-economics with the percentage of persons reporting poor health

	Unstandardised Beta Coefficients	Confidence Levels	
	β	**Lower Bound**	**Upper Bound**
Constant	2.79**	2.51	3.08
Overall Index	0.01	-0.03	0.09
Over 65	0.31**	0.29	0.33
Minority Groups	0.04**	0.03	0.05
IMD Score	0.004	-0.001	0.01
Elementary Occupations	-0.04*	-0.06	-0.02
No Qualifications	0.33**	0.31	0.34
Unemployed	0.58**	0.53	0.63
R^2 = 0.79 **Adjusted R^2 = 0.78**			

$^*p < 0.05$, $^{**}p < 0.01$

The addition of socio-economic variables, as shown in *Table 8*, further improves the model. Model 3 can explain 78% of the variation in self-reported health across London (Adjusted R^2=0.78), demonstrating a strong model fit. Inevitably, the impact of existing demographic variables declines reflecting the relative influence of additional variables on the model (Neter et al., 1996).

Socio-economic variables added to Model 3 aid understanding of the predictors of health. Both IMD and those working in elementary occupations are shown to have no association with health, perhaps reflecting their lack of strong influence on health. This is unexpected given the theoretical framework developed by Marmot et al. (2010) which highlights deprivation and skill level to be implicated in quality of life and consequent health outcomes, in direct contrast to this investigation. Conversely, both unemployment and qualification level show stronger associations with health, accounting for 0.58% and 0.33% increases in poor self-reported health, respectively. This yields consistency with health geography literature; international research, conducted by Case and Deaton (2017) in the USA, documented health effects of unemployment, noting it to be attributed to reductions in mental wellbeing, citing further work conducted in Spain that consolidated their findings. Although this cannot be directly compared to findings of this thesis due to differing cultures between countries in which research was undertaken, it highlights an undeniable link between unemployment and health, supplementing this thesis. Similarly, this finding follows previous research that has indicated how individuals with no qualifications face hardship in terms of health outcomes (Ross and Wu, 1995). Specifically, the finding is consistent with other London research by PHE (2013) who attributed the lack of basic qualifications to poorer mental health in later life.

However, the addition of these variables, once again further reduces the impact of accessibility on the model, with the β-coefficient decreasing to 0.01. This demonstrates that accessibility has no useful contribution to the model, which is instead dominated by demographic and socio-economic measures, ultimately diminishing its usefulness as a predictor of health within London.

Model 4:

Table 9: regression analysis examining associations between the overall accessibility index, demographic, socio-economic, and household variables with the percentage of persons reporting poor health

	Unstandardised Beta Coefficients	**Confidence Levels**	
	β	**Lower Bound**	**Upper Bound**
Constant**	0.37**	0.04	0.69
Overall Index**	0.08**	0.03	0.10
Over 65**	0.39**	0.37	0.40
Minority Groups**	0.04**	0.03	0.05
IMD Score**	0.008**	0.003	0.01
Elementary Occupations**	0.04**	-0.06	-0.02
No Qualifications**	0.35**	0.34	0.36
Unemployed**	0.32**	0.27	0.36
No Car Access**	0.06**	0.05	0.07
No Central Heating**	0.06**	-0.09	-0.02
Over-Occupied Bedrooms*	0.03*	0.007	0.04
R^2 = 0.83 **Adjusted R^2 = 0.82**			

$*p < 0.05$, $**p < 0.01$

The final regression model, with the addition of household-level variables, once again proves beneficial for understanding health variation across London LSOAs *(Table 9).* The overall model fit is strong (Adjusted R^2=0.82), explaining 82% of the variation in self-reported health across London LSOAs. However, none of the additional variables can be deemed to have a particularly strong association with health, accounting for only a 0.06% increase in poor health with a 1% increase in no car or no central heating variables, and a 0.03% increase in poor health with a 1% increase the over-occupied bedrooms variable. Although the literature has identified a proven link between each of these variables and health, establishing associations that suggest households with no car access, no central heating or overcrowded conditions have an increased likelihood of suffering poorer health outcomes (Burns, 2017), few researchers have endeavoured to explore whether these factors can actually explain or predict health. Therefore, this finding contributes to the literature, expressing how household-level variables may be an unsuitable level to obtain an understanding of how health varies across an area, thus emerge as limited explanatory factors or predictors of health.

The addition of these variables has limited impact on existing model variables, although slightly improves the β-coefficient of the accessibility index to 0.08. This implies that accessibility has slightly more ability to predict health and explain the variation of health in comparison to household variables. Although, as this relationship is still very weak, accessibility, nevertheless, has limited utility as a predictor of health within London. Instead, the model identifies age, qualification level, and unemployment as the major influences on health in London, accounting for 0.39%, 0.35% and 0.32% increases in the health variable, respectively. This suggests that physical health is more heavily influenced by aspatial determinants of health, as identified by Diez-Roux (2001), Varbanova and Beutels (2020), and Jindrová and Labudová (2020), as opposed to physical accessibility of environmental features.

Chapter 6: Research Limitations

There are several methodological and conceptual limitations of the accessibility index created in this investigation. Firstly, while the construction of the multidimensional accessibility index is imperative for understanding the spatial dimension of health and assessing inequalities in the availability of health-related environments (Cummins et al., 2007), it is crucial to acknowledge that accessibility is underpinned by more than just distance. This investigation assumes that accessibility to healthy-environments can be measured simply using network distance to find the shortest possible distance along London's road network, from each LSOA to its closest health-related feature, constraining the amount of knowledge that can be gained regarding accessibility in London. While this method has been heavily adopted within the wider literature, demonstrating obvious benefits for understanding access to environmental features across given locations (Tonner, 2020), such a measure ignores other aspects of accessibility that may help to provide a more realistic overview of accessibility across neighbourhoods. Accessibility, in addition to proximity, incorporates cost (how much it may cost for memberships, registrations, travel, or access), quality and attractiveness (are the features a good source of what they are providing, do they provide access to disabled individuals), and travel choice (by what means of travel does an individual have to use to reach the service), meaning access may be evaluated in different ways depending on what is important to the user (Handy and Niemeier, 1997; Moscelli et al., 2018). Consequently, although the results of this investigation demonstrate an obvious pattern to accessibility, with those living in outer-London facing greater levels of inequality regarding their access to health environments, it may be useful to further develop the index, through use of gravity models that provide a measure of proximity, opportunity and, attractiveness, as implemented by Liu and Kwan (2020) who quantified inequality in job access for those seeking employment. Extending the index in this way may better reflect the overall accessibility of each London LSOA to health-related features, important for ensuring the index accurately reflects overall accessibility. Nonetheless, the measure used for analysing access in this investigation establishes a clear indication of areas of inequity providing useful practical benefits for targeting areas to improve health-related features of the environment, which, as indicated by Green et al. (2018) cannot be overlooked.

Additionally, it is possible that the indicators used in this investigation did not account for all features that create a healthy environment. Here, the focus was on health-related features of which, firstly, there was accessible data on, secondly, had a proven association with health, and thirdly, could only be interpreted to affect health in one way, either health-promoting or health-negating. Given this, it is possible that the work underrepresented behaviours and issues that it aimed to capture. For example, Green et al. (2018) highlighted how off-licences and fast-food outlets may not be entirely representative of people's access to alcohol and unhealthy food consumption since these products can be purchased outside specialist retail outlets; Håkansson (2020) indicated that through the COVID-19 pandemic, gambling activities have transitioned online so accessibility may be better represented by understanding access to online gambling services, and Sibley and Weiner (2011) recognised that healthcare uptake may not be entirely represented by hospitals and GPs with health centres and drop-in clinics becoming an increasingly used pathway to receive medical care. On a similar note, it may have been useful to incorporate features of the social environment, including access to schools (Peters et al., 2008), access to good-quality housing (Buck and Gregory, 2018), access to colleges, universities or training centres, and access to job opportunities (Liu and Kwan, 2020), all of which have impacts on socio-economic status, deemed to implicate health. The inclusion of such factors may not only help to aid the understanding of accessibility inequalities across London but may also improve the utility of the index, enabling it to be a better predictor of general health across London LSOAs; for instance, given no qualifications was one of the factors most likely able to predict health in this investigation, it may be that access to good schools, universities or training centres, may be a crucial determining factor of health and consequently may help to develop a stronger relationship between the accessibility index and health variation. However, given the scope of this thesis, it was decided to reduce the number of features included in the index to be able to develop a small, but high-quality measure of accessibility. The indicators included provide an excellent basis for understanding the geographical dimension of health, allowing health inequality to be quantified in terms of access to healthy environments, a concept that few researchers have aimed to understand. Nonetheless, there is exciting opportunity for future work to further explore features of the environment that may be implicated in health, and how this may change the pattern of access inequality across London LSOAs. Incorporating other features of the environment would refine the index to ensure it holistically reflects healthy environments, making it a stronger platform to inform policy makers on which neighbourhood features require priority action.

Finally, it is possible that the scope of the investigation is somewhat restricted due to the use of only general health variables when assessing the utility of the index, limiting its generalisability. The work utilised the self-reported health variable, in correlational and regression analysis, and the LLHP variable, in correlational analysis, neither of which provide any detail surrounding the specific health issues a person may face. As neither variable exhibited associations with accessibility, potentially limiting the utility of the index, it may be beneficial to utilise measures that separate out distinct types of poor health. By using different measure to encapsulate overall physical health, overall mental health, and specific health conditions, such as obesity, respiratory and cardiovascular issues, or physical disability, different relationships may be established between accessibility and health in London. This would allow the results to not only be applicable to general population health but specifically to mental and physical wellbeing, providing a better understanding of how accessibility may be implicated in London’s health outcomes. For instance, Green et al. (2018) noted that their overall accessibility index had strong associations with mental wellbeing, while the wider literature has placed great emphasis on the impact of the retail environment on physical health and obesity (Fraser and Edwards, 2010) and has demonstrated strong associations between recreational environments and mental wellbeing (Mitchell and Popham, 2008). However, due to data being unavailable freely or at the appropriate LSOA scale, it was not possible for such measures of health to be included in this investigation. Nonetheless, it offers potential for stronger analysis into the role of access on specific health issues, providing useful applications for the delivery of neighbourhood-level interventions aiming to improve specific health-related outcomes. However, based on the available data, this investigation provided an interesting insight into the pattern of accessibility which can be used by policy-makers to ensure equitable access and to improve health-related environments across neighbourhoods in London, despite not identifying a relationship with general health.

Chapter 7: Conclusions

This research aimed to identify inequalities in accessibility to healthy environments and understand the extent to which these could be used to understand and predict health variation across London LSOAs. Based on quantitative analysis, the study contributes to literature through creation of an accessibility index to understand variations in proximity to health-related environments across London. Previous research sought to understand how demographic and socio-economic factors were associated to health outcomes, with few researchers endeavouring to explore wider environmental features that may impact health. Through analysis of inequities in accessibility and creation of a regression model to understand whether accessibility may be able to predict health, this work provides a framework that better represents the 'holistic environment that influences health' (Green et al., 2018).

Regarding the first research question, it is evident that accessibility provides a suitable platform for understanding inequality across London. Results demonstrate a distinguished inner-outer London divide in accessibility to healthy environments, driven by the relative inaccessibility of outer-London areas to healthcare and recreational environments. Supporting evidence from Green et al. (2018) and Daras et al. (2019) supplements this conclusion, highlighting how a similar divide between rural and urban areas also exists. Results in the individual domains further corroborate the answer to the research question, demonstrating obvious inequalities in relation to specific environmental features, in line with Hart (1971), Widener (2018) and NHS England (2013). The conclusion of these results provides important and beneficial information for policy-makers. The direct measurement of accessibility to features of the environment allows for targeting of those areas that perform poorly, both in the overall index and domains, providing a powerful tool for policy makers. Nonetheless, a more interesting insight to patterns of inequality may be to identify accessibility to features, and domains, and determine which of these may be of greatest influence on health and health inequality. This presents an opportunity for future research to further refine the accessibility index, allowing the index to reflect healthy environments with greater accuracy, improving its applicability for neighbourhood-targeting policies.

Surrounding the remaining two research questions, results make it clear that the overall accessibility index has little utility in predicting health. The results conclude that there is no association between the overall index to general population health measures, showing no correlation between the index and both poor self-reported health and LLHP. The results did, however, present associations between accessibility and population density, age, and ethnicity, supporting the underlying characteristics of the population (Thomas et al., 2015). Research further concludes that individual domains are better platforms for understanding associations between area characteristics and health, supporting previous research that demonstrated each of these aspects of accessibility to be associated with health and wellbeing (Lovett et al., 2002; Shortt et al., 2016; McCormick, 2017). A more revealing analysis may be to replicate this work when 2021 Census data is released to understand whether the association between accessibility and health, or lack of, holds true ten years on.

Regarding linear regression, the accessibility index had no useful contribution to the model fit, confirming the suggestion that there is no association between accessibility and health within London, thus accessibility to healthy environments cannot be used as a predictor of London's population health. Instead, demographic, and socio-economic factors, specifically, age, employment status, and education level, emerged as the key determinants of health across London, indicating these may be the best perspectives to assess for predicting health. However, better results may have been achieved through incorporating individual accessibility domains within the regression model, as these were demonstrated to have a more obvious association with health. Due to the limited scope of this report, it was not possible to construct further regression models incorporating the health, retail, and recreational domains. Thus, it is recommended that future work should adopt an approach that incorporates domains to take advantage of a stronger overall model fit that may be achievable with this data. Understanding whether these platforms may provide a better perspective for understanding and predicting health variation may allow accessibility to emerge as a more crucial determinant of London's health.

Irrespective of the lack of associations between the accessibility index and health, this work develops a model that has wider applicability for understanding inequalities in access to healthy environments, creating a powerful tool for policy-makers. Few researchers have created such a measure looking at general population health, specifically none across the London region, contributing to address this gap within the literature, offering a useful resource for understanding the accessibility of London LSOAs to positive and negative features of the environment. The work extends on previous health indicators, concluding that, although accessibility across London is not a suitable platform for predicting health, the index provides a commanding position for further work to examine inequities in healthy environment access, helping to aid the decision-making process when targeting areas displaying poor health-related environments.

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