20 Minute Neighbourhoods and Allostatic Load:
How unequal access to public space
'Gets under the skin'

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Contents

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List of Abbreviations

20MN	=	20 Minute Neighbourhood
AL	=	Allostatic Load
BHPS	=	British Household Panel Survey
BMI	=	Body Mass Index
BPM	=	Beats per minute
CCTV	=	Closed Circuit Television
CRP	=	C-Reactive Protein
CVD	=	Cardiovascular Disease
DBP	=	Diastolic Blood Pressure
DHEAS	=	Dehydroepiandrosterone Sulphate
ELSA	=	English Longitudinal Study of Ageing
GC	=	Glucocorticoid Hormones
GIS	=	Geographic Information Systems
GP	=	General Practitioner
GPS	=	Global Positioning System
GUTS	=	Generalised Unsafety Theory of Stress
HbA1c	=	Glycated Haemoglobin
HDL	=	High-Density-Lipoprotein Cholesterol
HPA axis	=	Hypothalamic-pituitary-adrenal axis
IGF-1	=	Insulin-Like Growth Factor-1
IMD	=	Index of Multiple Deprivation
LSOA	=	Lower Super Output Area
MAUP	=	Modifiable Areal Unit Problem
OA	=	Output Area
OS	=	Ordnance Survey
Chapter 2	=	Do Perceived Neighbourhood Qualities Explain the Relationship Between Deprivation and Allostatic Load in Understanding Society?
Chapter 3	=	Cross-sectional associations between 20-Minute Neighbourhoods and Allostatic Load in Understanding Society
Chapter 4	=	Longitudinal associations between 20-Minute Neighbourhoods and Allostatic Load in older age groups
PNQ	=	Perceived Neighbourhood Quality
POI	=	Points of Interest
PWC	=	Population Weighted Centroid
SBP	=	Systolic Blood Pressure
SNS	=	Sympathetic Nervous System
UGCoP	=	Uncertain Geographic Context Problem
UKHLS	=	United Kingdom Household Longitudinal Study: Understanding Society

Abstract

Living in areas with high levels of poverty and deprivation is associated with poorer health outcomes across the life-course, even after wide-ranging individual characteristics have been accounted for. However, understanding the processes through which neighbourhood conditions ‘get under the skin’ and which aspects of the built environment are most salient for health remains an important area of research. A promising avenue of study to understand this process points to the stress pathway, measured by the concept of Allostatic Load (AL), as a biologically plausible mechanism explaining how where we live impacts longer term health outcomes. The stress pathway represents the body’s biological response to environmental and psychological stressors and is impacted by the interplay between multiple physiological systems including the nervous, neuroendocrine, and immune systems. Tools from Geographic Information Systems also make it possible to assess detailed aspects of the built environment that may have shared effects across space. Moreover, evolutionary and neurobiological evidence points to feelings of safety being the primary driver of the stress response, indicating the potential importance of subjective experiences of neighbourhoods and objective aspects of the built environment. Chapter 2 introduces the literature surrounding neighbourhood effects and 20-minute neighbourhoods, allostatic load, and the importance of feelings of safety for the stress response. Chapter 3 uses cross-sectional data from Understanding Society to assess whether positive and negative subjective measures of neighbourhood environments predict AL. Chapter 4 links measures of proximal access to 20-minute Neighbourhood domains using OS Maps Points of Interest data to Understanding Society data to assess whether access to domains considered key to daily living predict AL, with consideration given to spatial aggregation effects. The final empirical chapter uses 4 waves from the English Longitudinal Study of Aging to assess the effects of proximal access at the area level on AL.

1 Introduction

Living in areas with high levels of poverty and deprivation predicts poorer health outcomes across the life-course, even after accounting for individual markers of class and income, highlighting the importance of understanding which aspects of areas and deprivation may instil these effects over time (Godhwani et al., 2019a; Jivraj, Murray, et al., 2019; Murray et al., 2013; Olsen, Thornton, et al., 2022; Roux & Mair, 2010). Moreover, an increasing body of evidence (Awad et al., 2022; Benninger et al., 2021; Kamel et al., 2014), has recognised that "the conditions in the environments where people are born, live, learn, work, play, worship, and age …affect a wide range of health, functioning, and quality-of-life outcomes and risks" across the life-course (Social Determinants of Health - Healthy People 2030 | Health.Gov, 2024). This understanding has typically been summarised under the rubric of the social determinants of health (SDH) and highlights the importance of a wide range of non-medical factors that shape people's opportunities for living healthy and fulfilling lives (Hinnant et al., 2022).

Studies have also shown that physiological dysregulation (or bodily wear and tear), measured by the concept of Allostatic Load (AL) (McEwen & Stellar, 1993a), mediates the relationship between neighbourhood deprivation and poorer downstream health outcomes (Prior et al., 2018a), with evidence from the US highlighting the effects of deprivation are partially mediated by subjective assessments of neighbourhood quality (Carbone, 2020a; Robinette et al., 2016; A. J. Schulz et al., 2013). High AL scores are also associated with a variety of poorer health outcomes in advance of their presentation as chronic conditions (Duru et al., 2012; Guidi et al., 2020; McCrory et al., 2023). This pre-clinical position highlights the public health utility of considering AL as an outcome when seeking to explain what features and aspects of neighbourhoods may contribute to poorer health outcomes over time. Given the effect sizes of neighbourhood level exposures are likely to be small relative to health, or take place over long time periods (Murray et al., 2013), the inclusion of a multi-system construct that has predictive validity over and above its individual components and reflects overall levels of physiological 'wear and tear' on the brain and body (McEwen, 1998a; McEwen & Stellar, 1993a), is valuable when seeking to explain how neighbourhoods 'get under the skin'.

The COVID-19 crisis has also exacerbated a trend towards the increasing atomisation of civic and cultural space in the UK, which is likely to impact people's ability to access amenities, work, and social opportunities with implications for social cohesion, stress, and health (AlWaer & Cooper, 2023; Beckes & Coan, 2011). The response to the crisis also led to the necessity to implement strict social distancing measures and complete lockdowns for extended periods of time, creating and exacerbating existing economic, social, and public health challenges. This included the enforced closures and reductions in use of schools, cultural venues, public transport, workplaces, and many of the places where people travel to come together collectively, in what could broadly be defined as 'public space', 'social infrastructure', or the key services and amenities required for good quality daily life. As such, this changed how and where people were able to engage in public spaces and to interact socially with others outside of the household.

These dramatic alterations in the ability of people to access the full realm of public space also builds on decades of privatisation and centralisation that has often seen local institutions generally (from fire stations, to post offices, libraries, transport routes, swimming pools, and small-scale businesses), be they public or private, either closed (We Own It, 2024), or moved further 'away from home' (Becker et al., 2021). The built environment that remains could be said to act as a measure of how the effects of these, and other, challenges have been distributed across communities, space, and time. Given that health is the "result of a complex interplay between contextual socio-economic, built and natural environmental [contexts] as well as individual- and population-level factors" the built environment and neighbourhood contexts may act as a form of exposure and as long term drivers or predictors of ill-health and disease (Chinmoy Sarkar, Chris Webster, & John Gallacher, 2015).

A new way to map access to the features of neighbourhood spaces that may influence how people behave, and the resultant effects on their health (M. A. Green et al., 2018; Kwan, 2009; Sarkar et al., 2013a), is through the use of Geographical Information Systems (GIS). There is already a large and growing body of research exploring the relationship between neighbourhoods and health (G. C. Galster, 2012; Ige-Elegbede et al., 2022; Jivraj, Murray, et al., 2019; Knies et al., 2008; Pérez et al., 2020; van Deurzen et al., 2016). However, in recent literature, the focus of research has shifted from asking whether the neighbourhood matters to why neighbourhoods matter (Matthews & Yang, 2010). As such, moves have been made towards understanding how and what features of neighbourhoods impact health, with one avenue of study focused on defining biologically plausible pathways that can explain how these effects transpire (Diez Roux & Mair, 2010a; Prior et al., 2018b).

Building on this background, this thesis seeks to explain how the effects of neighbourhood composition 'get under the skin' to impact health (Taylor et al., 1997). It achieves this by explaining the relationships between both subjective and objective aspects of neighbourhoods and the built environment with AL drawing on the work of Galster to identify potential causal pathways from the neighbourhood effects literature (G. C. Galster, 2012), as outlined in this introductory chapter below.

AL is considered a suitable outcome measure as it is theorised to capture the effects of cumulative exposures to psychosocial and environmental stressors that may be linked to where people live and how they engage with others (Guidi et al., 2020). Moreover, AL is selected as an outcome as it is associated with a wide range of poorer health outcomes prior to their presentation as disease (Carbone, 2020a; Guidi et al., 2020; Matthews & Yang, 2010; Pérez et al., 2020). Identifying associations with AL, rather than downstream health outcomes, can help clarify how key risk factors for place-based health inequalities contribute to chronic disease. This approach has the potential to better inform interventions to address these inequalities.

The first chapter considers whether subjective perceptions of neighbourhood qualities explain the relationship between area-deprivation and AL. It builds on a previous study using Understanding Society data that identified AL as a mediator of neighbourhood deprivation on poorer mental and physical health outcomes, moving upstream in this mediatory pathway to consider how this takes place (Prior et al., 2018b).

The second and third chapters calculate measures of proximal access to 20-Minute Neighbourhood (20MN) domains using R as a Geographic Information System (GIS) to link OS Maps Points of Interest data (PointX & OS, 2025)[1] with the Understanding Society and English Longitudinal Study of Aging (ELSA) datasets to explore associations with AL cross-sectionally and longitudinally respectively. Given AL's well documented association with a broad range of health outcomes (Guidi et al., 2020), these chapters explore whether areas that demonstrate greater 20-minute-neighbourhood-type attributes are associated with AL, and

[1] The Ordnance Survey's Points of Interest (POI) dataset is a comprehensive, location-based directory of public and privately-owned businesses, education, and leisure services across Britain. It contains over four million records and is updated quarterly to ensure current information.

which aspects of 20MNs are most salient in this relationship after accounting for individual characteristics.

1.1 Literature Review(s)

The following sections of this introductory chapter outline reviews of the literature that provide the theoretical framework for the thesis. This starts with an overview of the potential causal pathways between neighbourhoods and health identified by Galster in a wide-ranging review of the neighbourhood effects literature (G. C. Galster, 2012). Potential pathways were selected from this review for assessment in the empirical chapters that follow. It then outlines challenges surrounding defining neighbourhoods and briefly introduces concepts relevant to the stress pathway that guide interpretation of results throughout each empirical chapter of the thesis[2]. A detailed review of the 20MN framework then follows, identifying the reasoning behind the inclusion of the domains included in chapters 2 and 3 relative to their potential association with AL through the pathways identified. Following this, three common and ever-present concerns when conducting spatial analysis are then outlined and discussed in relation to their relevance to the proceeding chapters: ecological fallacy, the modifiable areal unit problem (MAUP) and the uncertain geographic context problem (UGCoP). Finally, the research questions and hypotheses of each empirical chapter are presented.

1.2 Neighbourhood Effects - Galster's causal pathways

There has been a burgeoning literature exploring the relationship between the neighbourhood context and a wide variety of physical and mental health and wellbeing outcomes. However, a number of reviews note that "a striking limitation of much of the neighbourhood effects literature is the lack of explanation of how causal mechanisms

[2] Allostatic Load and the stress pathway are described in greater detail in each of the empirical chapters.

operate" (Jivraj et al., 2020). In an effort to address this, Galster explored the potential mechanisms through which neighbourhood effects might transpire across the sociological and epidemiological literature and identified 15 potential pathways grouped under four overarching dimensions (G. Galster, 2010). These mechanisms, or pathways, are outlined below with consideration given to the how these pathways could theoretically be affecting AL. Pathways that were considered in the subsequent empirical chapters are highlighted here.

1.2.1 Social interactive mechanisms

Social interactive mechanisms refer to effects that could be considered endogenous to neighbourhoods, or effects that might take hold and spread within them based on the social relations within them. For example, it includes ideas such as social contagion, collective socialisation, and social networks, which each relate to the idea that how people behave and what they aspire to may be impacted by who their neighbours are and how they interact with them, with the potential for 'epidemic' style consequences from the emergent relationships and behaviours. Under this dimension, Galster also directly identifies social cohesion and control as potential causal pathways within this domain due to their potential influence both the behaviours and psychological responses of residents, with related measures present in the Understanding Society dataset.

Measures of perceived cohesion and disorder have also been identified within the wider neighbourhood effects literature as potential mediators of neighbourhood deprivation on health (O. L. Meyer et al., 2014; Murayama et al., 2012; Nazmi et al., 2010; Ross & Mirowsky, 2001; Weden et al., 2008), and on AL specifically in a US context (Carbone, 2020a; A. J. Schulz et al., 2013), making them good candidates for inclusion to assess this pathway within the UK context. Cohesion may be expected to reduce AL as, in a neighbourhood with strong social ties, residents may regularly engage with their neighbours, feel an enhanced sense of belonging, have greater resources for collective advocacy, and be more likely to actively help one another in times of need, such as during illness or financial hardship (E. S. Kim et al., 2020; Mendes de Leon et al., 2009). The subjective assessment of the presence of such a social support system may also itself provide signals of safety to prevent chronic activation of the stress-response. Conversely, in a neighbourhood with high levels of crime and disorder, residents may experience persistent anxiety, insecurity, a lack of social ties, a sense of neglect, and fear of using public spaces, which may repeatedly signal unsafety and promote chronic activation of the stress-response. As such, chapter 2 considers whether summary measure of perceived neighbourhood cohesion and perceived crime and disorder explain the relationship between neighbourhood deprivation and AL (Baranyi et al., 2020; Derose et al., 2019).

1.2.2 Environmental mechanisms

Galster describes environmental mechanisms as effects resulting from “natural and human-made attributes of the local space that may affect directly the mental and/or physical health of residents without affecting their behaviours” (G. C. Galster, 2012). There were just 3 potential mechanisms identified under this dimension which included: exposure to violence, the importance of physical surroundings, and toxic exposures. The exposure to violence mechanism reflects fears of violence to property or person that may be expected to trigger a chronic stress response both in the face of an actual or perceived[3] experience. For example, persistent perceptions of unsafety can lead to heightened vigilance and activation of the stress-response system. When individuals perceive their neighbourhood as dangerous, they

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[3] Here perceived includes worry and expectations for the future and trauma and past experiences.

may experience ongoing anxiety, fear, and hypervigilance, emotions likely to trigger sustained responses

The role of gender may be particularly relevant for this measure of the environmental mechanisms. For example, fear of the walking environment amongst women and girls may most often relate to a fear of sexual assaults and harassment by men (Ferraro, 1996; K. Johansson et al., 2012), built on experience (EVAW, 2021; ONS, 2022). Sexual minorities are also more likely to report fear of walking alone at night than men (D. Meyer & Denise, 2014), due to experience (Flores et al., 2020). Other social groupings, such as race, age, ethnicity, sexuality, and socioeconomic class, can also amplify or mitigate disadvantage, (A. Walker, 2020), as “the youngest and oldest women as well as those with lower socioeconomic status are generally found to feel unsafe, for instance, outdoors late at night” (S. Johansson & Haandrikman, 2023).

Secondly, the physical surroundings mechanism is premised on the idea that where people live may have psychological impacts. These mechanisms are akin to the ideas of the ‘broken windows’ hypothesis that posits that visible signs of disorder in a community, such as vandalism, graffiti, litter, or abandoned buildings, create an environment that encourages further disorder and potentially more serious crimes (Lanfear et al., 2020; Troxel et al., 2020). Observing deteriorated physical surroundings can also amplify fears of crime, even if actual crime rates are low (Navarrete-Hernandez & Afarin, 2023).

Thirdly, the toxic exposures dimension reflects more direct physiological pathways, such as exposure to air-pollution (Hajat et al., 2013; Williamson, Tim, 2021). As such this dimension reflects mechanisms of place that instil a sense of fear, neglected physical environments, and biological exposures to pollutants. Overall, the broad environmental dimension is explored across each of the empirical chapters, with a measure of perceived safety walking alone at night identified as reflective of the exposure to violence mechanism considered in relation to AL in chapter 2. The subjective measure of perceived crime and disorder, included in chapter 2 based on its identification as a social interactive mechanism that may influence AL, could also be considered as a measure of the physical surroundings mechanism, as described here, further justifying its inclusion. However, perceived safety reflects a more direct relationship to the mechanisms of exposure to violence identified here and reflects a distinctive dimension of fear of crime and unsafety, particularly for certain groups, that warrants individual assessment (Camacho Doyle et al., 2022).

Chapter 4, which explores the effects of proximal access to key services and amenities from the 20-minute neighbourhood literature (outlined in section 1.5), considers differences between urban and rural environments which themselves reflect aspects of each of the mechanisms identified under this dimension. For example, urban environments typically expose residents to greater levels of pollution (Xu et al., 2022), higher levels of crime (GOV.UK, 2025), and experience higher concentrations of degraded public spaces (Hipp & Williams, 2020). Moreover, the Generalized Unsafety Theory of Stress (GUTS) posits that prolonged stress responses arise from generalised and largely unconscious perceptions of unsafety, rather than from specific stressors (Brosschot et al., 2018). This theory also suggests that the stress response is a default mechanism that remains active but is inhibited by the prefrontal cortex when safety is perceived. According to GUTS, urban environments may be more likely to lead to persistent perceptions of unsafety and lead to heightened vigilance and activation of the stress-response system. In chapter 4, the sample is stratified by urban or rural area to assess this.

1.2.3 Institutional mechanisms

Institutional mechanisms refer to largely exogenous forces resulting from how resources, such as public, private, and/or non-profit actors, are allocated to and across specific areas. Again, three mechanisms were identified here: stigmatisation; local institutional resources; and local market actors. Stigmatisation mechanisms identify effects resultant from neighbourhoods neglected due to present or historical prejudices, geographical location or topology, and the conditions of public spaces. A relevant contextual example in the UK might be the government's 'levelling-up' fund (Dixon & Everest, 2021; GOV.UK, 2021), with wealthy areas receiving more funding than the poorest areas (McIntyre et al., 2022), and the potential outcomes resulting from how these funds are distributed and spent (Shaw, 2023). Even were decision making processes fair, such decisions still reflect institutional actors discriminating through the control and delivery of resources to certain areas over others. Such mechanisms may influence AL through restricted opportunities, internalisation of stigma, or feeling left-behind signalling unsafety and releasing the stress response.

Mechanisms regarding 'local institutional resources' assess the impact of what resources are present within areas and the quality of services on offer. Areas lacking access to quality services may impact AL through reduced access to social capital and support that may be reflected by the presence or absence of infrastructural resources. The 'local market actors' pathways describe effects influenced by behaviours that depend on the types of businesses and services present in the area. For example, services or businesses that promote or discourage behaviours that may be healthy or unhealthy may influence AL if their presence or absence predicts or promotes risk taking or coping mechanisms (Brenner et al., 2015; M. A. Green et al., 2018; Macdonald et al., 2018; Suvarna et al., 2020). These mechanisms are explored in chapter 2, with a measure of perceived local service quality assessing subjective assessment of this dimension, and chapters 2 and 3, which examine how access to services across 10 commonly included 20MN domains influence AL.

1.2.4 Geographical mechanisms

There were two pathways described under this dimension which describes aspects of neighbourhoods that arise "purely because of the neighbourhood's location relative to larger-scale political and economic forces" (G. Galster, 2010). The first pathway, 'spatial mismatch', identifies pathways assessing effects of living in areas that lack access through either spatial proximity or transport to opportunities commensurate to the skillsets of their residents. These sorts of mechanisms may relate to AL through a lack of satisfaction in work (Chandola et al., 2019a), or employment or financial insecurity (Chandola & Zhang, 2018; French, 2023). The second identified pathway, 'public services', focuses on effects relating to disparities in the quality and availability of public facilities and infrastructure. For example, social mobility, employment, health, and social engagement opportunities may be impacted by the availability of essential resources, such as high-quality schools, transportation networks, healthcare services, and access to greenspace. Relative to AL, the presence or absence of such resources, or their proximity may signal feelings of safety or unsafety to residents, with impacts on AL.

These mechanisms are explored in chapters 2 and 3 using the 20MN framework. The 20MN framework appears particularly well suited to address the identified geographical mechanisms through its emphasis on the value of equitable access to essential services, fostering social and local connections, and reducing environmental stressors. These factors may influence AL through the encouragement of behaviour change through physical activity, improving access to social support, improving access to greenspace and reducing exposure to pollution, and reducing stress from commuting and health disparities (Egorov et al., 2017; Friel et al., 2024; Saxbe et al., 2020b).

1.3 Defining Neighbourhoods

Neighbourhood effects research seeks to test whether there is a causal relation between the spatial context where people live and specific outcomes (Petrović et al., 2022). The concept of the neighbourhood is also widely recognized in policy and research as it invokes a sense of understanding about what a neighbourhood is. However, defining what a ‘neighbourhood’ is often depends on the disciplines and research questions being asked and likely means different things to different people akin to an ‘empty signifier’ (Jeffares, 2008; Laclau, 2001; C. Wang, 2022). As such, neighbourhoods have been variously described as: places where people are expected to live and spend much of their time; the immediate residential environment around people’s homes; as specific territorial and administrative units used to aid in the planning of local services and facilities; areas of homogenous housing and/or populations; and areas that share a certain degree of collective social, cultural, emotional, or reputational significance for residents, amongst others (C. Coulton, 2012; Ribeiro et al., 2022; Roux & Mair, 2010; Weiss et al., 2007).

Neighbourhood definitions are often context specific and may vary by country, between regions, and between the urban and rural divide, presenting a challenge when trying to consider the health impacts of ‘neighbourhood’ environments even prior to considering how they are actually used and experienced by the people within them (Kershaw et al., 2024). However, across this spectrum of definitions, neighbourhoods are typically assessed: based on resident perceptions; based on community/demographic characteristics; by using existing administrative boundaries; by implementing custom-designed boundaries using Geographic

Information Systems (GIS) or; by creating objective measures of activity space using Global Positioning Devices (GPS) (C. Coulton, 2012; Diez Roux, 2001a; Pearson et al., 2024).

Within the concept of the neighbourhood, characteristics of both the built and natural environment have been found to shape how people engage with space, influence behaviours, and impact downstream health outcomes. For example, infrastructure and the built environment can achieve this by providing “the spaces and places that support social connection and sociality” in public and quasi-public spaces (Latham & Layton, 2019). Literature focusing on social infrastructure highlights how local infrastructure acts as a “complex system of facilities that provides the space for programs, and social networks that aim to improve the quality of life” of residents of a given area, with its presence or absence expected to impact the psychosocial resources available to those living there (Yhee et al., 2021a). As such, infrastructure can serve as an indicator of aspects of neighbourhoods that signal feelings of safety that inhibit the stress response through the formation and development of social networks, community organizations, and wider support systems that, combined, foster and support the connectivity, cohesion, wellbeing, and quality of life of communities.

How people engage with space and behavioural changes can also be encouraged by how the built environment is structured and perceived, with potential benefits related to AL and downstream health outcomes through the promotion of physical activity, access to nature, and access to social capital (Egorov et al., 2017, 2024). These sorts of behaviour changes are also evidenced by consistent positive associations evident in the literature with active travel modes in areas with greater levels of walkability, higher population density, good quality public transport, and proximity to a variety of destinations (Albanese et al., 2022; Frank et al., 2007; Mouratidis, 2018; Sarkar et al., 2013b). When seen in this way, individual conceptions of the neighbourhood and objective measures of the built environment that shape it can play a role in both improving individual AL and reducing wider health inequalities (Olsen, Thornton, et al., 2022).

Whilst it is recognised in the literature that neighbourhoods are multifaceted and neighbourhoods intrinsically reflect both objective and subjective characteristics, most studies tend to use census tracts, postcodes, or other administrative units as proxies for neighbourhoods and only a single measurement unit of scale (Arcaya et al., 2016; C. J. Coulton et al., 2001). Reliance on administrative units is often related to their availability, standardised nature, and use in official statistics, aiding comparison. Research findings are also often expected to be more relevant for policy when tied to administrative units which may serve as the territorial unit for the planning and delivery of local facilities and services (Ferrer-Ortiz et al., 2022). However, research highlights the fluidity of neighbourhood boundaries which are shaped by the shared access to and use of public spaces, strength of social ties, and physical barriers that are not always well reflected in such measures. As such, this thesis seeks to address this by assessing relationships between both subjective (chapter 2) and objective definitions of neighbourhoods and AL using constructing measures of access that function across administrative boundaries (chapters 2 and 3).

1.4 The Stress Pathway

1.4.1 Allostatic Load[4]

The concept of allostatic load (AL) was developed by McEwen and Stellar (1993) to explain how repeated physiological stress responses lead to wear and tear on the body and brain, potentially accelerating health deterioration and increasing the risk of disease. As such,

[4] Additional detail on AL is provided in each of the empirical chapters.

AL refers to the cumulative physiological burden that results from repeated or chronic exposure to stressors. It arises when the body's stress response, which is essential for short-term adaptation, becomes dysregulated due to prolonged activation (McEwen, 1998a; McEwen & Stellar, 1993a). AL reflects the wear and tear on regulatory systems, including the sympathetic nervous system, the hypothalamic-pituitary-adrenal (HPA) axis, and the immune system, which work together to maintain stability (homeostasis) through change (allostasis) in response to environmental challenges. As such:

"the concept of AL provides a conceptual and methodological basis for elucidating the behavioral [sic] and physiological mechanisms by which i.e. early life experiences, living and working environment, and other lifestyle factors all converge to affect body chemistry, structure, and function over a life-time" (Hansen et al., 2022).

Allostasis allows the body to adapt to psychosocial and environmental challenges by temporarily shifting physiological set points. However, chronic activation of the stress-response can lead to allostatic overload, impairing the body's ability to recover and increasing the risk of poor health outcomes. AL is commonly operationalised as a composite measure of biomarkers representing dysregulation across multiple physiological systems, though the exact biomarkers used and how they are combined into a composite measure varies between studies (Beckie, 2012). Despite inconsistencies in its measurement, research consistently links higher AL to a wide range of poorer physical and mental health outcomes, including cardiovascular disease, cognitive decline, and mortality, situating it as an important risk factor for health inequities (Karlamangla et al., 2002; T. E. Seeman et al., 2001).

Studies have also shown that AL has greater predictive power for health risks than individual biomarkers alone, further demonstrating its utility in identifying individuals at risk of chronic conditions before symptoms emerge (Castagné, Garès, Karimi, Chadeau-Hyam, Vineis, et al., 2018; Juster et al., 2010). This is important when considering neighbourhood environments as exposures due to their potentially small short-term, but long-reaching, impact that may be missed when past residence is not accounted for (Murray et al., 2013). Whilst debates continue regarding standardisation (McCrory et al., 2023), evidence supports AL's robustness as a framework for understanding the biological consequences of chronic stress and its role in long-term health disparities (McLoughlin et al., 2020; Prior et al., 2018b).

1.4.2 The Generalised Unsafety Theory of Stress

Even if it is accepted that perceived neighborhood qualities and distances to 20MN domains act as an exposure to stress (as this thesis proposes), considering whether this can lead to physiological dysregulation requires elaboration as to how this may transpire. Specifically, consideration needs to be given to the theory of how the presence or absence of particular psychosocial contexts may lead to chronic stress, or how the composition of an area acts as a stressor to such an extent that it contributes to physiological dysregulation manifested in AL. Brosschot et al.'s 'Generalized unsafety theory of stress' (GUTS) offers a useful explanation of how this process may take place conceptually, building on neurobiological and evolutionary insights that turn conventional wisdom on the stress response on its head (Brosschot et al., 2017). They argue that typical explanations of stress both recognise "that chronic physiological stress responses are the crucial causal factor leading to disease" and fail to recognise that the duration of stress exposures frequently outlasts the stressful events themselves. They note that the focus on actual threats in the environment (or acute exposures to stressors) insufficiently explains the sorts of prolonged manifestations of stress that are necessary for physiological dysregulation of the body's subsystems and organs to take place (Brosschot et al., 2018).

Evolutionary and neurobiological evidence points to the stress response as being a default and unconscious response of the brain that is "phylogenetically extremely old, [and] developed far before conscious awareness developed in humans" (Brosschot et al., 2018). As such, the stress response does not need to be triggered and is in fact always activated as the default response unless inhibited by perceived safety. This is explained evolutionarily as disinhibition (or letting go) is more cost-effective in terms of energy use than inhibition (Waldvogel et al., 2000). Where safety is not perceived, the stress response is instantly ready as it is always 'on' and only 'switched off' by feelings of safety. They note that "animals (and by extension humans) do not wait for certainty about a threat in an uncertain or new situation: they immediately show a stress response, prepared to err on the side of caution" as it is better to flee 10 times unnecessarily rather than the one time it matters (Brosschot et al., 2018). Moreover, "the behavior [sic] of organisms is not controlled directly by external variables but by the regulation of internal perceptions that convey data from sensory receptors" (R. M. Nesse, 2005). At the neurobiological level, evidence shows perceived safety is a necessary pre-requisite for the pre-frontal cortex to suppress the areas of the brain that control the stress response, such as the amygdala (Brosschot et al., 2018; Maier, 2014; Waldvogel et al., 2000). As such, perceived safety should be seen as the primary determinant of the stress response, particularly in relation to physiological dysregulation and chronic stress, rather than actual threats in the environment.

From this perspective, stressors are not required for stress responses to be unleashed as perceived safety is the primary determinant of the stress response. Questions on prevention should focus on what stops stress rather than what causes it as well as what supports or inhibits feeling of safety. This relates to 20-minute neighbourhoods, as theoretically they are designed to provide opportunities for employment (Chandola et al., 2019a; Chandola & Zhang, 2018), social connections (Saxbe et al., 2020b; Stephen et al., 2021), increased physical activity (Bu & Li, 2023), lower pollution (Qiu et al., 2023), and access to nature (Egorov et al., 2024), all of which might contribute to both the opportunity for and actual experience of feelings of safety, that may be measured and represented by lower AL (AlWaer & Cooper, 2023; Moreno et al., 2021; Thornton et al., 2022)[5]. They may also provide spaces and places where activities or social interactions can take place that provide a sense of security and buffer against the stress response being unleashed or disinhibited (Chau et al., 2022). Conversely, the car-oriented legacy of organising cities, a feature of areas that 20MNs seek to address, has resulted in significant issues that may trigger feelings of unsafety, such as air pollution (Thomson, 2019), traffic congestion and longer commute times (Conceição et al., 2023), reduced accessibility to amenities (M. A. Green et al., 2018; Zahnow, 2024), sedentary lifestyles (Chauntry et al., 2022), and the fragmentation of communities (Carbone, 2020a), which are all aspects of the built environment found to be associated with AL in the research referenced here.

This is not to say that actual stressors do not play a part in explaining any relationship between how the effects of place may 'get under the skin' as studies have shown that "living in an environment that is appraised as threatening induces chronic psychological stress, and

[5] The literature outlined here highlights evidence in the literature assessing relationships between the 'opportunity' and AL.

the chronic stress response can cause adverse physiological changes that in the long run might impair health" (van Deurzen et al., 2016). Thinking about stressors and ruminating about past or future stressors has been evidenced to affect cardiovascular, autonomic, and endocrine nervous system activity (Brosschot et al., 2017; Ottaviani et al., 2016; Roest et al., 2010; Yoshino & Matsuoka, 2009). However, the principles outlined in the GUTS highlight that it is often the unconscious feelings of unsafety that are responsible for the prolonged physiological stress responses linked with disease as this disinhibits the (always switched on) stress response.

This is important in terms of understanding how access to 20MN can be considered as an exposure relative to AL, which is itself an indicator of chronic stress, as access to the included features representing domains are expected to be associated with healthier outcomes and invoke feelings of safety and security rather than a threat. Given that chronic physiological stress is largely reliant on signals of safety, according to GUTS, this evidences how the absence of resources may themselves act as a stressor through their signalling of unsafety. That the stress response is also theorised to be a largely unconscious process, is also important here, as it is challenging to consider the presence or absence of features in the built environment to be stressful in and of themselves, such that they would meet the definition of an exposure. For this thesis, it is what these spaces and places represent collectively (*#ACFM Microdose*, 2021), as places that support community life, foster sociality, allow people to come together in crowds (*#ACFM – Trip 2*, 2019; *#ACFM – Trip 13*, 2021), and that promote exercise and play, that is theorised to link their presence or absence to the stress response (Latham & Layton, 2022).

1.5 20-Minute Neighbourhoods

The 20-minute-neighbourhood (20MN) framework offers the potential to explore whether specific attributes of the built environment and the social relations, opportunities, and interactions that they facilitate or hinder, help to explain health inequalities related to place that are mediated through AL (Lamb et al., 2023). As Sarkar et al. note, "the quality and extent of local environmental exposures influences individual physical activity behaviour, lifestyle and social interactions, general well-being and consequently, specific health outcomes including weight outcomes, stress levels, cardio-metabolic and mental health risks" (Chinmoy Sarkar, Chris Webster, & John Gallacher, 2015). Relatedly, the fundamental premise of the 20MN is that access to key infrastructure is provided locally and poorer or improved access to this may mitigate or contribute to many of the social determinants of health that impact people's quality of life and health outcomes (AlWaer & Cooper, 2023). However, within the 20MN framework, access to the built environment or overall 20MNs may better be considered as an enabler of health rather than as a determinant given that the physical design of places can only encourage, rather than enforce, activities and social interactions within these spaces (Tigran et al, 2020).

The model of the 20MN (or x-minute city (Lu & Diab, 2023)) actually began life in France with Carlos Moreno's concept of the 15-minute city who argued services that met six functions should be included: living, working, education, healthcare, commerce, and entertainment (Calafiore et al., 2022; Dunning et al., 2023, p. 20; Moreno et al., 2021). However, this has subsequently extended to the broader 20MN framework with many additional domains included. Popular in the urban planning literature (Wiewel & Kafoury, 2012), it has garnered increasing policy interest in the wake of the COVID-19 pandemic (Calafiore et al., 2022; Kamruzzaman, 2022; Silva et al., 2019). Its simple premise is to improve people's proximal access to the fundamental activities essential for daily living so that they can, ideally, be accessed by walking, wheeling, cycling, or public transport (SUSTRANS, 2020). The expectation of implementing 20MNs is that they will encourage local spending, increase social interactions, encourage healthier choices, and improve environmental outcomes (Thornton et al., 2022).

Due to the wide-ranging nature of what infrastructure can be considered key, the design of 20MNs necessarily requires the involvement of a variety of stakeholders in the planning process for the delivery and definition of key destinations, such as (but not limited to) grocery stores, libraries, recreational facilities, healthcare, and retail and commercial services, within a short distance from people's homes. The policy has gained global traction and become attractive to national and regional governments seeking to reduce urban sprawl, to create communities that are more resilient to health and economic crises, and with an interest in tackling inequalities in access to key services, which were made particularly apparent by the pandemic (AlWaer & Cooper, 2023; Moreno et al., 2021). The 20MN concept has been described as either building on or rebranding previous ideals of the urban planning literature, such as Garden Cities (Cailar, 1968), walkable neighbourhoods (Carson et al., 2023), or compact cities (Anabtawi, 2023), and shares features with measures of access to social infrastructure (Davern et al., 2017) and low traffic neighbourhoods (Xiao et al., 2023).

A major strength of the concept lies in the fact that it has succeeded in sparking global dialogue about creating "sustainable, connected, walkable places that are intended to be beautiful and safe" (AlWaer & Cooper, 2023). However, there is no common definition, be that which amenities are to be considered as 'key' to daily needs, or what a suitable distance threshold should be that would represent access, with 15-minute cities also a common framing (Willsher, 2020)[6]. Beyond ensuring people have access to key services and amenities within a short distance of their home (Lamb et al., 2023), proponents of the 20MN argue its implementation will lead to broader beneficial outcomes for health, the environment, and communities (Calafiore et al., 2022). The deliberate design of places in support of active forms of travel, in place of cars, and to support all ages to live with access to mixed economies and greenspaces is expected to: boost local economies; reduce poverty, isolation and loneliness; improve people's health and wellbeing; and to contribute to efforts to tackle climate change. As well as facilitating health benefits through promoting active travel (Jarrett et al., 2012), better access to key amenities is expected to achieve these wider benefits, in part, through their ability to act as "the scaffolding of social capital – [that] includes all of the community organisations, groups, and spaces in which we organically congregate as members of local communities and become anchored in neighbourhood networks" (Bell et al., 2021).

In this way 20MNs may be considered as akin to larger urban areas that act as "a supra-organism with its component spatial road networks as the vascular system channelling the positive and negative externalities of urban agglomeration to individuals" (Chinmoy Sarkar, Chris Webster, & John Gallacher, 2015). Defined in this way, 20MNs go beyond the existence of physical structures where people come together, and can be conceptualised as a "dynamic and complex ecosystem" that mixes "hard infrastructure" – buildings and other spaces – and "soft infrastructure" – the groups, networks, online forums and individuals that bring the physical facilities to life" (Bacon et al., 2020). Nevertheless, the objective features

[6] Sometimes described as 20-minute neighbourhoods, 15-minute cities, social infrastructure, or walkable neighbourhoods, X-minute neighbourhoods are conceptualised as spaces that can be designed collaboratively so that residents can meet most of their daily needs within a reasonable distance from their home, however, any type of x-minute city is referred to as a 20MN in this thesis.

of neighbourhoods (such as hospitals, schools, shopping centres, transport infrastructure and so on) that can be measured based on characteristics such as their number, density, and proximity, offer a useful proxy to operationalise people's access to 20MNs in different areas and at varying scales. As such, features such as these are often used to calculate and assess 20MN provision, although the associated benefits of measured provision (or operationalised 20MNs) have only very rarely been investigated.

An additional, but fundamental, aspect of 20MNs is that they involve communities, planners, and businesses in the implementation process and, as such, there is no uniform approach to what amenities are considered 'key' to daily living. Indeed, that there is no blueprint is intrinsically important to the 20MN concept, given that what is deemed essential is expected to be contested and decided upon across local, regional, and national scales as well as between urban and rural settings (Lamb et al., 2023). This is important given "urban environments can be grossly unequal, contain all sorts of barriers to entry, and that much commercial and political activity can close down particular kinds of public space" (Latham & Layton, 2019). Given that different communities will have their own specific contexts and aspirations "plans to create a 20-minute neighbourhood should be based on what the local community wants" (TCPA, 2021). Nevertheless, whilst there is no single conception of what a 20MN neighbourhood should look like, commonality exists across existing policies in cities and countries that have sought to implement this type of policy in practice.

The C40 knowledge hub, which acts as an online "resource for cities wanting to act on climate change" and lead "the way towards a healthier and more sustainable future" notes that 20MN type neighbourhoods tend to have: easy access to goods and services, with a focus on fresh food and healthcare; mixed housing across affordability levels to enable diverse groups to live closer to where they work; clean air and green spaces to enjoy, and; varied local employment opportunities with spaces for remote working (C40, 2020). Other common aspects or targets of 20MN designs include well-connected paths, streets, and spaces safe for active travel, schools being at the heart of communities (such as in Paris where schools opened up facilities 'after hours' (Gongadze & Maassen, 2023)), making neighbourhoods a place for all ages (TCPA, 2021), and ensuring community buy-in that fosters behaviour change, such as increased active travel and improved community cohesion (ClimateXChange, 2021). For 20MNs to be successfully implemented, they should include the sorts of physical spaces in which regular interactions can be facilitated between and within diverse sections of a community, and where meaningful relationships and trust can be fostered amongst people (TCPA, 2021).

To operationalise the concept, meeting people's daily needs through the provision of 20MNs is typically reflected by measuring access to certain key domains (such as community services), that are assessed as being met based on the presence or absence of specific features (such as libraries or community halls) within predetermined ranges (calculated within certain Euclidean buffer ranges ('as the crow flies' or 'straight-line' distances) or using network analysis (that considers the actual topology of places and/or travel routes in Geographic Information Systems (GIS)). For example, one study looked at access to 20MN domains across Scotland where the government intends to apply the concept of 20MNs across the whole country (Olsen, Thornton, et al., 2022). They outlined and measured access to 10 fundamental domains (healthy food retail; public transport; local primary health care facilities; education; financial; community health resources; accessible public open space; recreational, sports pitches and facilities; social and cultural; and eating establishments) that were defined based on consultations with relevant stakeholders and literature searches.

Elsewhere, one study included five domains (healthy food, recreational resources, community resources, public open space, and public transport) in an assessment of Melbourne and Adelaide 20MN implementations (Thornton et al., 2022). Similarly, a separate Australian study sought to develop a social infrastructure index by grouping features into six domains (community centres, culture & leisure, early years, education, health and social services, and sport and recreation) and assessing access using pre-defined distance thresholds (Davern et al., 2017). Despite common ground across studies of 20MNs, these operationalisations serve to show that the included domains, and the features included to indicate domains, often vary or overlap. For example, the number of domains included in 20MN definitions are not uniformly selected across studies. Moreover, domains tend to be represented by access to specific resources, such as libraries and community centres, and these underlying features can additionally differ both by their inclusion/exclusion as indicators of a domain or even by the overarching domain they are selected to represent. One typology might include a library as an indicator of community facilities, whilst another might include it within a broader domain of public infrastructure. This reflects the nebulous nature of the 20MN concept in terms of both how it has been practically implemented and assessed in the literature.

In addition to selecting what features and domains to include within any 20MN definition, categorising areas by the extent to which they demonstrate 20MN qualities also requires consideration to be given to how access is itself measured. To begin with the concept has its 15-minute and 20-minute framings, which inevitably lead to different ranges. Within these differing time frames, the idea of access is typically considered based on ‘average’ walking speeds estimated uniformly for all people, with research from Australia showing 800-metres each way as the maximum threshold people are likely to choose to walk to and from a resource or area (Planning, 2024). However, the extent of reach 800-metres offers can also vary as it can be calculated as a network distance (factoring in actual routes and barriers) or as a buffer range (calculated in an 'as the crow flies' manner, such as with a circle forming the perimeter about a central point or simply an a to b distance).

A review of 15-minute cities literature (Lima & Costa, 2023), highlights a number of other ways 'access' to 20MNs has been measured in the literature. This includes the importance of considering land-use mix within given areas, as having access to varied amenities within local areas is likely to reduce the need for long-distance travel, so consideration needs to be given to overall access[7]. Measures of land-use mix typically involve consideration of included 20MN domains collectively within a score or index, that may be assessed based on how many domains are accessible within a pre-determined range (Calafiore et al., 2022; Olsen, Thornton, et al., 2022), how much physical space is used by each type (Frank et al., 2004; Sarkar et al., 2013c), or require multiple features to be present in order to be included (Latham & Layton, 2019; TCPA, 2021).

The importance of proximity of services is also fundamental to assessing 20MNs as a proxy measure of the ability of people to save time accessing the things they need closer to home (*#ACFM Microdose*, 2021). More computationally intensive approaches include assessment of the degree to which areas offer pedestrian-friendly designs, including pedestrian-friendly streets and dedicated cycling infrastructure as indicators of greater ease of movement that might encourage active travel, and minimise the travel distances people need to make whilst saving them time. Access to efficient public transport systems are also often measured due to their ability to extend an individual's reach with a lower carbon footprint, as

[7] This is achieved in the analysis through the inclusion of each domain measure within single models.

the concept is neither "dictating to people that they must choose to access services within 15 minutes of their house" nor a "sinister…idea that local councils can decide how often you go to the shops…ration who uses the roads" policed with CCTV as the then Conservative transport and energy ministers maligned (Addley, 2023).

Although there is a growing body of research that has sought to assess the extent of 20-minute neighbourhood provision, this has often fallen at the city or lower regional levels (Lamb et al., 2023; Thornton et al., 2022), rather than looking at the national picture or using nationally representative data. Only a few studies have sought to assess any of the potential beneficial outcomes that increased access to 20-minute neighbourhoods are theorised to offer (Fernandez et al., 2024; Lamb et al., 2023; Olsen, Thornton, et al., 2022), with the literature more often stopping at the assessment of provision stage (ClimateXChange, 2021; Fang et al., 2021; Hu et al., 2023; Thornton et al., 2022; Weng et al., 2019). This study seeks to address these gaps by outlining the overall picture of 20MN access at the national scale in England and assessing whether areas that indicate greater properties of 20MNs are associated with lower AL (in chapters 2 and 3). AL is selected as an outcome due to being an indicator of physiological dysregulation and as a predictor of poorer health outcomes prior to their presentation as disease. AL has also been found to mediate the relationship between deprivation and poorer health outcomes at the neighbourhood scale, over and above the individual level characteristics of the people living within them.

1.5.1 Defining 20MN Domains and Features

The 20MN domains were selected based on existing operationalisations of 20MNs in the literature (Calafiore *et al.*, 2022; Thornton *et al.*, 2022, p. 20; Lima and Costa, 2023). Whilst some approaches include multiple representations of similar domains within a single

20MN operationalisation, such as primary healthcare and community healthcare (Olsen, Thornton, et al., 2022), or primary greenspace and secondary greenspace (TCPA, 2021), only distinctive domains in the literature were retained to allow for their concurrent inclusion in models. This resulted in the selection of the following 10 domains: 1) Community Facilities; 2) Culture; 3) Education; 4) Eating and drinking; 5) Food Services; 6) Financial Services; 7) Greenspace and Recreation; 8) Health services; 9; Public Transport; and 10) Retail Services. Features included to represent domains were selected from the Ordnance Survey Points of Interest data (PointX & OS, 2025). Details of the features included to represent domains and justification for their inclusion within both the 20MN framework and relative to AL are outlined in table 1 below[8].

[8] This table drew on the domains selected in a review of the Scottish context which was the only other nationwide review of 20MNs found in the literature (Olsen, Thornton, et al., 2022).

Table 1: Description of 20-Minute Neighbourhood Domains and included features and relevance to Allostatic Load

Domain	Features	General justifications for 20MN inclusion (Olsen, Thornton, et al., 2022)	Allostatic Load relevance
Community Facilities	Social Clubs, Halls and community centres, Libraries, Sports Clubs and Associations	Can be used to run activities and become key community spaces, increase social connection, and foster community cohesion.	Positive community perceptions associated with lower AL (Carbone, 2020a; van Deurzen et al., 2016). Multi-group-membership and social relationships attenuate physiological reactivity to stress with benefits for AL (Stephen et al., 2021).
Culture	Historic Buildings, Historic Structures, Historical Ships, Museums, Art Galleries, Cinemas, Theatres and Concert Halls, Places of Worship	Evidence that spatial access to cultural destinations represent opportunity structures increasing probability of use across many population groups (Brook, 2016).	Frequent participation in arts, attending cultural events, visiting museums or galleries or historical sites associated with lower AL in Understanding Society (S. Wang et al., 2021).
Eating and Drinking	Cafes, Snack Bars and Tea Rooms, Pubs, Restaurants	Evidence areas are providing more than basic necessities. Offer opportunities for social engagements outside the home.	Evidence that people are more likely to feel happy and satisfied with their lives the more often the eat with others, have wider social networks, improved wellbeing, and

		Venues that facilitated residing in the venue were retained which excluded fast food outlets but not pubs.	sharing meals with others promote closeness (Bernardi & Visioli, 2024; Dunbar, 2017; Middleton et al., 2022).
Education	First, Primary, and Infant schools, further education, independent and preparatory schools, secondary schools, special schools and colleges, higher education, other schools	Indicator of being a place for all ages. Educational infrastructure supports skill development, social and economic mobility, human flourishing, and community anchors.	Higher educational attainment associated with lower AL in some (but not all) groups/populations (Ding et al., 2019; Hansen et al., 2022; Howard & Sparks, 2015; L. J. Richardson et al., 2021). Education a vehicle for both social and economic success and an institution that reproduces generational inequality (Zajacova & Lawrence, 2018).
Food-Services	Bakeries, Butchers, Frozen Foods, Grocers, Farm Shops and Pick your own, herbs and spices, organic, health, gourmet and kosher foods, convenience stores	Provide a range of fresh and healthy foods and other core household food items. Large supermarkets offer wide range of goods at more affordable prices(Olsen, Thornton, et al., 2022).	Food insecurity and poor diet has been linked to increased stress, anxiety, and metabolic risk factors (Chiu et al., 2024; Myers, 2020; Stone et al., 2024; Wolfson et al., 2021). High presence of online and physical store food deserts in UK (Janatabadi et al., 2024). Higher cardiovascular risk associated with living in food deserts

	and independent supermarkets, markets, supermarket chains.		(Kelli et al., 2019). Living closer to supermarkets associated with lower BMI (Zhou et al., 2021), and higher fruit and vegetable consumption in urban areas (Michimi & Wimberly, 2010).
Financial Services	ATMS, Banks, Post Offices	Access to cash and other in person financial services ensures financial inclusion. Cash particularly important for older people and those on lower incomes.	Lack of access to financial services may lead to financial exclusion for vulnerable groups (Iscenko et al., 2020; parliament.uk, 2017). Financial exclusion prevents vulnerable groups accessing services and credit, with financial worries linked to stress (Ryu & Fan, 2023). Post office may act ad multi-purpose facilities (Goodwin-Hawkins et al., 2021).
Greenspace and Recreation	Commons, country and national parks, picnic areas, playgrounds, municipal parks and gardens, gymnasiums, sports halls and	Help to mitigate effects of climate change, offer opportunities for physical activity, improved mental and physical outcomes through opportunities for play. Proximity	Greenspace may indicate better air quality (Ai et al., 2023), promote physical activity (Jimenez et al., 2021), reduce stress (Egorov et al., 2024), promote mindfulness and suppress anxiety (Bray et al., 2022; van den Berg et al., 2015), and foster cohesion (Braubach et al., 2017).

	leisure centres, sports ground, stadia, and pitches, allotments	to greenspaces promotes increased use (Olsen, Nicholls, et al., 2022).	Greenspaces may foster social interactions and conectednes that buffer against the stress repsonse (Maas et al., 2009). Physical activity and reduced BMI associated with proximty to recreational resources (Ellaway et al., 2016; K. H. Lee, 2020).
Health Services	Doctor's Surgeries (GPs), Chemists/Pharmacies	Provide access to local primary care services	Some of the most vulnerable groups lack confidence they will receive care needed in timely manner leads to potential issues with delayed treatment (Healthwatch, 2023). GP's and pharmacist may act as gatekeepers of health (Bi & Liu, 2023; Hindi et al., 2018).
Public Transport	Bus stops, railway stations, junctions and halts, tram, metro and light railway stations and stops	Provide access and greater reach to employment, education, or social engagements. Particularly important for younger and older populations (parliament.uk, 2022).	Absence of transport links can be symbol of neglect for communities (Stonehaven, 2024; Twelves, 2024). Access to transport impacts opportunities for employment, services, and social participation and engagement (Lucas, 2019; Lucas et al., 2018). Public transport use linked to reduced mortality risk (Patterson et al., 2024), and free bus travel

			associated with lower depressive symptoms and feelings of loneliness in older populations (Reinhard et al., 2018).
Retail Services	General Household goods, department stores, discount stores, shopping centres and retail parks	Mixed-use streets can encourage active travel, increase footfall, and boost local economies. Considered important in promoting healthy high streets and strong locations to support daily living (*Everyday Places*, 2021; *Healthy High Streets*, 2018).	Access to amenities improves connections to place and neighbourhood satisfaction (Mouratidis & Yiannakou, 2022). Greater land-use mix (more varied services within areas) associated with reduced psychological distress (Sarkar et al., 2013c). Walkability measures that incorporate access to amenities associated with increased physical activity and improved health outcomes (Carson et al., 2023; Wedyan & Saeidi-Rizi, 2025).

1.6 Spatial Analysis and Geographic Information Systems

1.6.1 Ecological Fallacy

A common challenge in spatial research is the ecological fallacy (W. S. Robinson, 1950). This refers to the risk of assuming that area-level characteristics apply uniformly to all individuals within a given area. However, this concern is less relevant to the present study, as the empirical chapters either consider subjective measures of neighbourhoods or directly link individuals to their spatial context, rather than making inferences about individuals based purely on aggregate characteristics. For example, chapter 2 considers associations between self-reported perceptions of neighbourhood qualities and AL. This helps to minimise the effects of the ecological fallacy as individuals define their own neighbourhoods (including where they begin and end) and their relation to it, rather than assuming that all individuals within the area have the same relationship to aggregated actual crime statistics, for example.

Chapter 3 also seeks to minimise the effects of the ecological fallacy by calculating measures from the postcode grid reference of participants and comparing these results with an aggregated measure. Again, the models also assess individual relationships between proximal access and AL and even associations with the aggregate measure reflect these individual associations rather than vice versa. Chapter 4 additionally uses a multi-level-modelling approach, with time-points nested within individuals. This explicitly accounts for individual variation in AL across 4 biomarker waves, the repeated measures design, and time-invariant characteristics. For example, by incorporating individual identifiers as a random effect, the analysis ensures that variation in AL at the individual level is properly accounted for and differences between and within participants is separated. This structure allows for a more nuanced understanding of how proximity to each 20MN domain relates to individual AL by controlling for unmeasured heterogeneity in AL between individuals. However, it's important to note that this model does not fully control for potential time-varying confounders, such as sudden life events or built environment changes, that may influence both AL and 20MN domain access.

1.6.2 The Modifiable Areal Unit Problem

Another issue present in all spatial analysis is the modifiable areal unit problem (MAUP), which was first officially coined by Openshaw (Openshaw, 1979). Previous research has also suggested that the MAUP cannot be solved but should be acknowledged (Manley, 2019). The MAUP arises when the scale of spatial aggregation or the shape of spatial boundaries influences the results of an analysis (Buzzelli, 2020), even where the underlying data has not changed. It is typically described as having both a scale effect and a zoning effect. The scale effect relates to the size or number of spatial units used for analysis and the influence of this on results. For instance, data aggregated at a larger spatial unit, such as the Lower Super Output Area (LSOA), might produce different results than data aggregated at a smaller unit, such as the Output Area (OA). Often, the larger the unit of aggregation, the more likely lower-level variation within a given area will be averaged out. On the other hand, the zoning effect refers to how the boundaries within units are drawn may influence results. The same number of zones may be used, but changing their shape or orientation may influence interpretations of results (Stillwell et al., 2018). One way of zoning or scaling may not be 'right' or 'wrong', but the presence of the MAUP in spatial analysis highlights that it is necessary to think of an appropriate scale for the analysis and research question being considered and the potential impacts of aggregation at the scale selected.

Each chapter seeks to minimise issues relating to the MAUP in different ways. Chapter 2 relies on IMD quintiles calculated at the Lower Super Output Area (LSOA) level which may better capture deprivation in smaller areas but smooth out variation in areas with lower population density, such as rural LSOAs, which will be larger by design. However, the inclusion of subjective measures, where neighbourhoods are defined by the participants, mitigates this by using individual perceptions that do not rely on spatial aggregation.

Chapter 3 works to reduce scale effects by calculating more precise distances at the postcode level to compare with measures calculated first at the Output Area (OA) population weighted centroid (PWC) level before aggregation at the LSOA level. This allows for a comparison of the distance measures calculated at both the postcode and OA PWC levels, allowing for an assessment of whether results are sensitive to the choice of spatial aggregation and providing insight into how the MAUP might influence the interpretation of access to 20MN domains.

Chapter 4 relies on the aggregate measure as calculated and compared in chapter 3. However, the aggregate measure itself addresses scale and zoning effects by calculating distances from the locations where most people live (OA PWCS) to each 20MN domain prior to aggregation at the LSOA level and without limiting distances by predefined boundaries. Importantly, it avoids using predefined boundaries and arbitrary central points. By doing so, this approach reduces the potential scale effect that could arise from relying on LSOA boundaries alone, ensuring a more accurate representation of the spatial relationships in the data.

1.6.3 The Uncertain Geographic Context Problem

The Uncertain Geographic Context problem (UGCoP) is also ever-present in most spatial analysis and describes the problem that “health researchers normally have little or no prior knowledge about the precise spatial configuration and boundary of the geographic area that, through its physical or social characteristics, has significant influence on an individual's health" (Kwan, 2012). As outlined above, numerous studies have sought to measure 20MN access, but only rarely have studies investigated their effects. In part, this may be because thinking of a 20MN, or its underlying domains, as an exposure poses a major challenge that is captured by the UGCoP. As Kwan outlines in their description of the UGCoP, just by being in a place that has access to certain amenities doesn't necessarily expose anybody to anything (Kwan, 2012). Something's presence in an area does not indicate how long any exposure has taken place for, even before questions of service quality are considered (Brown et al., 2019).

Twenty-minute neighbourhoods tend to take residential neighbourhoods as the key contextual unit to consider, these units "might not accurately represent the actual areas that exert contextual influences on the health outcome under study" (Kwan, 2012) and "even within the same neighbourhood residents may not share the same 'environmental worlds'" (Sait & Jivraj, 2022). For example, for adolescents their school environment, or where their friends live, may be a more relevant area to consider (see, for example Ribeiro *et al.*, 2019), while for working adults the workplace may exert more influence than the home environment when it comes to opportunities to access food environments, physical activities, and broader social engagements than it might do for retired or younger populations (Osmënaj et al., 2024).

In chapter 4, this thesis analyses the English Longitudinal Study of Ageing (ELSA) which only includes those over the age of 50. As ageing in place is both the main preference of individuals (Nowossadeck et al., 2023; Pani-Harreman et al., 2021), and has long been a policy commitment to support older people to remain in their own homes for as long as possible (C. Lewis & Buffel, 2020; Means, 2007), this dataset offers a sample where the neighbourhood context likely exerts the greatest influence on the daily activities of this population. As such, focusing on this sample in chapter 4 (and in the stratified analysis in chapter 3), which uses a sample that is nationally representative of the population aged 50 and over living in private households in England (*Study Documentation*, 2024), seeks to minimise issues relating to the UGCoP. It does this when trying to unpick the relationship between access to 20MN and AL as it focuses analysis on the age cohort that are least likely to move area (Roy et al., 2018), and most likely to "spend more time at home and in the surrounding environment than other age groups" (Padeiro et al., 2021).

In addition, using multi-level-modelling to account for the repeated measures design allows for consideration of how variations in 20MN access impacts AL over time, whilst accommodating for individual level differences. In an effort to isolate the effect of 20MN domain access on AL, this approach helps to address the UGCoP by modelling AL as influenced by both stable and changing contextual factors within the same individuals, independently of other temporal or individual-level factors known to be associated with AL.

1.7 Thesis Hypothesis

The hypothesis for this thesis was that improved subjective assessment of neighbourhood environments, and proximal access to key domains in the 20-Minute Neighbourhood framework, would be independently associated with AL. AL is also hypothesised to operate as a measure of chronic activation of the stress-response in response to signals of unsafety that can be both consciously and unconsciously perceived. The primary aims of this thesis were to:

1. Assess whether subjective measures of perceived neighbourhood qualities explain how neighbourhoods 'get under the skin' (Chapter 2).
2. Assess whether objective measures of access explain how neighbourhoods 'get under the skin'.
    a) Use Geographical Information Systems (GIS) technology to map and objectively measure access to 20MN domains relative to Understanding Society (Chapter 3) and ELSA (Chapter 4) participants
    b) Investigate cross-sectional associations between access to 20MN domains and Allostatic Load using data from Understanding Society (Chapter 3)
    c) Investigate longitudinal associations between access to 20MN domains and Allostatic Load using data from the English Longitudinal Study of Aging (Chapter 4).

1.8 The Empirical Chapters

The 3 empirical chapters that follow assess the identified pathways in this introduction, drawing on subjective measures in chapter 2 and measures of proximal access using the 20MN framework in chapters 2 and 3. Here their aims and objectives, research questions, and hypotheses are summarised.

1.8.1 Do Perceived Neighbourhood Qualities Explain the Relationship Between Deprivation and Allostatic Load in Understanding Society? (Chapter 2)

This study explored whether subjective measures of neighbourhoods help to explain the relationship between neighbourhood deprivation and allostatic load (AL) using UK data. Building on the work of Prior et al. (2018a) and previous studies conducted in the US (e.g., Carbone, 2020a; Robinette et al., 2016; Schulz et al., 2013), it investigated four of Galster's

(2012) identified pathways that may explain this association. To support the aims of the thesis it was guided by the following research questions and hypotheses:

1. Is higher deprivation associated with poorer subjective assessment of perceived neighbourhood qualities (PNQs)?

    H1) Higher deprivation will be associated with poorer perceived neighbourhood qualities (after controlling for socioeconomic characteristics).

2. Do perceived neighbourhood qualities predict AL, when controlling for IMD?

    H2) Poorer perceived neighbourhood qualities will be associated with higher AL.

3. Does the strength of the relationship between perceived neighbourhood qualities and AL change depending on level of deprivation?

    H3) Poorer PNQs will have stronger effects on AL in areas with higher levels of deprivation. For example, where deprivation is higher, perceived crime will be higher

4. Are the effects of IMD on AL explained by perceived neighbourhood qualities?

    H4) PNQs will mediate the effects of deprivation on AL.

Pathway 1 – Social Cohesion (Social Interactive)

Perceived cohesion represented the ‘social cohesion and control’ pathway defined under Galster’s ‘social interactive' dimension of neighbourhood effects. High perceived cohesion indicates neighbourhoods with collective efficacy characterised by trust, solidarity, and supportive social connections. Such environments promote collective advocacy, psychological support, and are expected to signal feelings of safety that inhibit (constrain) the stress response.

Pathway 2 – Perceived Crime & Disorder (Social Interactive & Environmental)

Perceived crime and disorder reflect the ‘social control’ and ‘physical surroundings’ pathways that were defined under the ‘social interactive’ & ‘environmental’ dimensions respectively. Perceived crime and disorder indicates neglect and decayed physical conditions of the built environment, signalling unsafety. Even where levels of actual crime and disorder are low, high levels of perceived crime and disorder may elicit worry, anxiety, mistrust, and fear of public spaces, signalling unsafety, and disinhibiting (releasing) the stress response.

Pathway 3 – Perceived Safety (Environmental)

Fear of walking alone at night represented the ‘exposure to violence’ pathway under the ‘environmental’ dimension. Fear of walking alone focuses on personal safety, a sense of individual vulnerability, and the anticipated risk of harm likely to signal unsafety and to release the stress response.

Pathway 4 – Local Service Ratings (Institutional)

A summary score of local service ratings represented the ‘local institutional resources’ pathway under the ‘institutional’ dimension. Poor service ratings indicate limited opportunities for health, employment, and social engagement, each expected to signal unsafety and disinhibit the stress response.

1.8.2 20-Minute Neighbourhoods and Allostatic Load in Understanding Society (Chapter 3) and ELSA (Chapter 4)

Chapters 2 and 3 bridge the gap in the 20MN literature between operationalisation and assessment of outcome by assessing whether proximal access to 10 distinct 20MN domains impacts AL. This was assessed both cross-sectionally (in Understanding Society) and longitudinally (in ELSA). To achieve this these chapters aimed to:

1. Define the domains and features to include as indicators of 20MN access at the national scale (defined in chapter 3 and used in both chapters 2 and 3).

2. Calculate distances:
    - Understanding Society (chapter 3):
        - Calculate distances from postcode grid references of Understanding Society participant addresses to the addresses of the nearest OS Maps Points of Interest (POI) feature of each included 20MN domain (chapter 3).
        - To facilitate comparison of results with the more precise postcode measures: Calculate distances from each Output Area (OA) Population Weighted Centroid (PWC) to the nearest address of the OS Maps Points of Interest feature representing each included 20MN domain. Aggregate these distances for each domain at the Lower Super Output Area (LSOA) level (also used in chapter 4).
        - Assess the differences in results between the two distance measures.
    - ELSA (Chapter 4):
        - Use the measures that were calculated from OA PWCs to each included domain and aggregated at the LSOA level.
3. Describe the distribution of 20MN access by sample:
    - Understanding Society (Chapter 3):
        - Relative to postal code grid references
        - Relative to OA PWCS
    - ELSA (Chapter 4)
        - Relative to OA PWCS only

4. Explore the effect of distance to domains on Allostatic Load:

    - Understanding Society (Chapter 3):

        1. Is there cross-sectional evidence of an association between distances to 20MN domains and AL?
        2. What domains appear most salient to the relationship?
        3. Are these relationships independent of individual socioeconomic and demographic characteristics?
        4. How do these associations vary across the life-course (what domains are important before/after 50)?

    - ELSA (Chapter 4):

        1. Is there longitudinal evidence of an association between distances to 20MN domains and AL?
        2. What domains appear most salient to this relationship?
        3. Are these relationships independent of an individual's socioeconomic and demographic characteristics?
        4. How do these associations vary by urbanicity and car access?
        5. Does adjusting for medication in the construction of AL influence the findings?

2 Neighbourhood Deprivation and Allostatic Load in Understanding Society: The Role of Subjective Measures of Neighbourhood Qualities (Chapter 2)

2.1 Introduction

A growing body of research points to increasing geographical inequalities in health outcomes for those born and living in the most deprived areas, with individuals born into the wealthiest areas expected to live almost a decade longer than those born in the most deprived neighbourhoods (Castagné, Garès, Karimi, Chadeau-Hyam, for the Lifepath Consortium, et al., 2018; Diez Roux, 2001b; Marmot, 2010; Ribeiro et al., 2018; Wise, 2022). Studies have shown that area level health inequalities exist over and above individual level characteristics, such that classic explanatory factors of risk do not wholly account for existing differences in mortality rates or other health outcomes (Szanton et al., 2005). For example, regional differences that are not wholly explained by the characteristics of residents have been found in the incidence of cardiovascular disease (CVD) (Ford & Highfield, 2016; L. G. Kim et al., 2010) both within and between countries worldwide (Okwuosa et al., 2016). Regional disparities have been highlighted for a variety of chronic diseases and conditions, such as diabetes (Davis et al., 2019; Khan et al., 2021), type 2 diabetes (Bush et al., 2023), and depression (Sarkar, 2018). Such findings highlight the potential for place to impact health outcomes over and above the individual characteristics of those who live within them and are often described as 'neighbourhood effects'.

More recent works have been directed towards understanding how and what features of neighbourhoods drive such associations (Diez Roux & Mair, 2010a), with a greater emphasis placed on explaining the biological plausibility of these effects, or how they 'get under the skin' (Prior et al., 2018b). To this end, a promising avenue of study points to the stress response as a biologically plausible mechanism that might explain how place impacts longer term health outcomes. Since the stress pathway, which systematises the body's biological response to environmental and psychological stressors, is impacted by the interplay between multiple physiological systems, multisystem measures of stress may offer additional explanatory power when examining the relationship between neighbourhood effects and exposure to stress (Carbone, 2020b).

The theory of Allostatic Load (AL), which has been described as a "multisystem construct theorized to quantify stress-induced biological risk" (Szanton et al., 2005), provides a useful framework that may help to explain and measure how neighbourhood effects on health transpire. Neighbourhood deprivation has consistently shown associations with elevated AL (Bird et al., 2010; Robinette et al., 2016), with a scoping review finding that higher AL was associated with higher levels of neighbourhood deprivation in 12 out of the 14 included studies (Ribeiro et al., 2018). In another innovative study using a multilevel mediation design, the authors sought to explore whether the stress pathway offers a plausible route through which neighbourhood effects might impact physical and/or mental health functioning, noting that exposures to stress may be shaped by poorer quality access to social and physical resources in deprived areas (Prior et al., 2018b). In this study, they found that allostatic load mediated the relationship of neighbourhood deprivation with physical health function and (to a lesser extent) mental health. However, they did not explore the specific characteristics of deprived neighbourhoods that might explain this relationship, or what aspects of deprivation within neighbourhoods might exert the greatest influence on exposure to stressful experiences. Given neighbourhood deprivation is a measure designed to capture the negative aspects of place, highlighting that higher deprivation is associated with poorer health outcomes offers little in the way of potential solutions if the relationship between neighbourhood deprivation and AL is not unpacked.

Objective conditions of local environments shape exposures to many situations that contribute to stress (Bird et al., 2010; Merkin et al., 2009), with stress associated with a wide-range of poorer health outcomes prior to their presentation as chronic conditions. However, individuals exposed to the same environment likely experience objectively similar situations differently based on past experiences and their own appraisals and determination of an appropriate response. As such, subjective measures of neighbourhood environments offer a special potential to explain how relationships between objective measures of deprivation and AL take place (Carbone, 2020a). Subjective measures offer a route to unpack how living in areas of high deprivation may 'get under the skin' over and above the individual characteristics of individuals living there. In particular, they offer the benefit of the neighbourhood definition being self-defined by participants, rather than relying on administrative units that may not reflect actual communities, experiences, or the activity spaces of individuals (E. S. Kim et al., 2020).

Previous research has also shown that subjective aspects of neighbourhoods, such as measures of perceived social cohesion, crime, and safety, may mediate the relationship between neighbourhood deprivation and health (O. L. Meyer et al., 2014; Murayama et al., 2012; Nazmi et al., 2010; Ross & Mirowsky, 2001; Weden et al., 2008). Relationships between such subjective measures and AL have also been identified in the US context (Carbone, 2020a; Robinette et al., 2016; A. J. Schulz et al., 2013). However, to my knowledge this has not been considered using UK data. This chapter uses data from Understanding Society, a nationally representative study of the UK, to assess whether neighbourhood perceptions help to explain the association evident in the literature between neighbourhood deprivation and AL in the UK context. To do this, it moves upstream in the mediatory pathway identified by Prior et al. (Prior et al., 2018b) to assess whether higher levels of neighbourhood deprivation are associated with poorer perceived neighbourhood qualities (PNQs)[9] and whether individual PNQs associate with AL. It then considers whether these objective and subjective measures interact relative to AL, and whether PNQs explain or mediate the association between IMD and AL using data from Understanding Society.

2.2 The Stress Pathway

Evolutionary theory highlights that the stress response is "universal in organisms, occurring from microbes to vertebrates" and describes the process that enables organisms to quickly respond to physical and ecological challenges (Taborsky et al., 2022). Stress responses work by triggering a rapid rise in certain molecules, such as glucocorticoid hormones (GC), when a stressor is perceived or predicted, such as a predator or the cold, in order to mobilize the sympathetic nervous system (SNS). Through this signal the SNS can be triggered to supress digestion, to provide a burst of energy, to redirect oxygen and nutrients, or to force a change in behaviour to overcome a perceived stressor. Once a threat is no longer perceived, the parasympathetic system works to calm the body, returning physiological functions to baseline levels (Havard Health, 2024). This process is termed 'Allostasis' and represents the promotion of stability through change.

This adaptive process evolved to fine-tune the thresholds and intensity of stress responses based on an individual's past experiences, with GC helping to encode memories of

[9] Research has also shown that the relationship between observed characteristics of neighbourhoods and subjective perceptions of neighbourhoods are linked but distinct constructs, with subjective measures found to be closer to health (Sampson & Raudenbush, 2004; A. J. Schulz et al., 2013; Wen et al., 2006).

stressful events to moderate future responses (Taborsky et al., 2022). For example, over the life-course, the repeated activation of physiological systems involved in the stress response, such as the autonomic nervous, neuroendocrine, metabolic, and immune systems, help the body and brain to gather information about the environment and how to respond. Through these adaptations the stress response system learns about potential threats, such as dangers or stressors, and potential opportunities, such as resources and safety. It then uses this knowledge in the face of new environmental challenges to predict the need to trigger an adaptive response. Over time, this process of gathering and responding to information shapes the set points (or baseline levels) of the individual's stress response system, as well as the intensity of reactions to perceived stressors and the duration of the recovery. This process reflects the different experiences of, and reactions to, stress and serves to highlight that the stress response involves "many aspects of daily life that may not qualify as stress but nevertheless may have adverse effects on the body" (McEwen, 1998b).

The Generalised Unsafety Theory of Stress (GUTS) builds on evolutionary insights, arguing that the stress response is an ancient, default, and often unconscious reaction of the brain, that is always activated unless inhibited by perceived safety, with disinhibition being more energy-efficient than inhibition from an evolutionary standpoint (Brosschot et al., 2018). Conceptually, objective measures of deprivation may signal signs of unsafety through exposure to under-resourced physical and social environments that may be characterised by unsafe streets (Berman et al., 1996; O. L. Meyer et al., 2014), pollution (Matthews & Yang, 2010), lack of green spaces (Egorov et al., 2017; Hoffimann et al., 2017), poorly maintained public spaces (Roux & Mair, 2010), and low-quality services (A. Schulz & Northridge, 2004). These more material aspects of deprivation may also be reflected in subjective experiences of place through perceived levels of crime and disorder (Sampson &

Raudenbush, 2004), cohesion (Carbone, 2020a), safety (Pearson et al., 2021; Velasquez et al., 2021), and ratings of service quality and access (GOV.UK, 2019; Tanner et al., 2020; The Health Foundation, 2024). From the GUTS perspective, when unsafety is perceived, be that consciously or unconsciously, the stress response is released to trigger adaptive behaviours to respond to danger (Taborsky et al., 2022). However, such "stress responses are shaped by trade-offs, sometimes with benefits and costs occurring in different parts of the life cycle" (R. Nesse et al., 2016).

2.3 Allostatic Load

Allostatic Load (AL) measures the overall effects of trade-offs resultant from the stress-response for the body and brain (McEwen, 1998b). AL theory also explains how chronic stress leads to harmful health effects through the temporal adaptation of interacting systems over time (Ganster & Rosen, 2013). For example, according to the AL framework, the stress response progresses from an initial adaptation phase (triggered by the release of primary mediators), to a secondary phase of set-point adjustments (secondary outcomes), followed by a tertiary phase where the health impacts from these adjustments emerge (disease). However, AL seeks to measure the effects of the body's adaptation to psychosocial and environmental stressors throughout life by measuring the consequences of maladaptation to chronic activation of the stress response, prior to its presentation as clinical disease. This is important as research has linked higher AL with a wide range of poorer health outcomes, such as diabetes (Mattei et al., 2010), cardiovascular disease (Parker et al., 2022), and mortality (T. E. Seeman et al., 2001). As such, the construction of AL relies on the use of biomarkers reflecting primary mediators and secondary outcomes, which are typically summed together in a summary score following the original approach which classifies included measure into binary risk scores based on the sample distribution before summation (McEwen, 1998a).

In the initial phase, when real or interpreted stressors are perceived, the sympathetic-adrenal medullary (SAM) system and hypothalamic-pituitary-adrenal (HPA) axis trigger the stimulation of stress hormones, catecholamines, and GC (primary mediators). These changes signal to the metabolic and cardiovascular systems to mobilize energy for a fight or flight response to deal with the immediate demands posed by the stressor and allows systems to operate outside of their normal range. However, "each mediator system produces biphasic effects and is regulated by other mediators, often in reciprocal fashion, leading to non-linear effects upon many organ systems of the body" (Juster et al., 2010). Chronic stimulation of primary mediators disrupts other systems, which can lead to the dysregulation of metabolic, cardiovascular, and immune systems through such changes to their normal operating ranges. When these changes are prolonged, new set points can be established far away from the normal operating ranges. This may be present in elevated levels of systolic blood pressure, triglycerides, or C-Reactive Protein (CRP), for example. Individually, these changes may be small and not be predictive of health outcomes. However, when multiple systems become dysregulated, these changes can result in allostatic overload, characterised by clinical disease outcomes.

2.3.1 The Present Study

The purpose of this study was to assess whether subjective measures of neighbourhoods explain the relationship between neighbourhood deprivation and AL using UK data. Building on the work of Prior et al. (Prior et al., 2018b), and previous studies exploring such relationships using US data (Carbone, 2020a; Robinette et al., 2016; A. J. Schulz et al., 2013), this study tested 4 potential pathways that may drive this association identified by Galster in a wide-ranging review of neighbourhood effects research (G. C.

Galster, 2012). The included subjective measures are thought to reflect social processes tied to place that may help to explain the health risks associated with living in disadvantaged communities.

The first pathway considered perceived social cohesion which reflected the 'social interactive mechanism' identified by Galster (2012). High perceived cohesion may indicate individuals who experience their neighbourhood as an area characterised by trust, solidarity, and supportive social connections (Mendes de Leon et al., 2009). Such environments may be conducive to improving: collective advocacy for community resources; social and psychological support; and information sharing (E. S. Kim et al., 2020). Using the framing of the GUTS, which notes that the stress response is always 'switched on' unless signals of safety are perceived (Brosschot et al., 2018), such experiences are expected to provide conscious and unconscious signals of safety likely to inhibit the stress response.

The second pathway explores the converse of cohesion with a summary score reflecting perceived levels of crime and disorder that may be expected to signal signs of unsafety. This measure reflects aspects of both the social interactive and environmental mechanisms described by Galster (G. C. Galster, 2012). High perceived crime and disorder may indicate individuals who experience their neighbourhood as an area characterised by neglect and decay, threatening social conditions, lacking in social ties, and discouraging the use of public spaces (Curry et al., 2008; E. S. Kim et al., 2020; Taylor et al., 1997). High levels of perceived crime may also trigger specific feelings of worry and anxiety likely to elicit a stress response (Lorenc et al., 2014).

The third pathway explores perceptions of safety reflecting the environmental mechanisms identified by Galster (G. C. Galster, 2012), specifically exploring a single measure related to the fear of walking alone at night as this was found to be the more consistent subjective predictor of health status relative to perceived crime, in a small-scale UK study (Green et al., 2002). It also reflects a specific dimension of neighbourhood engagement that perceived crime and disorder may not capture (Forde, 1993). For example, fear of walking alone at night directly reflects an individual's emotional and psychological response to their environment, capturing a personal sense of vulnerability that perceived crime or broader notions of disorder may not fully encompass (Dubey et al., 2025).

The fourth pathway (reflecting institutional mechanisms) considers ratings of service quality which are theorised to reflect barriers to services that may place constraints on individuals, limit opportunities for employment, health, and social engagement, and suppress or facilitate physical activity (Gary et al., 2008). For example, low ratings of public transportation services may reflect perceived difficulties in accessing healthcare, employment, and services, limiting opportunities to maintain health and build social connections, and creating challenges in daily life. Similarly, negative perceptions of leisure services may discourage physical activity and contribute to sedentary behaviours which have been associated with heightened AL (Bu & Li, 2023). Conversely, high service ratings may indicate a sense of access to opportunity and social engagement as well as quality of provision which themselves indicate signals of safety.

2.4 Research Questions and Hypotheses

1. Is higher deprivation associated with poorer subjective assessment of perceived neighbourhood qualities (PNQs)?

H1) Higher deprivation will be associated with poorer perceived neighbourhood qualities (after controlling for socioeconomic characteristics).

2. Are PNQs associated with AL, when controlling for IMD?

H2) Poorer perceived neighbourhood qualities will be associated with higher AL.

3. Does the strength of the relationship between PNQs and AL change depending on level of deprivation?

H3) Poorer PNQs will have stronger effects on AL in areas with higher levels of deprivation. For example, where deprivation is higher, perceived crime will be higher

4. Are the effects of IMD on AL explained by PNQs?

H4) PNQs will mediate the effects of deprivation on AL.

2.5 Methods

2.5.1 Participants

This study uses data from the UK Household Longitudinal Study (UKHLS), commonly known as Understanding Society, which is a nationally representative household panel survey of the UK's non-institutionalized resident population (Knies, 2018a). It began collecting data in 2009, with around 40,000 households interviewed. All adults aged 16 and older, within primary sampling unit households, are interviewed annually, covering around 100,000 individuals. The British Household Panel Survey (BHPS) was incorporated into the UKHLS starting at Waves two and three (collected between 2010 and 2012), and a subset of respondents from both the general population sample and the BHPS were invited to participate in nurse health visits, approximately five months after the main survey (Barry et al., 2021). This involved various psychological and physical health evaluations, including blood sample collection. Respondents were eligible if they were aged 16 or older, were not pregnant, lived in England (restricted to 81% of the primary sampling units), Scotland, or

Wales, completed their interview in English, and had finished a full face-to-face interview in the corresponding wave (Knies, 2018). From a potential pool of 35,937 eligible adult respondents,10,175 individuals from the general population sample and 3,342 former BHPS participants consented to provide blood samples, resulting in a total possible sample of 13,517 for whom a measure of allostatic load can potentially be calculated. The sample was further restricted to those who had not moved address to ensure IMD values represented deprivation experienced for a least one wave prior to the collection of PNQ data, reducing the sample to 12,849. Participants with complete case data further restricted the sample to 10,675, with differences between the samples outlined below. Following Prior et al. (Prior et al., 2018b), the two biomarker waves were treated as a single cross-sectional sample.

2.5.2 Allostatic Load

AL was calculated using a simple risk score as this is the original and most commonly used approach in the literature on a potential scale of (0-15) (Beckie, 2012). The included biomarkers represented the dysregulation of the: cardiovascular system (Systolic blood pressure (SBP), diastolic blood pressure (DBP), pulse pressure, total cholesterol level and High-Density-Lipoprotein (HDL)); metabolic system (BMI, Waist circumference, triglyceride level, glycated haemoglobin (HbA1c), and the primary mediator Insulin-Like Growth Factor-1 (IGF-1)); immune and inflammatory systems (C-reactive protein (CRP), albumin, and fibrinogen); and the hypothalamic-pituitary-adrenal axis (DHEAS). Table 2 below highlights mean values for included biomarkers and the relevant cut-points used to calculate binary risk quartile cut-points, with a value of one assigned to values falling in the risk category and a maximum score of 15 being possible. Figure 1 below shows the distribution of this measure of Allostatic Load in Understanding Society.

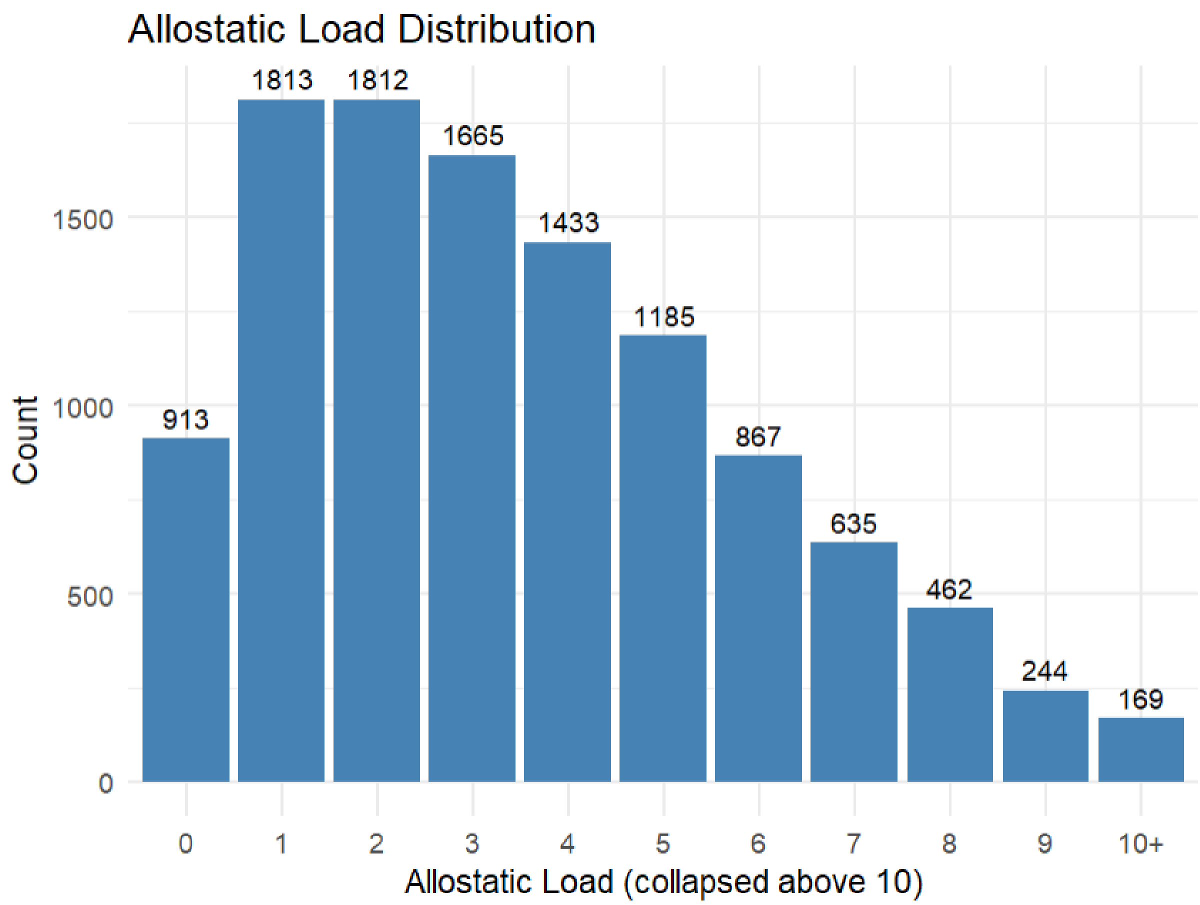

Figure 1: Histogram of Allostatic Load in Understanding Society (Analytic Sample)

Pulse pressure, SBP, DBP, total cholesterol level and HDL represented the level of dysregulation of the cardiovascular system. The mean (across three measurements) SBP of the UKHLS sample was 127 millimetres of mercury (mmHg) with the upper risk quartile cut-off used to calculate the overall AL summary risk score including those with a mean SBP greater than 136 mmHg. For DBP, the sample mean was 73.1mmHg and the upper risk quartile cut-off was for those with measurement mean DBP readings greater than 80 mmHg. The mean pulse pressure for the sample was 69.9 beats per minute (bpm), with a risk cut point of greater than 75.5 bpm. The mean total cholesterol level was 5.4 millimoles per litre, with a risk cut point of 6.1. The lowest risk quartile was assigned the risk value for HDL which had a mean of 1.6 millimoles per litre and a risk cut point of less than 1.2 millimoles per litre.

Dysregulation of the metabolic system was represented by five biomarkers, which included BMI, Waist circumference, triglyceride level, HbA1c, and IGF-1. The mean BMI of the sample was 27.9kg/m2, falling in the overweight category of BMI, with the upper risk quartile cut-off being 30.8 which falls under the obese categorisation. Mean waist circumference was 93.8cm, with a risk cut-off value of 103cm. The mean triglyceride level was 1.8 millimoles per litre with a risk cut point assigned to values greater than 2.2 millimoles per litre. HbA1c was measured in millimoles per mole and had a mean of 37.3 with a risk cut-off value assigned to those with greater than 39 millimoles per mole. IGF-1 was measured in nanomoles per litre (nmol/L) with a mean of 18.4 nmol/L and risk cut-point of greater than 22nmol/L.

There were three measures of the immune system and inflammation included. These were CRP, albumin, and fibrinogen. CRP was measured in milligrams per litre which had a sample mean of 3.3 and a risk cut-off value of 3.2. Both the mean and the cut-point reach the clinical risk threshold for CRP (Castagné, Garès, Karimi, Chadeau-Hyam, Vineis, et al., 2018). Albumin had mean levels of 46.8 grams per litre (g/l) and the lowest risk quartile is assigned the risk score, with the cut-point assigned to those with less than 45g/l. The mean fibrinogen level was 2.8 (g/l) with the risk cut-point assigned to those with greater than 3.2 g/l. DHEAS was included as a measure of dysregulation of the hypothalamic-pituitary-adrenal axis (HPA-Axis), which is vital in the body's stress response system and "returning critical systems to a set point within a narrow range of operation that ensures survival" (Stephens & Wand, 2012). DHEAS was measured in micromoles per litre and the lowest quartile was assigned the risk score of 1. The mean DHEAs was 4.6 with a risk cut-off point of less than or equal to 2.2.

Table 2: Biomarker Descriptives and High-Risk Cut-off values

System	Biomarker	N	Mean (SD)	High Risk Cut-Off Values
HPA-Axis/Neuroendocrine	DHEAs	12873	4.6 (3.24)	< 2.2 µmol/l
Cardiovascular	Systolic Blood Pressure	10908	126.54 (16.61)	≥ 136 mmHg
	Diastolic Blood Pressure	10908	73.12 (10.78)	≥ 80 mmHg
	Pulse Pressure	10908	68.85 (10.74)	≥ 75.5 bpm
	Total Cholesterol	12895	5.37 (1.16)	≥ 6.1 mmol/l
	High Density Lipoprotein Cholesterol	12876	1.55 (0.46)	< 1.2 mmol/l
Immune System & Inflammation	Fibrinogen	12837	2.79 (0.61)	≥ 3.2 g/l
	Albumin	12920	46.78 (2.95)	< 45 g/l
	C-Reactive Protein	12530	3.26 (7.14)	≥ 3.2 mg/l
	Insulin Like Growth Factor	12831	18.37 (7.38)	≥ 22
Metabolic	BMI	12863	27.94 (5.56)	≥ 30.8 kg/m2
	Waist Circumference	13079	93.81 (14.46)	≥ 103 cm
	Triglycerides	12898	1.79 (1.21)	≥ 2.2 mmol/l
	HbA1c	12162	37.25 (8.19)	≥ 39 mmol/mol
	Total: HDL Cholesterol Ratio	12875	3.75 (1.36)	≥ 4.42

Note: For all biomarkers other than DHEAS, Albumin, and HDL, the upper quartile of the sample distribution represented the risk classification

2.5.3 Neighbourhood Deprivation - IMD

Neighbourhood deprivation was measured using the Index of Multiple Deprivation (IMD), which is an indicator of relative deprivation combining various indicators, grouped and weighted by domains, including access to services, crime, education, employment, health, housing, and the physical environment (GOV.UK, 2010). The IMD is used to rank small areas in each country of the UK by overall deprivation. In England and Wales, IMD values are calculated at the LSOA level, reflecting areas with an average of 1,500 people, with the Scottish IMD assigned to Data Zones (DZs), reflecting populations of between 500-1,000 on average. To account for variations in the construction of the IMD across the constituent nations, country of residence was also included as a covariate. The data used to calculate and assign IMD measures were taken from different time points spanning 2011-2016, due to the measures being calculated separately across the devolved administrations (Prior et al., 2018b). IMD quintiles were derived from the latest available official data for each country's 2011 LSOA equivalent (England: 2015; Scotland: 2016; Wales: 2014), with rankings converted into quintiles based on a weighted sum of deprivation scores across seven domains (UKHLS, 2016).

2.5.3.1.1 Perceived Neighbourhood Qualities (PNQs)

Measures of neighbourhood quality were selected that were based on subjective assessment of both the quality itself and the neighbourhood definition (ie. the respondent considered the extent of their own neighbourhood with no guidance as to its boundary). Scores were coded so that values towards zero reflected perceptions expected to provide signals of safety such that the stress response may be inhibited (ie. to be associated with lower AL), whilst higher scores were expected to represent signals of unsafety expected to disinhibit the stress-response (ie. to be associated with higher AL). The measures were selected to assess potential causal pathways between neighbourhoods and health identified by Galster (2012)[10]. These included: perceived neighbourhood cohesion (selected to represent the ‘social interactive mechanisms’, and ‘collective efficacy’ pathway); perceived crime and disorder (social interactive mechanisms, social control and environmental mechanisms,

[10] With pathways across each of the four dimensions identified by Galster in the nieghbourhood effects literature included for assessment across the overall thesis.

physical surroundings); perceived neighbourhood safety (environmental mechanisms, exposure to violence); and local service ratings (institutional mechanisms, local institutional resources).

2.5.3.1.2 Perceived Neighbourhood Cohesion (PNC)

Perceived neighbourhood cohesion was calculated based on responses to eight questions adapted from Buckners Neighbourhood Cohesion Instrument (Fone et al., 2006). This instrument was designed to capture the concepts of: a psychological sense of community; an attraction to neighbourhood; and social interactions within the neighbourhood, within a single measure (Buckner, 1988). This scale was initially constructed from eighteen components in the context of the United States, validated as seventeen items in a Canadian study (D. Robinson & Wilkinson, 1995), and adapted down to eight measures in the UK (Fone et al., 2006). The eight remaining items asked whether people felt: they belonged to their neighbourhood; local friends meant a lot; advice was obtainable locally; they could borrow things from neighbours; willing to improve their neighbourhood; they expected to stay in the neighbourhood; they were similar to others in the neighbourhood, and; they talked regularly to neighbours. Responses were assessed on a five-point Likert-scale (coded as 0=strongly agree, 1=agree, 2=neither agree nor disagree, 3=disagree, and 4=disagree strongly). Their internal consistency was good, with Cronbach’s alpha equal to 0.86, suggesting the individual items are highly correlated and suitable for summation. A continuous total summary score was calculated by summing responses, creating a possible range of 0-32, with 32 indicating lowest perceived cohesion. Low scores indicated high perceived cohesion.

2.5.3.1.3 Perceived Neighbourhood Crime (PCr)

Perceived neighbourhood crime was calculated based on responses to nine questions relating to how common people felt it was within the area for there to be: cars stolen or broken into; issues similar to rubbish on the street; drunks or homeless people on the street; insults or attacks to do with someone's race or colour; vandalism and deliberate damage to property; teenagers hanging around in the streets; graffiti on walls or on buildings; people attacked on the streets, and; homes broken into. Responses were assessed on a four-point Likert-scale (coded as 0=Not at all common, 1=Not very common, 2=Fairly common, 3=Very common). Their internal consistency was acceptable, with Cronbach's alpha equal to 0.74, allowing for summation. A continuous total summary score was calculated by summing responses, creating a possible range of 0-36, with 36 indicating highest perceived crime. Lower scores indicated lower levels of perceived crime.

2.5.3.1.4 Perceived Neighbourhood Safety (PNS)

Neighbourhood safety was assessed based on the response to a single question which asked 'how safe do you feel walking alone at night?'. This was assessed on a five-point Likert-scale (coded as 0=Very safe, 1=Fairly safe, 2=A bit unsafe, 3=Very unsafe, and 4= Never go out after dark). Lower scores indicated feelings of safety.

2.5.3.1.5 Local Service Ratings (LSRs)

Local service ratings (LSRs) were calculated based on ratings of six services within the local area, including: leisure; shopping; public transport; health; secondary schools; and primary schools. How individuals felt about the quality of local services represented this dimension of the neighbourhood context. Responses were assessed on a four-point Likert-scale (coded as 0=Excellent, 1=Good, 2=Fair, 3=Poor). Their internal consistency was poor, with Cronbach's alpha equal to 0.60, with the removal of public transport service ratings providing the greatest improvement but still only improving Cronbach's alpha to 0.65. As such, all items were summed, but caution was used when interpreting the composite score, as the low internal consistency suggests that the items may not reliably measure a single, cohesive construct. A total summary score was calculated by summing all responses (including public transport ratings), creating a possible range of 0-24. Lower scores indicated better ratings of local service quality.

2.5.4 Covariates

Covariates were selected in line with the analysis outlined in Prior et al. (Prior et al., 2018a). This was to aid assessment of whether subjective measures of neighbourhood quality helped to explain (i.e. mediated) the relationship between neighbourhood deprivation and AL on the causal pathway to physical health as they outlined. Covariates were included that controlled for individual traits that might simultaneously influence PNQs and AL and so could confound the relationship between neighbourhood deprivation and health. These included binary measures of: sex (0=Female, 1=Male), ethnicity (0=white, 1=not white), and partnership status (0=in a relationship, 1=single). Employment status was recoded into a 3-level factor (0=employed, 1=inactive/other[11], 2=retired). Highest qualification was considered as a 5-level factor (0=Degree, 1=A-Level, 2=GCSE, 3=Other, 4=None). Housing tenure was considered as 4-level factor (0=Mortgage owner, 1=Owner, 2=Private Renter, 3=Social Renter)[12]. Country was coded as a 3-level factor (0=England, 1=Wales, 2=Scotland). Continuous measures included age and individual income (transformed using the inverse hyperbolic sin transformation[13]).

[11] The inactive or other level included those who: were unemployed; had a long-term illness or disability; cared for family or homes; or were in full-time education.
[12] Factors and binary measures listed as 0 values indicate the reference category.
[13] This approach deals with skewness, is able to deal with zero and negative values, and avoids misrepresentation through stacking (Friedline et al., 2015).

2.5.5 Analytic Approach

Prior et al.'s illuminating study highlighted that the effects of neighbourhood deprivation on physical health are mediated through AL (Prior et al., 2018a). Moving upstream on this pathway, this chapter assessed whether subjective measures of neighbourhood quality explained how deprivation may impact AL. This was assessed through a series of weighted least squares linear models fitted with and without interactions between the Index of Multiple Deprivation (IMD) and PNQs. Where an interaction was present, mediation analysis was also conducted to assess whether the direct effects of IMD and AL are mediated by PNQ. This approach seeks to explain the process through which a 'treatment' causes an outcome, with the treatment in this analysis considered to be IMD quintile and the outcome being AL (Tingley et al., 2014). Whilst mediation typically requires longitudinal data, temporal ordering of IMD prior to PNQs was ensured by restricting the sample to those who had not moved address (Y. Li et al., 2023). Prior et al.'s methodology, which utilised Multi-Level-Modelling (MLM), was also modified to align with the requirements of standard linear regression analysis. This adaptation facilitated evaluation of whether IMD was associated with subjective measures of perceived neighbourhood quality as an initial step, in the openly accessible Understanding Society dataset. Where this was present, interactions tested whether IMD moderated the effect of PNQs on AL. IMD was theorised to shape PNQs by influencing access to resources, amenities, and neighbourhood characteristics such as safety and social cohesion. If an interaction was present, mediation with interaction was considered.

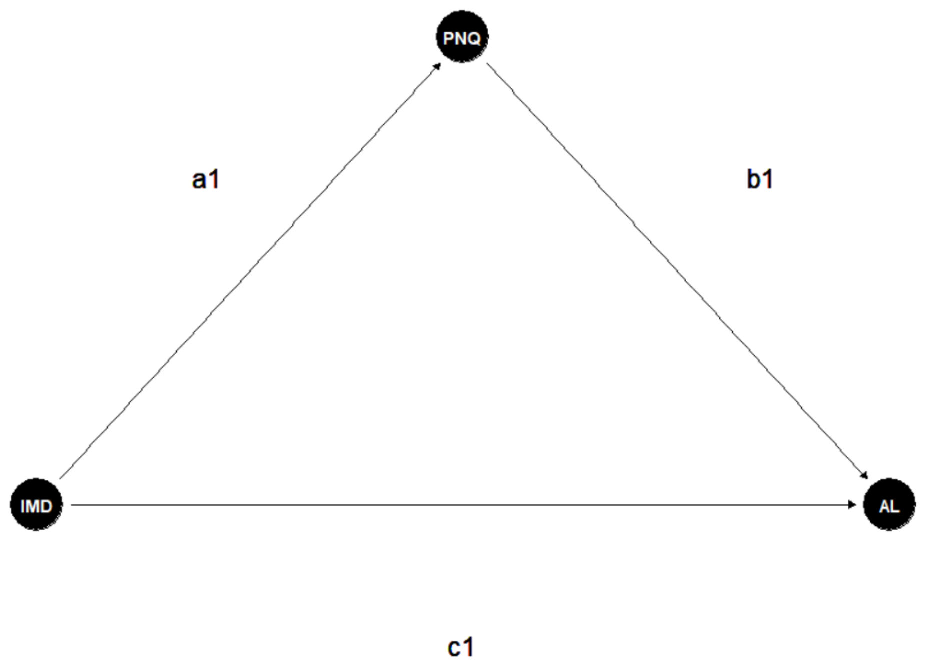

Figure 2: Conceptual diagram of mediation pathway

Note: *Pathway models were fitted for each perceived neighbourhood quality (PNQ) measure that had a significant association with AL. The A1*B1 pathway indicates indirect effects of IMD through PNQ on AL. C1 indicates direct effects of IMD on AL.*

Firstly, *mediator models* (path a1) were run to assess H1[14] using multiple linear regression (MLR) with IMD[15] regressed on the measures of PNQ expected to act as mediators of the relationship between IMD and AL. These models included covariates but excluded the outcome measure of AL. Secondly, *outcome models* were run to assess total effects and H2[16], with models including AL as the outcome regressed on IMD and each PNQ (in separate models), controlling for covariates. These models also tested for an interaction term between the treatment (IMD) and the mediator (PNQ) to assess H3[17]. This followed the approach of Prior et al. who noted evidence from the causal inference literature underscores

[14] H1) Higher deprivation will be associated with poorer perceived neighbourhood qualities.
[15] Treated as a 5-level categorical factor (0-4) with higher scores indicating greater deprivation.
[16] H2) Poorer perceived neighbourhood qualities will be associated with higher AL
[17] H3) *Poorer PNQs will have stronger effects on AL in areas with higher levels of deprivation*.

the critical role of addressing potential interactions between the exposure variable (IMD) and the mediator (PNQ) in order make correct inferences from mediation (Prior et al., 2018a; Valeri & VanderWeele, 2013). However, again this took a step back (or upstream) in the relationship they identified to try and explain how neighbourhood deprivation impacts AL or what it is about living in deprived areas that 'gets under the skin'.

Finally, based on whether the interaction term significantly improved model fit, mediation was assessed with or without interaction using the mediate function from the *'Mediator'* package in R for each PNQ measure (Tingley et al., 2014). The mediate function takes the mediator model[18] and the outcome model[19] and simulates comparisons between them to test the significance of indirect effects of the PNQ on AL (Blair, n.d.), using non-parametric Bootstrapping. Bootstrapping was run to create 5,000 resampled estimates. This allows the effects of IMD on AL to be decomposed into direct effects[20] and indirect effects[21]. The purpose of these models was to formerly assess whether subjective measures of neighbourhood quality that were associated with AL explained the relationship between neighbourhood deprivation and AL. The first part of the mediation model (the mediator model) tested the effect of IMD on the subjective measure, controlling for covariates but excluding AL. The second part of the mediation model (the outcome model) assessed whether a given subjective measure of neighbourhood quality was associated with AL after also accounting for IMD and covariates. All analyses were weighted using the nurse blood weight which accounts for the complex survey design and adjusts for non-response at the nurse visit.

[18] Example mediator model: mediator_model = lm(PNQ ~ imd + covariates, data=analytic_sample, weights=weights).
[19] Example outcome model: outcome_model = lm(AL ~ PNQ + imd + covariates, data=analytic_sample, weights=weights).
[20] Noted as ADE (Average Direct Effects) in the mediate() output from the mediation package in R (Tingley et al., 2014).
[21] Noted as ACME (Average Causal Mediation Effects) in the mediate() output.

2.6 Results

Table 3 (below) outlines descriptive statistics for the full nurse sample data (n=13,258) and the analytic sample (AS) with complete case data for those who had not moved address from the previous wave[22] (n=10,675). The AS had mean AL of 3.5 (SD:2.47) when accounting for medication in its construction[23]. The sample had a mean age of 52 (SD:16), were 56% female, 96% white, and 60% were in a relationship. In terms of employment status, 56% were in employment, 29% were retired, and 15% were inactive or other (which included the unemployed, people with a long-term illness or disability, those caring for family or homes and people in full-time education). A plurality of the AS had a degree (36%) as their highest qualification, whilst 19% had A-levels or equivalent, 21% had GCSE's or equivalent, 11% had some other form of highest qualification and 13% had no qualifications. In terms of housing tenure, the largest group were mortgage owners (40%), with 39% owning their house outright, 8% being private renters, and 13% being social renters. The mean IMD quintile was 1.8, highlighting that, on average, the sample population lived in areas of moderate deprivation with an IMD quintile score of 1.8 situated between the second and third levels of deprivation (out of 5), with 0 indicating the lowest deprivation and 4 representing the highest.

With regards to the measures of PNQ, the measures considered as potential mediators of neighbourhood deprivation on AL, perceived crime was relatively low, with a mean score of 6 (SD:4.5), on a scale running 0-36. The high SD relative to the mean indicates that perceptions of crime are varied, with some rating it very low and others rating it highly.

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[22] People who had moved address were removed from the sample to establish temporal ordering of IMD prior to PNQ.

[23] Risk values were adjusted to indicate risk when participants were taking medications outlined in Read & Grundy irrespective of whether the value of relevant biomarkers were inside or outside the risk quartile cut-off (Read & Grundy, 2014).

Average cohesion was rated relatively poorly, with a mean score of 19 (SD:5.3), on a scale running 0-32, with views on cohesion better represented by the mean here. Mean scores also represented local service ratings well, with services overall rated as average, with a mean score of 13 (SD:3.3), on a scale running 0-24. Perceived safety also sat in the middle of the scale running 0-4, at 2 (SD:1.2), with variation around the mean higher than for perceived cohesion and rating of services but lower than for ratings of crime.

In terms of formal significance tests of sample differences, participants with complete data who had not moved address (ie. the AS) were more likely to be in a relationship (t=4.039, p=0.000), white (t=2.786, p=0.005), older (t=3.465, p=0.000), and to live in areas of lower deprivation (t=-2.12, p=0.034) than the total eligible sample who gave blood samples. For categorical measures Chi-square tests were used to highlight significant differences, with post-hoc pairwise comparisons using Bonferroni adjustment indicating significant group differences. There were significant differences in employment, with highest qualification ($\chi 2(3)=11.33, p=0.023$), with the AS more likely to have A-levels or equivalent relative to no-qualifications (p = 0.010) and to be in employment ($\chi^2(2) = 9.56$, p = 0.023) compared to those categorized as inactive/other (p = 0.009). There were no significant differences between samples based on sex, income, or AL. In terms of the predictors (and potential mediators), perceived crime (t=-17.73, p=0.000) and fear of walking alone in the dark (t=-1.988 p=0.047) were lower in the analytic sample, but cohesion (t= 24.399, p=0.000) and local services (t=15.221, p=0.000) were perceived as worse.

Table 3: Descriptive Summary of outcomes and Covariates

Sample n	Descriptive	Full Sample 13,258	Analytic Sample 10675	p.test
Allostatic Load	**mean (SD)**	3.51 (2.47)	3.54 (2.47)	0.489
Age	**mean (SD)**	51.54 (17.20)	52.30 (16.27)	0.001
Sex	**N (%)**			
Female		7333 (55.4)	5975 (56.0)	0.347
Male		5914 (44.6)	4700 (44.0)	
Partnership Status	**N (%)**			
Married/In a relationship		7548 (57.0)	6363 (59.6)	0.001
Single		5690 (43.0)	4312 (40.4)	
Ethnicity	**N (%)**			
Not White		620 (4.7)	424 (4.0)	0.006
White		12549 (95.3)	10251 (96.0)	
Employment Statius	**N (%)**			0.01
In employment		7260 (54.8)	5989 (56.1)	
Inactive/Other		2168 (16.4)	1562 (14.6)	
Retired		3810 (28.8)	3124 (29.3)	
Highest Qualification	**N (%)**			0.023
Degree		4545 (34.7)	3805 (35.6)	
A Level		2504 (19.1)	2036 (19.1)	
GCSE		2731 (20.8)	2247 (21.0)	
other		1450 (11.1)	1182 (11.1)	
None		1875 (14.3)	1405 (13.2)	
Housing Tenure	**N (%)**			0.001
Mortgage Owner		4918 (38.9)	4295 (40.2)	
Owner		4800 (38.0)	4210 (39.4)	
Private Renter		1218 (9.6)	827 (7.7)	
Social Renter		1694 (13.4)	1343 (12.6)	
Individual Income (£000's)	**mean (SD)**	3.5 (2.6)	3.5 (2.7)	0.157
Index of Multiple Deprivation Quintile		1.84 (1.38)	1.80 (1.38)	0.034

Perceived Crime (0-36)	7.00 (7.82)	5.58 (4.46)	0.001
Perceived Cohesion (0-32)	16.69 (7.96)	18.79 (5.31)	0.001
Local Services Rating (0-24)	12.21 (4.34)	12.95 (3.25)	0.001
Perceived Safety (0-4)	2.14 (1.22)	2.11 (1.20)	0.047

2.6.1 Perceived Neighbourhood Cohesion and Allostatic Load

Models were run following the steps outlined in the analytic approach section and are outlined in Table 4 below. Firstly, the *mediator model* explained how IMD influences PNC. Secondly, the *outcome model* considered how IMD and PNC influence AL. Finally, the *interaction model* tested for an interaction between IMD and PNC relative to AL. All models were adjusted for age, sex, partnership status, employment status, highest qualification, income, country, and housing tenure. The *mediator model* supported the first hypothesis for this measure of PNQ, with areas characterised as having higher (worse) deprivation associated with lower levels of perceived cohesion[24]. For example, living in the most deprived area was associated with higher negative ratings of perceived cohesion relative to the reference group of those living in the least deprived area (β=2.049, SE=0.177, $p<0.001$). Significant differences were also found for each quintile, with the magnitude of changes (in beta estimates) the largest between quintile 2-3 (increase of 92%), and quintile 4 to 5 (increase of 102%). In plain terms, living in the most deprived area was associated with the most negative perceived cohesion scores.

[24] Perceived cohesion was reverse coded so higher scores indicated lower perceived cohesion.

Table 4: Mediator and Outcome Models for Perceived Neighbourhood Cohesion and AL

	Mediator	Outcome	Interaction
PNC – Perceived Neighborhood Cohesion	9.658***		
	(0.674)		
Allostatic Load		2.395***	2.459***
		(0.358)	(0.363)
IMD - Quintile 2 (1=lowest deprivation)	0.455**	0.173*	-0.206
	(0.156)	(0.069)	(0.259)
IMD - Quintile 3	0.873***	0.256***	0.099
	(0.156)	(0.069)	(0.253)
IMD - Quintile 4	1.016***	0.423***	0.390
	(0.164)	(0.072)	(0.263)
IMD - Quintile 5	2.049***	0.505***	1.019***
	(0.177)	(0.078)	(0.259)
	(0.076)	(0.034)	(0.034)
Perceived Cohesion (PC) 0-32, 0=best		0.002	0.002
		(0.004)	(0.010)
IMD Q2 x Cohesion (PC)			0.020
			(0.014)
IMD Q3 x Cohesion (PC)			0.008
			(0.013)
IMD Q4 x Cohesion (PC)			0.002
			(0.013)
IMD Q5 x Cohesion (PC)			-0.024+
			(0.013)
Num.Obs.		10886	10886
R2		0.118	0.120
R2 Adj.		0.117	0.118
AIC		50081.7	50075.3
BIC		50249.5	50272.3
Log.Lik.		-25017	-25010
F		69.544	59.047
RMSE		2.33	2.33

- Notes: all models adjusted for age, sex, partnership status, employment status, highest qualification, income, country, and housing tenure.
- Model fit statistics are only reported for the outcome and interaction models as the mediator model was not comparable with traditional goodness of fit measures.
- p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

In the outcome model, IMD was significantly associated with AL, but perceived cohesion was not. However, the interaction model, including the interaction term between IMD and PNC, was still considered and is justified theoretically as the strength of the mediatory effect of PNC on AL may depend on the level of IMD (Tingley et al., 2014). For example, higher perceived cohesion[25] may be more important relative to AL in more deprived areas or amplify the benefits of living in low deprivation areas. Although the interaction was not significant ($p<0.05$) at any IMD quintile level, results of an ANOVA test comparing the two models indicated that the addition of the interaction term significantly improved the model fit ($F(4, 10860) = 3.59$, $p = 0.006$). Other model fit statistics in agreement were: AIC which was marginally lower (*Interaction:* 50075.3, *Outcome:* 50081.7) and log-likelihood, which was closer to 0 (*Interaction:* -25010, *Outcome:* -25017), although the BIC favoured the simpler model (*Interaction:* 50274.4, *Outcome:* 50251.9). This highlighted mixed evidence that the relationship between IMD, PNC, and AL was moderated. As such, the mediation analysis was run on the model including the interaction term, with the results outlined below considered with caution on this basis.

[25] Reflected in a lower PNC score.

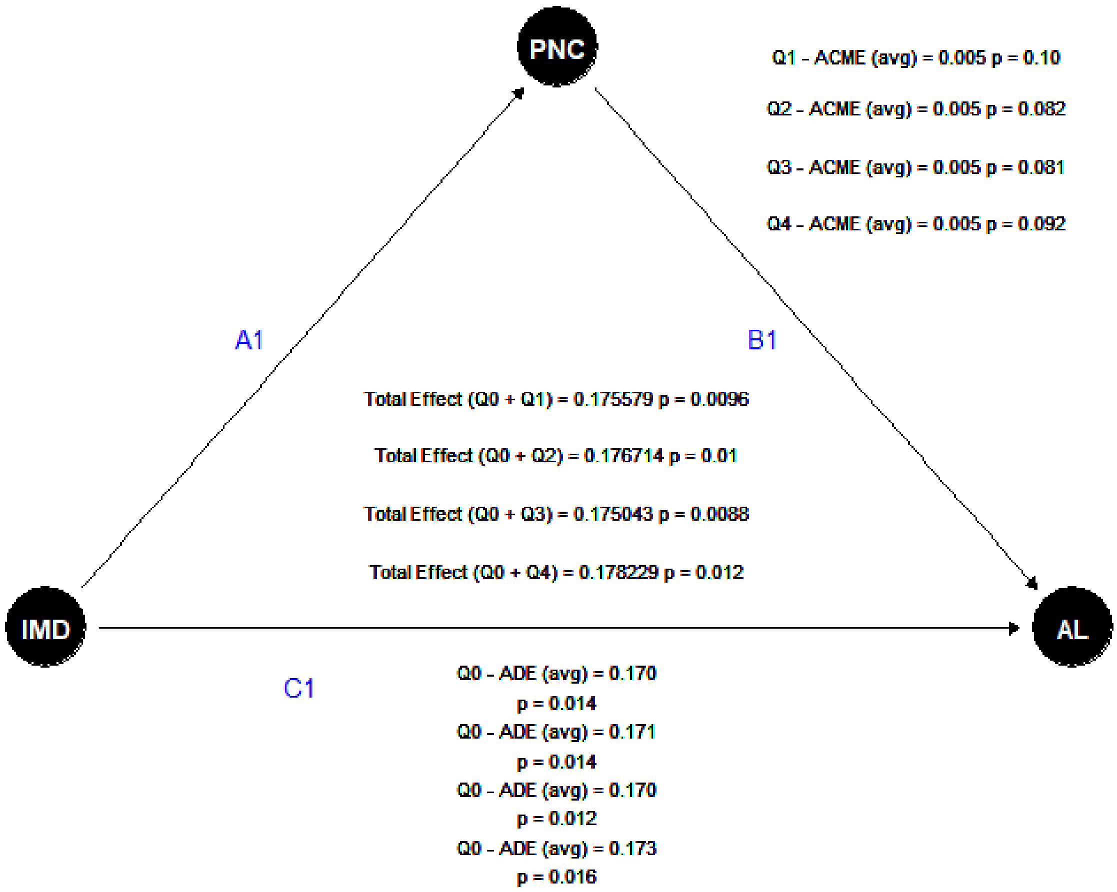

*Figure 3: Conceptual diagram of mediation pathway for IMD*Perceived Neighbourhood Cohesion*

Note: Pathway models were fitted for PNC for IMD quintile pairings, with Q0 always included as the reference group. The A1*B1 pathway indicates indirect effects of IMD through PNC on AL for each treatment group (Q1, Q2, Q3, and Q4). C1 indicates average direct effects of IMD on AL based on bootstrapped estimates (n=5,000).

The Preacher and Hayes bootstrapping method was used with the mediation package in R (Preacher & Hayes, 2008; Tingley et al., 2014). This approach calculates bias-corrected confidence intervals through resampling and does not impose the assumption of normality on the sampling distribution. Figure 3 (above) and Table 5 (below) show the results of bootstrapped (n=5000) models predicting the average direct effect (ADE) on path C1, average causal mediation effects (ACME) on path A1*B1, and total effects (A1*B1+C1) of IMD and PNC on AL in the centre of the diagram, with quintile 1 treated as the reference group for each pairing. For example, the mediate function takes a treatment (IMD quintiles 2-5) and reference group (IMD quartile 1) and produces bootstrapped estimates based on the effects of being in the 'treated' group, versus the reference group. The average results presented here are taken from the bootstrapped models across both the treatment and reference group for each pairing. The ACME shows a very small average indirect effect of IMD on AL through poorer perceived cohesion, although it falls short of significance for all quintiles, including in the most deprived areas (Q5: 0.005 (95% CI: [-0.0007, 0.01], p = 0.092). However, the vast majority of the relationship between IMD and AL remains unexplained by PNC, with the average direct effect of IMD on AL significant for each pairing across groups being 0.132 (95% CI: [0.093, 0.17], $p < 0.0001$), indicating less than 4% of the total effect being mediated by PNC.

*Table 5: Bootstrapped relative indirect effects (ACME), Average Direct Effects (ADE), and Total Effects for IMD*PNC on AL*

Measure	IMD Quintile	Estimate	Lower CI	Upper CI	p-value
Total Effect (IMD+PNC)	0 + 1	0.176	0.042	0.310	0.010
ACME (IMD*PNC)	1	0.005	-0.001	0.010	0.100
ADE (IMD on AL)	0	0.170	0.036	0.300	0.014
Total Effect	0 + 2	0.177	0.042	0.310	0.010
ACME	2	0.005	-0.001	0.010	0.082
ADE	0	0.171	0.037	0.300	0.014
Total Effect	0 + 3	0.175	0.046	0.310	0.009
ACME	3	0.005	-0.001	0.010	0.081
ADE	0 + 3	0.170	0.040	0.310	0.012
Total Effect	0	0.178	0.042	0.310	0.012
ACME	4	0.005	-0.001	0.010	0.092
ADE	0	0.173	0.037	0.310	0.016

Perceived Neighbourhood Crime and Allostatic Load

Here: the *mediator model* explained the relationship between perceived crime (PCr) and IMD; the *outcome model* considered the relationship between AL explained by IMD and PCr, and; the *interaction model* tested for an interaction between IMD and PCr and AL, with each controlling for covariates, as outlined in Table 6 below. The *mediator model* again supported the first hypothesis (H1) for this measure of PNQ, with areas characterised as having higher (worse) deprivation associated with lower levels of perceived crime and disorder when walking at night[26]. For example, living in the most deprived area was associated with higher negative ratings of perceived crime relative to the reference group of those living in the least deprived area (β=3.607, SE=0.148, $p<0.001$). Significant differences were not found in PCr for quintile 2, but were found for each quintile between 3-5, with quintile 1 the reference group. The coefficients rose sharply between quintiles 4 (β=1.819, SE = 0.137, $p <0.001$) and 5 (β=3.607, SE = 0.131, $p < 0.001$), suggesting a non-linear relationship where higher deprivation was increasingly associated with higher PCr.

[26] Perceived safety was reverse coded so higher scores indicated lower perceived safety.

Table 6: Mediator and Outcome Models for Perceived Neighbourhood Crime and AL

	Mediator	Outcome	Interaction
PCr – Perceived Crime (0-32)	9.658***		
	(0.674)		
Allostatic Load		2.395***	2.459***
IMD - Quintile 2 (1=lowest deprivation)	-0.073	0.173*	0.012
	(0.131)	(0.069)	(0.108)
IMD - Quintile 3	0.565***	0.261***	0.287**
	(0.131)	(0.069)	(0.108)
IMD - Quintile 4	1.819***	0.434***	0.350**
	(0.137)	(0.073)	(0.116)
IMD - Quintile 5	3.607***	0.527***	0.438***
	(0.148)	(0.080)	(0.128)
Perceived Crime (Cr) 0-36, 0=Lowest		-0.005	-0.019
IMD Quintile 2 x Crime (Cr)			0.036+
			(0.018)
IMD Quintile 4 x Crime (Cr)			-0.003
			(0.017)
IMD Quintile 4 x Crime (Cr)			0.017
			(0.017)
IMD Quintile 5 x Crime (Cr)			0.017
			(0.016)
		(0.005)	(0.013)
Num.Obs.		10886	10886
R2		0.119	0.119
R2 Adj.		0.117	0.117
AIC		50081	50082
BIC		50248	50279
Log.Lik.		-25017	-25014
F		69.597	58.730
RMSE		2.33	2.33

- Notes: both models adjusted for age, sex, partnership status, employment status, highest qualification, income, country, and housing tenure.
- Model fit statistics are only reported for the outcome and interaction models as the mediator model was not comparable with traditional goodness of fit measures.
- p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Similarly to PNC[27], perceived crime was not significantly associated with AL when accounting for IMD in the outcome model. Again, adding the interaction term between IMD and PNC was still considered to assess whether higher perceived crime may be more important relative to AL in more deprived areas. However, the interaction term between perceived crime and IMD was not significant at any IMD quintile ($p<0.05$), with results of an ANOVA test comparing the two models also indicating that the addition of the interaction term did not significantly improve the model fit ($F(4, 10860) = 1.48$, $p = 0.205$). In this instance, AIC and BIC fit statistics also indicated the simpler model should be favoured with only the log-likelihood indicating a slight preference for the model with the interaction. These results indicated that the inclusion of the interaction term did not lead to a statistically meaningful improvement in model fit and neither the outcome model nor the interaction model satisfied the necessary assumptions for conducting a mediation analysis. As such, mediation analysis was not run for perceived crime.

2.6.2 Perceived Neighbourhood Safety and Allostatic Load

Table 7: Here: the mediator model explained how IMD influences perceived neighbourhood safety (PNS); the outcome model considered how IMD and PNS influence AL, and; the interaction model tested for moderation of the effects of PNS on AL relative to IMD, with each model controlling for covariates, as outlined in Table 7 below. The mediator model supported the first hypothesis for this measure of PNQ, with areas characterised as having higher (worse) deprivation associated with poorer perceptions of safety when walking at night[28]. For example, living in the most deprived area was associated with higher negative ratings of perceived safety relative to the reference group of those living in the least deprived area ($\beta=0.423$, $SE=0.036$, $p<0.001$). Significant differences were found for each quintile, with the relationship appearing close to linear across quintiles. In the outcome model, PNS was associated with higher AL ($\beta=0.061$, $SE=0.021$, $p<0.01$), such that greater fear of walking alone at night predicted higher AL. However, the comparison of the outcome and interaction models using an ANOVA test showed that the addition of the interaction term did not significantly improve model fit ($F(4, 10860) = 0.7375$, $p = 0.5662$). As

[27] To address the positive skewness in PCr scores, the variable was log-transformed for analysis to meet the assumptions of the regression models. However, for clarity of interpretation, the estimates presented reflect results from the non-transformed PCr scores.
[28] Perceived safety was reverse coded so higher scores indicated lower perceived safety.

such, mediation analysis was tested without an interaction for the PNS measure of PNQ.Mediator and Outcome Models for Perceived Neighbourhood Safety and AL

	Mediator	**Outcome**	**Interaction**
Perceived Safety (PS)	2.050***		
	(0.162)		
Allostatic Load		2.731***	2.254***
		(0.357)	(0.364)
IMD - Quintile 2 (1=lowest deprivation)	0.083**	0.162*	0.218
	(0.031)	(0.069)	(0.138)
IMD - Quintile 3	0.183***	0.247***	0.391**
	(0.031)	(0.069)	(0.138)
IMD - Quintile 4	0.318***	0.406***	0.342*
	(0.033)	(0.073)	(0.146)
IMD - Quintile 5	0.423***	0.474***	0.513***
	(0.036)	(0.078)	(0.154)
Safety walking at night (0=Safest)		0.061**	0.082+
		(0.021)	(0.047)
IMD Q2 x Perceived Safety (PS)			-0.030
			(0.062)
IMD Q3 x Perceived Safety (PS)			-0.070
			(0.061)
IMD Q4 x Perceived Safety (PS)			0.025
			(0.062)
IMD Q5 x Perceived Safety (PS)			-0.020
			(0.062)
Num.Obs.		10885	10885
R2		0.118	0.118
R2 Adj.		0.116	0.116
AIC		50086.1	50091.1
BIC		50239.3	50273.5
Log.Lik.		-25022	-25020
F		76.148	63.027
RMSE		2.33	2.33

	Mediator	Outcome	Interaction

- Notes: both models adjusted for age, sex, partnership status, employment status, highest qualification, income, and housing tenure.
- Model fit statistics are only reported for the outcome and interaction models as the mediator model was not comparable with traditional goodness of fit measures.
- $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

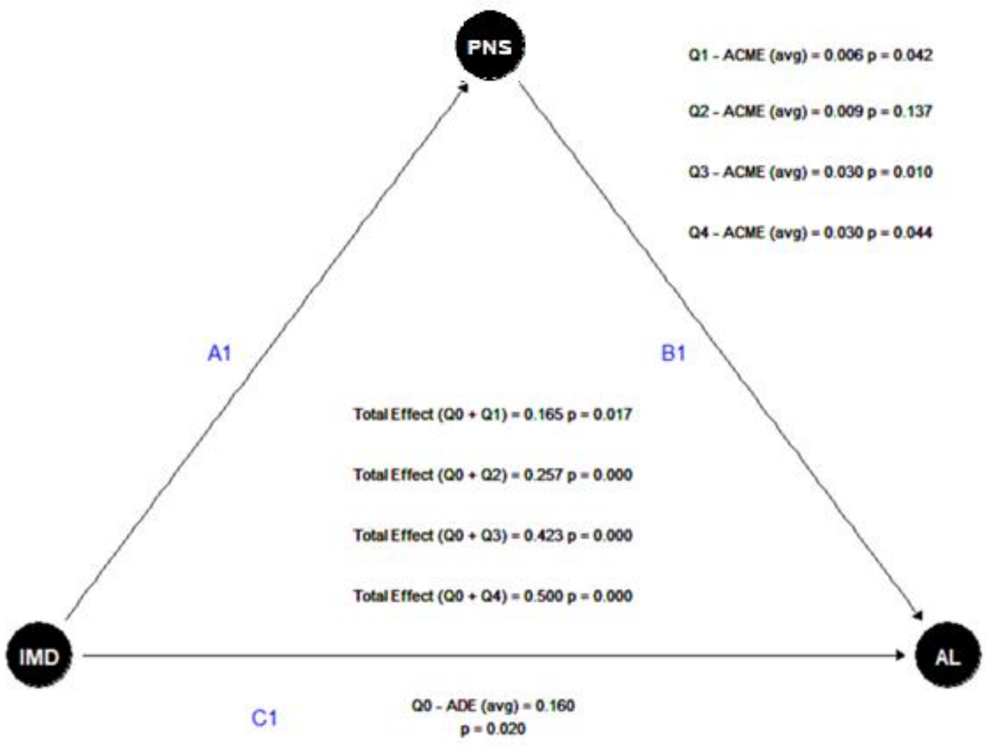

*Figure 4: Conceptual diagram of mediation pathway for IMD*Perceived Neighbourhood Safety*

Note: *Pathway models were fitted for PNC for IMD quintile pairings, with Q0 always included as the* reference *group. The A1*B1 pathway indicates indirect effects of IMD through PNC on AL for each treatment group (Q1, Q2, Q3, and Q4). C1 indicates average direct effects of IMD on AL based on bootstrapped estimates (n=5,000).*

Figure 4 (above) and Table 8 (below) show the results of bootstrapped (n=5000) models predicting the average direct (ADE), average mediated (ACME), and total direct effects of IMD and PNS on AL, controlling for covariates. The ACME showed that mediation of the effects of IMD on AL was small but significant for quintiles 2 (0.006 (95% CI [0.000, 0.010], p = 0.042), 4 (0.030 (95% CI [0.008, 0.050], p = 0.010,), and 5 (0.030 (95% CI [0.001, 0.060], p = 0.044). However, the proportion of the effect of IMD mediated appeared very small, with the average direct effect (ADE) explaining most of the total effects for each quintile pairing.

*Table 8: Bootstrapped relative indirect effects (ACME), Average Direct Effects (ADE), and Total Effects for IMD*PNS on AL*

Measure	IMD Quintile	Estimate	Lower CI	Upper CI	p-value	sig
Total Effect	0 + 1	0.165	0.035	0.300	0.017	*
ACME	1	0.006	0.000	0.010	0.042	*
ADE	0	0.160	0.029	0.290	0.020	*
Total Effect	0	0.257	0.113	0.400	0.000	***
ACME	2	0.009	-0.003	0.020	0.137	
ADE	0	0.248	0.104	0.390	0.000	***
Total Effect	0 + 3	0.423	0.267	0.580	0.000	***
ACME	3	0.030	0.008	0.050	0.010	**
ADE	0	0.394	0.236	0.550	0.000	***
Total Effect	0 + 4	0.500	0.331	0.670	0.000	***
ACME	4	0.030	0.001	0.060	0.044	*
ADE	0	0.470	0.296	0.640	0.000	***

2.6.3 Local Service Ratings and Allostatic Load

Here: the *mediator model* explained how IMD influences LSR; the *outcome model* considered how IMD and LSR influence AL; and the *interaction model* tested for moderation of the effects of LSR on AL relative to IMD, with each model controlling for covariates, as outlined in Table 9 below. The *mediator model* found some supporting evidence for the first hypothesis, with areas characterised as having higher (worse) deprivation associated with more negative ratings of services than the least deprived areas[29]. However, this only attained significance for IMD quintiles 2 (β=0.209, SE=0.098, $p<0.05$) and 3 (β=0.461, SE=0.098, $p<0.001$). In the outcome model, poorer LSRs were associated higher AL (β=0.015, SE=0.007, $p<0.05$). Results of an ANOVA test comparing the outcome and interaction models indicated that the addition of the interaction term did not significantly improve the model fit ($F(4, 10864) = 0.4397$, $p = 0.78$), with AIC and BIC fit statistics in agreement. As such, mediation analysis was run without interaction between IMD and LSR. However, as Table 10 (below on page 91) shows, LSR did not significantly mediate IMD on AL.

[29] With higher LSR scores reflecting negative ratings of service quality.

Table 9: Mediator and Outcome Models for Local Service Ratings and AL

	Mediator	Outcome	Interaction
Local Services Rating	12.987***		
	(0.504)		
Allostatic Load		2.160***	2.266***
		(0.365)	(0.386)
IMD - Quintile 2 (1=lowest)	0.209*	0.170*	0.246
	(0.098)	(0.069)	(0.289)
IMD - Quintile 3	0.461***	0.251***	0.120
	(0.098)	(0.069)	(0.287)
IMD - Quintile 4	0.124	0.423***	0.164
	(0.103)	(0.072)	(0.289)
IMD - Quintile 5	0.192+	0.505***	0.400
	(0.111)	(0.078)	(0.283)
Local Services Rating (0-24)		0.015*	0.008
		(0.007)	(0.016)
IMD Quintile 2 x Local Services			-0.006
			(0.022)
IMD Quintile 3 x Local Services			0.010
			(0.022)
IMD Quintile 4 x Local Services			0.020
			(0.022)
IMD Quintile 5 x Local Services			0.008
			(0.021)
Num.Obs.		10886	10886
R2		0.119	0.119
R2 Adj.		0.117	0.117
AIC		50076.7	50083.0
BIC		50244.5	50279.9
Log.Lik.		-25015	-25014
F		69.812	58.700
RMSE		2.33	2.33

- Notes: both models adjusted for age, sex, partnership status, employment status, highest qualification, income, and housing tenure.
- Model fit statistics are only reported for the outcome and interaction models as the mediator model was not comparable with traditional goodness of fit measures.
- $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

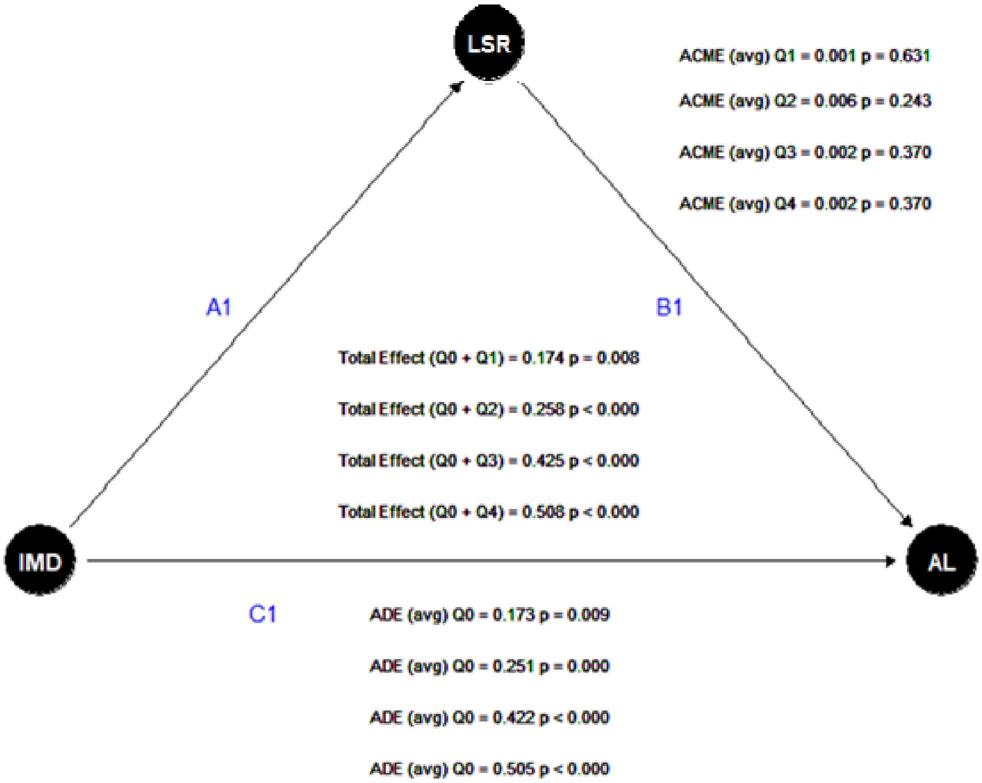

Figure 5: Conceptual diagram of mediation pathway for IMD + Local Service Ratings

Note: Pathway models were fitted for LSR for IMD quintile pairings, with Q0 always included as the reference group. The A1*B1 pathway indicates indirect effects of IMD through LSR on AL for each treatment group (Q1, Q2, Q3, and Q4). C1 indicates average direct effects of IMD on AL based on bootstrapped estimates from each pairing (n=5,000).

*Table 10: Bootstrapped relative indirect effects (ACME), Average Direct Effects (ADE), and Total Effects for IMD*LSR on AL*

Measure	IMD Quintile	Estimate	Lower CI	Upper CI	p-value	sig
Total Effect	0 + 1	0.17366	0.042874	0.31	0.0076	**
ACME	1	0.001158	-0.00384	0.01	0.6312	
ADE	0	0.172501	0.042345	0.31	0.0088	**
Total Effect	0 + 2	0.25764	0.1196	0.4	<0.001	***
ACME	2	0.00623	-0.00453	0.02	0.2428	
ADE	0	0.25141	0.11032	0.39	0.0004	***
Total Effect	0 + 3	0.42478	0.27291	0.58	<0.001	***
ACME	3	0.00229	-0.00218	0.01	0.37	
ADE	0	0.42248	0.27055	0.58	<0.001	***
Total Effect	0 + 4	0.50784	0.3344	0.68	<0.001	***
ACME	4	0.00241	-0.00231	0.01	0.37	
ADE	0	0.50543	0.33067	0.68	<0.001	***

2.7 Discussion

This study sought to move upstream in the mediation pathway identified by Prior et al. (Prior et al., 2018a), to consider how living in areas characterised as having higher deprivation impacts AL. This addresses a gap in the literature, with few studies considering AL relative to neighbourhoods outside of the US (van Deurzen et al., 2016). Reported findings have consistently indicated that people in low-income neighbourhoods tend to have higher levels of AL (Bird et al., 2010; Ribeiro, Fraga, Kelly-Irving, et al., 2019; Robinette et al., 2016; A. J. Schulz et al., 2013). However, since deprivation is intended to reflect the negative aspects of place, identifying that higher deprivation correlates with AL provides limited value unless the underlying mechanisms of how this transpires are explored. To achieve this, relationships between IMD and PNQs were first considered by the mediator model to test whether living in areas of higher deprivation was associated with more negative subjective assessments of neighbourhood qualities. This model assessed research question 1

(RQ1) “Is higher deprivation associated with poorer subjective assessment of perceived neighbourhood qualities (PNQs)?”. In line with H1 (higher deprivation will be associated with poorer perceived neighbourhood qualities after controlling for socioeconomic characteristics), higher deprivation was associated with poorer perceived cohesion and greater fear of walking alone at night. In each case, higher deprivation was associated with increasingly negative ratings of the individual perceived neighbourhood qualities. These results are in line with the findings of a study calculating perceived neighbourhood cohesion based on measures used in the Chicago neighbourhood project, which found neighbourhood deprivation predicted lower perceived cohesion over time (Salvatore & Grundy, 2021). Similarly, individual socioeconomic status was associated with lower neighbourhood safety fears in a US study (O. L. Meyer et al., 2014).

For the perceived crime measure, quintiles 2-4 were associated with higher levels of perceived crime and, although quintile 1’s estimate was not in line with this, it was not significant. Looking at the LSR measure, quintiles 1 and 2 of IMD were associated with poorer ratings of local services but quintiles 3 and 4 were not significant. Comparisons between the full sample and the AS showed significant differences between samples for both LSR and IMD, with the AS having a lower (better) IMD and higher (worse) LSR overall which may have contributed to these results. For example, although the AS lived in less deprived areas this sample tended to rate services more negatively. The low Cronbach’s Alpha rating for the measures included within the summary LSR score (0.60) means the results for this measure need to be considered with caution. Future research may wish to consider the included LSR dimensions separately.

To assess RQ2, "Are perceived neighbourhood qualities (PNQs) associated with AL, when controlling for IMD?", an outcome model was run testing associations between each PNQ on AL when controlling for IMD and covariates, with PNQs included in separate models. Both PNS and LSR supported H2 (poorer perceived neighbourhood qualities will be associated with higher AL), with higher fears of walking alone at night and poorer service ratings associated with higher AL when controlling for IMD and covariates. For the PNS model, this finding in the general population is in line with research from Liverpool that found feelings of safety when out alone after dark were the most consistent predictor of health status for a sample of individuals living in tower blocks (Green et al., 2002). The findings of the LSR model also support related evidence from Australia where living closer to social infrastructure was associated with improved social wellbeing of residents (Davern et al., 2017). In the present study, negative service ratings were associated with higher AL, additionally pointing to the importance of the quality of service provision.

The same Australian study recommended future research should assess relationships between access to social infrastructure and measures of perceived cohesion, safety, and crime, which were all considered here, although here they were considered relative to area deprivation rather than service access (ibid.). However, PNC and perceived crime and disorder were not significantly associated with AL in the outcome models. These null findings are different from a study in the United States which did find associations between measures of both perceived cohesion and perceived crime and a measure of cumulative biological risk (A. J. Schulz et al., 2013). Whilst this can in part be explained by the fact that both the independent and outcome variables in their study were constructed slightly differently, they shared many features and measured similar theoretical constructs. These results differ from a Danish study which found neighbourhood disorder was associated with higher AL (van Deurzen et al., 2016). However, a separate US study also found no evidence of mediation between neighbourhood deprivation and perceived cohesion on AL (Robinette et al., 2016). The results from the present study may also reflect the findings of an Australian study which found that the effects of real crime rates reduce life satisfaction more strongly than perceived rates, whereas there was significant variation in life satisfaction effects amongst people who perceive high-levels of crime (Ambrey et al., 2014).

To assess RQ3, "does the strength of the relationship between PNQs and AL change depending on level of deprivation?", an interaction term was added between IMD and each measure of PNQ. The only interaction term that significantly improved model fit was between IMD and cohesion. The inclusion of the interaction term amplified the estimate for the main effect of quintile 4, and quintiles 1-3 lost significance. This may suggest that PNC explains more of the relationship between deprivation and AL in areas where IMD was lower. The estimate for the interaction term also flipped for IMD quintile 4, with the interaction term for 'poorer cohesion x IMD quintile 4' associated with marginally lower AL for this combination. However, model fit statistics provided mixed support for the inclusion of the interaction term. No interaction between individual IMD quintiles and cohesion score attained significance, suggesting weak evidence for moderation of the effects of cohesion on AL by IMD quintile.

The unexpected direction of the interaction with IMD quintile 4 may be explained by a study which looked at relationships between objective measures of deprivation and subjective perceptions of cohesion over 18 years and found that perceived social cohesion did not strongly correlate with neighbourhood deprivation over time (Yakubovich et al., 2020). As such, whilst IMD was associated with perceived cohesion, the two measures are not always intrinsically linked in neighbourhood settings. A recent review also found that more cohesive relationships can, in some cases, be linked to poorer health and well-being outcomes, although reverse causation may be present in such findings (Villalonga-Olives & Kawachi, 2017). Given the variation in experiences between perceived cohesion and objective deprivation, the use of IMD quintiles also likely masked significant variation in patterns. For the other measures of PNQs, the interaction term never improved model fit. As such, H3 (that poorer PNQs would have stronger effects on AL in areas with higher levels of deprivation*)* was not supported. In the same study just mentioned, they also noted "the importance of accounting for the duration and timing of exposures when determining effects on health and wellbeing", which was not accounted for here (ibid.) and may explain the lack of findings for cross-sectional (within wave) interactions between IMD and PNQs on AL.

To assess RQ4, "are the effects of IMD on Allostatic Load explained by Perceived Neighbourhood Qualities?"*,* mediation analysis was utilised with the Preacher and Hayes bootstrapping method (n=5,000) to decompose direct, indirect, and total effects of IMD on AL through individual perceived neighbourhood qualities (Preacher & Hayes, 2008). Although there was little evidence to support H4 (PNQs would mediate the effects of deprivation on AL), perceived neighbourhood safety *was* found to significantly mediate the effects of IMD on AL for the treatment-control pairings of Q0 plus: Q1; Q3; and Q4 mediating 4, 7, and 6 % of the effects of IMD on AL respectively. This differs from the evidence in a study using data from the Midlife in the United States (MIDUS) longitudinal study which found perceptions of neighbourhood safety did not explain the relationship between neighbourhood socioeconomic status and AL (Robinette et al., 2016). Whilst they used a similar measure of perceived safety which also asked about fear walking alone at night, their measure included daytime fears, whereas only the night-time question was considered in the present study. The sample size of their study was also much smaller (999 versus 10,675). However, in line with this particular MIDUS study, there was limited evidence of mediation for any other PNQs at any level of IMD quintile, with the indirect effects of IMD through PNC the only other measure that came close to significance ($p<0.1$). As this study noted (Robinette et al., 2016), these null findings may be explained by variability within low-income neighbourhoods, with some characterised by low safety and/or cohesion and others fostering strong community ties and cohesion. However, elsewhere in the literature, a latent variable representing neighbourhood perceptions was found to mediate the effects of neighbourhood level poverty on AL (Carbone, 2020a). This latent construct was calculated using Structural Equation Modelling and incorporated similar dimensions to those considered in the present study (separately), with safety, trust, and conditions collectively defining neighbourhood perceptions within a single construct.

2.8 Limitations

There are several limitations of the present study which are addressed here. Firstly, this study was restricted to the use of a cross-sectional design to assess a mediation pathway due to a single wave of biomarker data being available, which precludes determination of the causal direction of associations between variables. For example, it makes it difficult to establish the temporal order of whether changes in IMD influence PNQs or vice versa. To partially address this, the sample was restricted to those who had not moved address. This approach sought to ensure that the IMD reflected area level deprivation from at least one previous wave that predated the subjective assessment of PNQs, reducing the risk of reverse causation. It is implausible that within wave assessments of PNQs could impact same wave IMD, further justifying this approach. However, the temporal sequencing between PNQs and

AL is not addressed here, which was not possible due to there being only a single biomarker wave.

Secondly, the cross-sectional nature of the analysis also means it is not possible to rule out compositional effects. For example, the possibility that the relationships identified are driven by the type of people who live within neighbourhoods represented by different IMD quintiles, rather than the PNQs themselves. To address this, all models controlled for covariates (including age, sex, partnership status, employment status, highest qualification, income, and housing tenure) to mitigate the risk that compositional differences were driving observed relationships between IMD, PNQs, and AL. However, there were significant differences between the analytic and full sample in terms of employment status and highest qualification level. Whilst there were no significant differences in sex, income, or AL, the analytic sample reported lower (better) perceived crime and fear of walking alone at night, but higher (worse) ratings of local services and cohesion. Selection bias cannot be ruled out which may affect the generalisability of the findings. It is also not possible to rule out unmeasured factors confounding mediator relationships (or their absence). By focusing on a single point in time, the overall, accumulated effect of both IMD and PNQs on AL may also be underestimated (Murray et al., 2013).

Thirdly, whilst this study adjusted for a range of covariates, it is important to acknowledge that cross-sectional analyses remain vulnerable to unmeasured confounding. Residual confounding may persist due to omitted variables, such as personality traits, perceived stress, or local-level exposures not considered by the models. Confounding factors can suggest associations where no real associations exist, mask associations, and fail to take account of potentially biasing factors (Skelly et al., 2012). Future work could benefit from undertaking sensitivity analyses to assess the robustness of associations to potential unobserved confounders.

Fourthly, the cross-sectional nurse visit blood sample weight was applied, as recommended for biomarker analyses using the Understanding Society dataset (Institute for Social and Economic Research, 2022). This weight accounts for the complex survey design and adjusts for non-response at the nurse visit. This seeks to ensure that the sample remains nationally representative of adults who consented to biomarker collection. However, using this weight does not fully adjust for missingness due to other forms of item non-response or due to the inclusion criteria for the analytic sample. As such, while the weight improves generalisability to the nurse sample population, it may not fully eliminate bias from selective participation or exclusion based on the included variables.

Finally, the allostatic load index was constructed using participants from the nurse assessment waves of the UKHLS. Whilst survey weights were applied to address selection bias due to survey response patterns, the findings remain based on a sample predominantly consisting of white individuals, with significant differences also present between the full sample and the sample with complete covariate information across a number of the included covariates. The biomarker sample has also been highlighted as a particularly 'engaged' subsample, with disengaged participants (who were more likely to be male, less wealthy, less social, and less culturally engaged) from the main sample less likely to participate in the nurse assessments (E. Walker, 2024). Such differences likely influence the generalisability of the results. Additionally, waves 2 and 3 of the nurse assessment data were considered as a single wave due to their representation of a single sample composed of the eligible British Household Panel Study continuation participants and the follow-on Understanding Society members. This is common for the nurse wave data (Prior et al., 2018a), however, due to the inclusion of subjective measures of PNQ, such a decision may bias results depending on overall economic conditions or national events that were taking place over the time period, although sensitivity analysis controlling for wave did not significantly alter results.

2.9 Conclusion

Using nationally representative data across the adult age-range in the UK, this study found that higher levels of neighbourhood deprivation (IMD) were associated with more negative perceptions of neighbourhood qualities, aligning with evidence from prior research using US data (Carbone, 2020a; Robinette et al., 2016; A. J. Schulz et al., 2013). Perceptions of neighbourhood safety and local service ratings were also found to associate with higher levels of AL, supporting the hypothesis that negative PNQs would contribute to increased stress. However, perceptions of neighbourhood cohesion and perceptions of crime were not significantly associated with AL, contrasting with the some of the findings from the US studies (Carbone, 2020a; A. J. Schulz et al., 2013) but supporting another (Robinette et al., 2016). There was also limited evidence of interaction effects between IMD quintile and any of the PNQ measures, suggesting that the effects of PNQs on AL were not strongly moderated by levels of deprivation, perhaps due to heterogeneity within the deprivation groups, which may not have sufficiently captured interactions. Mediation analysis revealed some evidence that PNS mediated the relationship between IMD and AL, particularly in high deprivation areas, although direct effects still explained most of the association. However, overall, there was limited support for the mediation hypothesis, with the effects of deprivation on AL largely unexplained by PNQs. Given these findings, future studies should explore the role of neighbourhood characteristics over time to better understand their long-term impact on stress and health. Studies should consider other aspects of neighbourhoods, such as objective characteristics, that may help to explain how living in deprived areas impacts AL over and above the individual characteristics of the people that live there.

3 Cross-sectional associations between 20-Minute Neighbourhoods and Allostatic Load in Understanding Society (chapter 3)

Having considered associations between subjective perceptions of neighbourhoods and AL in Understanding Society, the following chapters assesses whether objective aspects of the built environment, based on measures of proximal access to 20-minute neighbourhood domains (20MN), may help to explain identified associations in the literature between neighbourhood deprivation and AL. The theoretical background of the Generalised Unsafety Theory of Stress (GUTS) posits that the stress response is always 'switched on' and it is only feelings of safety that 'switch off' or inhibit this default response. It highlights that predominantly unconscious feelings of unsafety promote prolonged stress responses that are necessary to lead to the levels of physiological dysregulation associated with disease, poorer health outcomes, and earlier mortality (as highlighted in the Marmot review and its 10 year follow up report (Marmot, 2010; Marmot et al., 2020)).

The first chapter highlighted some supporting evidence to the GUTS with perceived safety associated with lower AL and as mediating the effects of IMD on AL. Poorer ratings of local services (representing signals of unsafety) were also associated with higher AL scores but did not explain the relationship between IMD and AL. However, neither perceived cohesion nor perceived crime and disorder were associated with AL. As such, the next chapter sought to assess whether objective characteristics of the built environment explain what it is about neighbourhoods that gets under the skin using the 20-Minute Neighbourhood (20MN) framework.

Given 20MNs are theorised to promote healthier local communities through the promotion of active travel, community cohesion, improved local economies, and better access to natural environments, the 20MN concept provides a framework through which to assess whether objective aspects of the built environment elicit feelings of safety and unsafety. For example, the presence of 20MNs can be theorised to represent infrastructural signals of safety, whilst their absence may foster a sense of neglect, disillusionment, and infrastructural barriers to access the 6 essential social functions for a high quality of life identified by Moreno et al. (2021) that may signal feelings of unsafety to their residents (Moreno et al., 2021; Stonehaven, 2024; Twelves, 2024).

To assess the broader research question of 'does proximal access to key amenities explain how neighbourhoods get under the skin?', this chapter will assess the specific research question 'is there cross-sectional evidence of an association between distances to 20MN domains and AL?'. It will also consider what aspects of where people live appear most salient to the stress response (independently of an individual's socioeconomic, area-based, and lifestyle characteristics), as measured by AL and compare associations between a stratified sample of those aged under 50, and a sample of those aged 50 and above to aid comparisons in chapter 4 with the ELSA dataset which is representative of the population aged 50 and over in England. AL was constructed in two ways to allow for this comparison, whilst also constructing a measure that contains primary mediators in line with the initial AL theory and composition. It was not possible to include primary mediators in the chapter 4 measure of AL as no primary mediators were present across each of the four waves in ELSA.

3.1 Introduction

Since the 2000s, numerous studies have sought to understand the relationship between where people live and health inequalities which persist over time between different areas and geographies (Diez Roux & Mair, 2010b; Hagedoorn & Helbich, 2021; Yang & South, 2020). Many studies have also demonstrated that, even when so called 'neighbourhood effects' on health outcomes are attenuated after adjustment for a variety of individual factors, these effects often remain significant for a variety of health outcomes (Albanese et al., 2022; Godhwani et al., 2019b; Ribeiro, Fraga, & Kelly-Irving, 2019). However, a common criticism of much neighbourhood effects research is that it fails to define the causal mechanisms that might drive these relationships between place and health and, specifically, to consider what it actually is about a given neighbourhood that affects those who live within it (Ham et al., 2012; Jivraj, Norman, et al., 2019).

Prior et al.'s novel chapter seeks to address how neighbourhood effects 'get under the skin' by identifying neighbourhood deprivation as activating the stress pathway, with more deprived neighbourhoods theorised to be more stress inducing (Prior et al., 2018a; Taylor et al., 1997). To assess this, they measure the effects of neighbourhood deprivation on the stress pathway using the concept of Allostatic Load (AL), a multi-system construct reflecting bodily wear-and tear and physiological dysregulation caused by maladaptation to chronic environmental stressors. They show that AL mediates the relationship between neighbourhood deprivation and mental and physical health and postulate "that the fewer and poorer quality social and physical resources that characterise deprived areas shape exposure to stressful experiences, as well as restricting opportunities for well-being" (Prior et al., 2018a, p. 26).

Relatedly, the Generalised Unsafety Theory of Guts (GUTS) highlights neurobiological evidence that the stress-response is always switched-on and only inhibited by feelings of safety. As such, in the language of the GUTS, these restricted opportunities present at the neighbourhood level can be seen to promote the stress response by signalling unsafety such that the stress response is disinhibited, even when individuals are not consciously experiencing acute exposures to stressors (Brosschot et al., 2018). However, whilst the association between deprivation and AL has been identified in a number of studies, this relationship remains underexplored with further research needed (Prior et al., 2018a; Ribeiro, Fraga, & Kelly-Irving, 2019). To my knowledge no studies have explored which objective aspects of the built environment[30], to which people are predominantly exposed though living in neighbourhoods, might help to explain the association between neighbourhood deprivation and AL.

Given that aggregate levels of area deprivation "cannot directly determine whether differences across areas are due to characteristics of the areas themselves or to differences between the types of individuals living in different areas" (Diez Roux, 2001), this chapter will consider whether specific aspects of the built environment where people live are associated with Allostatic Load (AL) at the individual level. It will achieve this using the Understanding Society dataset (Knies, 2018b) and the Ordnance Survey (OS) Points of Interest (POI) data (PointX & OS, 2025), and by integrating evidence from the AL (Beckie, 2012; Read & Grundy, 2014), neighbourhood effects (Gustafsson et al., 2014; Jivraj, Murray, et al., 2019), and 20-Minute Neighbourhood frameworks (Moreno et al., 2021, pp. 20-; Pozoukidou & Chatziyiannaki, 2021). Specifically, it will examine whether improved

[30] Two studies have explored associations between objective measures of greenspace and AL (Egorov et al., 2017, 2024).

proximal access to neighbourhood resources commonly included in 20MNs are related to AL and whether any relationship is maintained after accounting for confounders[31].

3.2 Background

Allostatic Load is theorized to represent the physiological consequences of maladaptive changes to chronic activation of the stress response triggered by repeated exposures to environmental and psychosocial stressors (McCrory et al., 2023). Repeated and long-term activation of the stress response impairs the part of the brain (the hippocampus) that "exerts a largely inhibitory effect to promote shut-off of the HPA [hypothalamic-pituitary-adrenal] stress response" such that non-threatening contexts can come to be perceived as stressful due to the reduced reliability of hippocampal regulation (McEwen, 1998a). As such, the stress pathway has been posited as a biologically plausible pathway through which where we live may impact health (Prior et al., 2018a). The stress pathway highlights that stability (homeostasis) is achieved through adaptation (allostasis) which results in costs for the body and the brain (allostatic load) that, in turn, impacts the ability to maintain homeostasis (promoted through a negative feedback loop involving the HPA axis which regulates stress responses).

For example, social and physical aspects of neighbourhood environments may influence individual health by disinhibiting[32] "stress-related physiological systems" in response to facing actual or perceived environmental, psychosocial, and/or behavioural

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[31] Distance measures were calculated using R as a Geographic Information System (GIS), and two approaches to calculating distances were compared. One measure is calculated from the postcode grid reference of Understanding Society participants to nearest domain features and one involves aggregating nearest distance measures across the Lower Super Output Area level (LSOA). This aggregate measure relies on the calculation of distances from Output Area (OA) Population Weighted Centroids (PWC).

[32] Whilst it is common in the literature for the stress response to be described as 'triggered' the language used here reflects the GUTS understanding that the stress-response is always 'switched on' and only 'switched off' by feelings of perceived safety.

demands (Brooks et al., 2014). When the stress response is disinhibited through conscious or unconscious feelings of unsafety, levels of primary mediators from across the autonomic nervous system (ANS), hypothalamic-pituitary-adrenal (HPA) axis, and immune system can be altered to maintain physiological balance (homeostasis). For instance, in response to immediate demands caused by stress-response activation, the body may compensate by suppressing digestion, growth, or repair processes, in order to prioritise resources for heightened neurological, cardiovascular, respiratory, and immune system activity through the release of primary mediators (Juster & Misiak, 2023). This may be beneficial to the initial stress response, as specific primary mediators are associated with enhanced cardiovascular functioning, anti-inflammatory properties, changes in glucose metabolism, or altering cognitive functions "to help the body cope with stress" through adaptation (Obasi et al., 2017). However, the release of primary mediators reaches and impacts multiple biological systems and repeated or prolonged activation of the stress response can cause a strain on these systems such that they fail to respond effectively.

Prolonged activation of the stress-response can also lead to changes in how primary mediators (such as DHEAS, adrenaline, and pro-inflammatory cytokines) are managed, which may take place through the insufficient deactivation and downregulation of primary mediators or the failure to activate systems. Long-term dysregulation can therefore lead to altered operating ranges of primary mediators which can impact secondary outcomes across cardiovascular, immune, and metabolic functions and the weakening of adaptive responses. These effects may be present in subclinical changes in biomarkers such as blood pressure, glucose levels, or fibrinogen (to name just three) that reflect secondary outcomes of the stress response. Tertiary outcomes ultimately result from these changes to secondary outcomes in the form of mental and physical ill-health and disease. Such outcomes represent allostatic overload which “occurs when environmental challenges exceed an individual's abilities to cope” (Carbone et al., 2022). As such, AL represents both the physiological consequences of long-term experiences of stress response activation and “the impact of behavioural habits and developmental processes that pattern exposure responses” (Prior, 2021).

AL is typically operationalised using a set of biomarkers to create a summary index that is theorised to capture the complex and interconnected physiological dysregulations that emerge over time as systems repeatedly respond to psychosocial and environmental demands (Bird et al., 2010)[33]. It was initially constructed using 10 biological parameters including four (adrenaline, noradrenaline, urinary cortisol, and DHEAS) primary mediators and six (SBP, DBP, WHR, HDL, HDL Cholesterol ratio, and HbA1c) secondary outcomes (McEwen, 1998a; T. E. Seeman et al., 1997). It was then scored by summing the number of biomarkers with values falling in the risk quartile after dichotomisation based on the sample distribution (either the top or bottom 25% of values for a given parameter). However, the initial parameters were not considered comprehensive, fixed, or prescriptive and its calculation into a score has also been highly varied in the literature (Beckie, 2012; McCrory et al., 2023).

This variation is in part due to AL being a multi-system index that typically includes biomarkers representing the neuroendocrine, immune, cardiovascular, and metabolic systems. Additionally, there is no prescriptive or uniform approach to its calculation as a score or its construction into a composite index, with simple risk scores, system risk scores, factor analysis, and z-scores just some of the construction methods used, further explaining its varied application in the literature. Decisions on biomarker inclusion are also often driven by

[33] Although there is considerable variation in both the number and type of biomarkers included and the process of constructing an index (Beckie, 2012; McCrory et al., 2023; McLoughlin et al., 2020).

data availability depending on the datasets being used, although variability in construction within datasets mean these decisions are not always solely data driven (Johnson et al., 2017).

These inconsistencies have long been pointed to in systematic reviews of AL as a barrier to comparing findings across studies and hampering its potential use as a screening tool (Beckie, 2012; Johnson et al., 2017; McCrory et al., 2023). However, despite the somewhat nebulous nature of AL in the literature, a study explicitly comparing scoring systems found that there was little difference in result interpretation based on the particular choice of scoring algorithm (McLoughlin et al., 2020). This review also highlighted the need for greater attention being placed on the potential impacts of biomarker selection[34]. Nonetheless, elsewhere the literature shows AL to be robust to compositional changes, with factor analysis showing a latent AL factor could be reliably identified regardless of which subsystems or biomarkers were included (Wiley et al., 2016). As such, whilst the variability in how AL is both composed and constructed is often criticised, even differently composed and constructed measures of AL may be more comparable than is typically assumed.

The urban planning and design literature provides a useful framework, under the rubric of the 20MN, to assess relationships between objective aspects of the built environment and AL relative to a policy programme that has gained increasing traction in recent years (Moreno et al., 2021; Pozoukidou & Chatziyiannaki, 2021). The 20MN can be simply defined as neighbourhoods where people's daily needs and services can be accessed within a short distance from their home, ideally through the use of walking, wheeling, or public transport (RTPI, 2021; SUSTRANS, 2020). Beyond this simple ideal, the aims of

[34] The overall thesis seeks to consider these issues with the inclusion of different biomarkers within measures of AL (chapters 2 and 3) and comparing results when adjusting for medication or not (chapter 4).

20MNs are also to: improve local economies through the regeneration of urban centres; facilitate local activity spaces; improve social cohesion; reduce carbon intensive travel to tackle climate change; improve local air quality; and improve health outcomes through the promotion of active forms of travel and movement.

Numerous studies have mapped access to 20MN and outlined approaches to operationalise the concept (Calafiore et al., 2022; Dunning et al., 2023; Olsen, Thornton, et al., 2022; Thornton et al., 2022). However, the focus of policy documents tends to be on effective implementation and the focus of research chapters is predominantly on mapping implementation in practice and stopping at this point, rather than considering any of the broader aims residing in 20MNs is theorised to address. As such, assessment of the impact of increased access to 20MNs on health outcomes is limited. No studies have considered whether having good quality access to specific resources may help to explain, materially, how associations between neighbourhood levels of deprivation and AL are embedded. It is also overlooked how neighbourhoods may impact health to such an extent that their effects take route beyond individual characteristics with negative externalities over and above those experienced through personal deprivation itself (Diez Roux & Mair, 2010b; Kershaw et al., 2024).

Yhee et al. (Yhee et al., 2021a) usefully outline how to measure access to key social infrastructure in a variety of ways, illustrating how these approaches can be used to highlight areas in a city in South Korea that are served by childcare centres, schools, parks, libraries, and sporting facilities. However, they do not then seek to explore any of the effects this may have on the people in areas with high or low scores on the accessibility index they create. Similarly, a number of studies have usefully outlined how they have operationalised 20MNs and considered in detail the equity of access to these measures, but do not go on to explain the variations in outcomes that may be resultant from their equity analyses (Calafiore et al., 2022; Dunning et al., 2023; Olsen, Thornton, et al., 2022; Thornton et al., 2022). These studies demonstrated that 20MN presence is aligned with existing socio-spatial inequalities, and that factoring in mobility issues impacts what is accessible and for whom, but again stop at this point without investigating the impact of the identified spatial relationships on the broader aims 20MN seek to deliver. Given that studies have shown that access to 20MNs or community resources is often higher in more deprived areas, taking this next step to understand the potential relationships between proximal access to specific resources and health is important to consider when assessing the impacts of neighbourhood design on health (Olsen et al., 2023; Olsen, Thornton, et al., 2022; Pearce et al., 2007).

Whilst operationalisation's of 20MNs are not measures of deprivation per se, they provide a useful framework to assess biologically plausible pathways between the built environment and health with clear policy implications given the broad popularity of the 20MN concept. This is important in terms of understanding the potential benefits or otherwise of 20MN type policies towards improved long-term health outcomes. However, to my knowledge no studies have explored associations between improved access to 20MNs and AL specifically, or other health outcomes more generally.

This chapter seeks to bridge the gap in the literature between both calculating access to (or operationalising) 20MNs and unpicking which features of neighbourhoods may contribute to relationships identified elsewhere in the literature between neighbourhood deprivation and AL. The 20MN framework is preferred to measures of deprivation as measures of deprivation are, by design, reflections of area-level attributes expected to create negative outcomes. Since both AL and deprivation are known to predict poorer health outcomes, showing that deprivation predicts higher AL (thereby increasing the risk of poorer health) does little to disentangle the specific aspects of living in deprived areas that may contribute to these outcomes over and above individual level characteristics. As such, this chapter assesses the relationship between proximal access to 20MNs and AL in an attempt to provide evidence that can be translated into more actionable insights (Ribeiro et al., 2022).

3.3 Aims and Objectives

To support the broader aims of the thesis, this chapter will:

1. Outline the 10 domains and features included as indicators of 20MN access.
2. Calculate distances to the nearest feature of each domain from postcode-grid references of participants in the Understanding Society sample.
3. Calculate distances from Output Area (OA) Population Weighted Centroids (PWC) to each 20MN domain and aggregate this at the Lower Super Output Area Level (LSOA) and link this distance measure to the Understanding Society sample.
4. Describe the distribution of access to the 10 domains within the Understanding Society dataset by the included covariates.
5. Explain the effect of distance to the 10 domains on Allostatic Load in the Understanding Society sample and assess differences between the 10 distance measures.
6. Consider whether there are differences in associations across the adult age range (16+) by stratifying the sample by age group (those under 50 years of age versus those aged 50 and above).
7. Consider the sensitivity of AL biomarker composition as recommended by Mcloughlin et al. (McLoughlin et al., 2020).

3.4 Research Questions & Hypotheses

To support the research aims of the thesis, this chapter asks the following research questions (presented below with their accompanying hypotheses):

1. Is there cross-sectional evidence of an association between distances to 20MN domains and AL and which domains appear to be the most salient[35] in this relationship?

    Hypothesis 1: Improved access to 20MN domains would be associated with a protective effect on AL.

2. Are these relationships independent of an individual's demographic characteristics?

    Hypothesis 2: Improved access to 20MN domains would be associated with a protective effect on AL over and above demographic characteristics.

3. Are these relationships independent of an individual's area-based characteristics?

    Hypothesis 3: Improved access to 20MN domains would be associated with lower AL over and above both demographic and area-based characteristics.

4. Are these relationships independent of an individual's lifestyle characteristics?

    Hypothesis 4: Improved access to 20MN domains would be associated with lower AL over and above demographic, geographical, and lifestyle characteristics.

[35] Salient associations were defined as significant associations ($p<0.05$) that survived Bonferroni correction for multiple testing. Corrections were applied on a hypothesis basis with p.values multiplied by 4 in the full sample and by 8 in the sample stratified by age.

5. How do these associations vary by age group?

    Hypothesis 5: There would be differences in salient associations between the samples stratified by age group.

6. Are there differences between the distance measurement approaches?

    Hypothesis 6: The distance measures would capture similar relationships to 20MN domains

7. Are there differences between the results based on AL composition?

    Hypothesis 7: The composition of AL would not influence the results.

3.5 Methods

3.5.1 Participants – Understanding Society

This chapter used data form *Understanding Society*: the United Kingdom Household Longitudinal Study (UKHLS), which is a nationally representative household panel survey for the UK's non-institutionalised resident population (Knies, 2018b). It follows on from the British Household Panel Survey (BHPS) but itself began collecting data in 2009, with around 40,000 households interviewed. All adults aged 16 and older, within households, are interviewed annually with the latest data available from wave 12 (collected 2020-22).

Between 2010-2012, at waves 2 and 3, a total of 35,937 eligible adult respondents were also invited to undertake an additional nurse health assessment interview which included a number of direct psychological and physical health assessments, including the collection of blood samples. Respondents were eligible "if they had completed a full face-to-face interview in the corresponding Wave, were aged 16 or older, lived in England, Scotland or Wales, completed their interview in English and for women were not pregnant" (Knies, 2018b). Eligibility was also further restricted at wave 2 to 0.81 of the Primary Sampling Units (PSU's) in England.

Of the 35,937 participants who were eligible for a nurse's visit (Chandola et al., 2019b), 10,175 adults from the UKHLS sample consented to a blood sample being taken at wave 2 with a further sample of 3,342 former BHPS participants consenting to a blood sample that was collected at wave 3, with data collection for both waves taking place between May 2010-2012. This resulted in a total possible sample of 13,517 for whom a measure of allostatic load could potentially be calculated. Following Prior et al. this sample is considered as a single cross-sectional sample. Participants from outside of England were also excluded to facilitate comparison with results in the third chapter of this thesis which looks at longitudinal evidence. The breakdown of the full sample to the analytic sample is outlined in Figure 6 below.

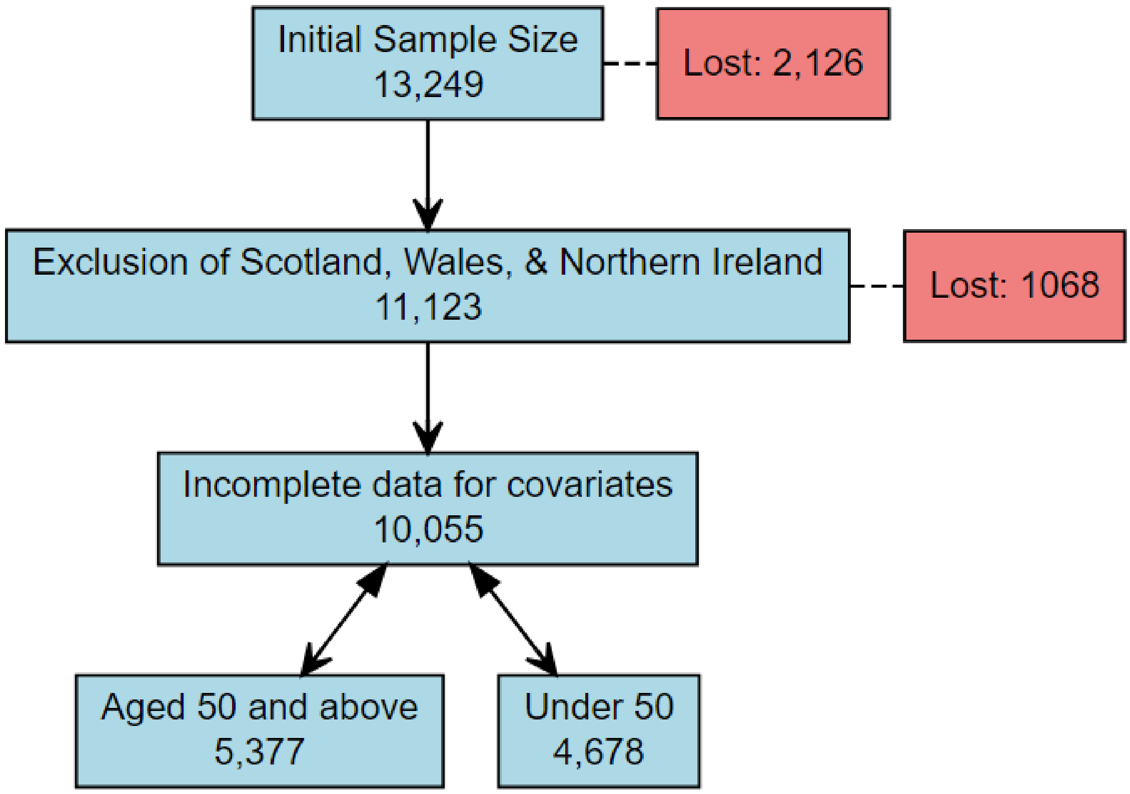

Figure 6: Flow Diagram of sample in Understanding Society

3.5.2 OS Maps Points of Interest

The OS maps Points of Interest (POI) data is a "location based directory of all public and privately-owned businesses, education and leisure services in Britain" and included data present in 2022 (PointX & OS, 2025). This includes close to 4 million features complete with their geographic location, collapsed into 9 groups at the first level of classification, 52 categories at the second level, and 621 classes at the third level of classification, as outlined Table 11 below:

Table 11: Groups, Categories and classes in the OS Maps Points of Interest data

Groups	# of Categories	# Classes	Example Classes
Accommodation, eating and drinking	2	15	Camping, caravanning, mobile homes, holiday parks and centres; Hotels, motels, country houses and inns; Cafes; Fast food and takeaway outlets; Restaurants; etc.
Attractions	6	35	Horticultural attractions; Zoos and animal collections; Historic buildings including castles, forts and abbeys; Country and national parks; Art galleries; Lakes and waters; etc.
Commercial Services	14	174	Building contractors; Gardening, landscaping and tree surgery services; Consultants; Computer systems services; etc.
Education and health	6	65	Education services; Optometrists and opticians; Sports and fitness coaching; etc.
Manufacturing and production	6	140	Garden goods; Energy production; Pesticides; etc.
Public Infrastructure	3	49	Courts, court services and tribunals; Job centres; Charitable organisations; etc.
Retail	4	69	Clothing; Computer shops; Music and video; etc.
Sport and entertainment	5	42	Children's activity centres; Swimming pools; Theatres and concert halls; etc.
Transport	6	32	Bridges; Petrol and fuel stations; Bus stops; Tram, metro and light railway stations and stops; etc.

The OS Maps POI data was linked to the UKHLS dataset using the ‘sf’ (simple features) package in R and columns from each dataset pertaining to relevant geometries (Pebesma, 2018). This involved transforming coordinates for latitude and longitude to British National Grid (BNG) coordinates using the ‘27700’ coordinate reference system (CRS). LSOA boundaries were linked using the Office for National Statistics (ONS) “Lower Layer Super Output Areas (December 2011) Boundaries Super Generalised Clipped (BSC) EW V3”

(*Lower Layer Super Output Areas (December 2011) Boundaries Super Generalised Clipped (BSC) EW V3*, n.d.)" shape file available through the Open Geography Portal.

3.5.3 Allostatic Load

Following the recommendations of McLoughlin et al.'s review[36] (McLoughlin et al., 2020), the influence of biomarker selection was considered by constructing AL in two ways. Firstly, AL was constructed following a combination of the approaches of Prior et al. and Allen et al. (Allen et al., 2019; Prior et al., 2018a), including 14 biomarkers which summed to 15 with the calculation of total HDL cholesterol ratio. Detail on the measurement procedures utilised for each biomarker is available in the Understanding Society Biomarker User Guide (Institute for Social and Economic Research, 2022).

The included biomarkers represented anthropometric (Body Mass Index (BMI), Waist Circumference), cardiovascular (Systolic Blood Pressure (SBP), Diastolic Blood Pressure (DBP), Pulse Rate), inflammatory (C-Reactive protein (CRP), Fibrinogen, Albumin), metabolic (High Density Lipoprotein Cholesterol (HDL), HDL/Cholesterol Ratio, Total Cholesterol, Triglycerides, Insulin-like growth factor 1 (IGF-1)), and the hypothalamic-pituitary (HPA) axis and neuroendocrine systems (dehydroepiandrosterone sulphate (DHEAS)). DHEAS and IGF-1 were included as primary mediators with the remaining biomarkers representing secondary outcomes resultant from the cumulative effects of primary mediator outcomes.

In line with the original approach to calculation, a simple risk score was calculated (rather than a systems risk score as used by Prior) as this approach is more widely used in the

[36] That noted the impact of biomarker selection needed further consideration.

literature[37]. The second AL score excluded measures not available at every wave in ELSA to allow for comparison of results in chapter 4 and added biomarkers that were available in every ELSA wave. This meant the removal of the following biomarkers form the ELSA comparison measure: BMI; waist circumference; IGF-1; DHEAS; and Albumin. The biomarkers added that were not included in the 15-biomarker measure were Haemoglobin (HGB) and Ferritin which represented the cardiovascular and metabolic systems respectively. Figure 7 below highlights the distribution of AL scores for the analytic sample.

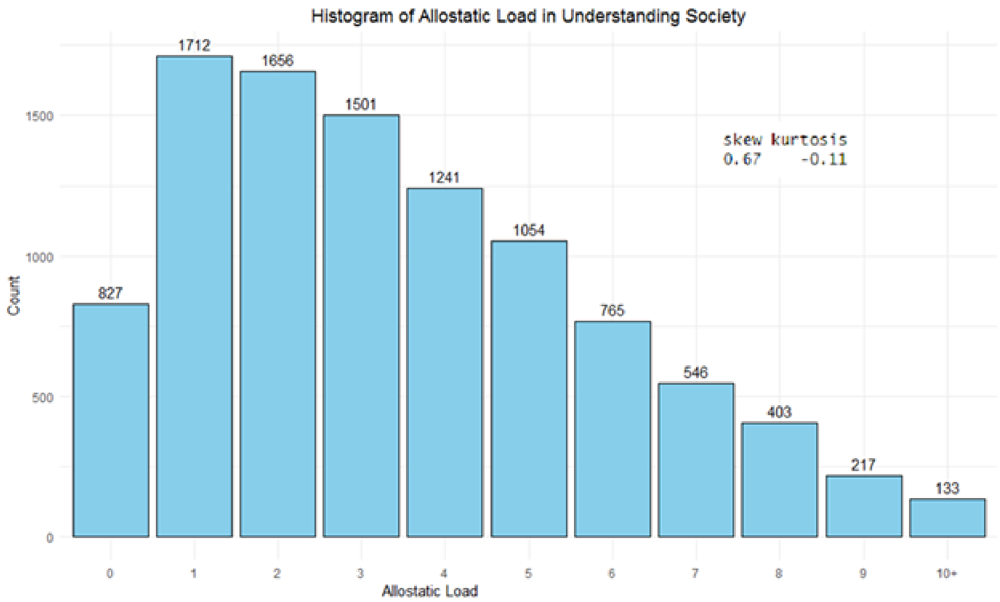

Figure 7: Histogram of Allostatic Load in Understanding Society (Analytic Sample)

Descriptive summaries of the included biomarkers are presented in Table 12 (below) alongside the risk cut-off values used to assign risk cut-off thresholds. Prior to dichotomising values, the following values were added to underlying measurements if participants were taking relevant medications, following the approach of Robertson and Watts (Robertson &

[37] In a systematic review of Allostatic Load and social economic status, Johnson et al. found 73% of chapters eligible for inclusion used the original simple risk score approach to AL score calculation (Johnson et al., 2017).

Watts, 2016): SBP + 10 mmhg (blood pressure lowering medication); DBP + 5 mmhg (blood pressure lowering medication); total cholesterol + 1.18 mmol/L (statins); total cholesterol reduced by 4% (diuretics)[38]; HDL + 10% (beta blockers). To calculate the overall AL scores, each biomarker was dichotomised when the value indicated it fell within a risk quartile (0=Not Risk Factor, 1=Risk Factor). For the majority of the included biomarkers, the upper quartile of the sample distribution indicated the risk factor. However, for HDL, DHEAS, and albumin, the low quartile indicated the risk factor. Maximum bias imputation was applied for individuals with missing biomarker data by classifying them as ‘no risk factor’ for any missing biomarkers, provided they were not missing data for all included measures (Barboza Solís et al., 2015).

Table 12: Biomarker Summaries and high-risk quartile cut-offs

Biomarkers	AL15	AL12[39]	Mean	SD	Risk Cut point
BMI – Body Mass Index	X		27.8	5.27	>=30.8 kg/m2
Waist Circumference	X		93.6	14.2	>= 103 cm
SBP- Systolic Blood pressure	X	X	129	17.8	>=140 mmhg
DBP – Diastolic Blood pressure	X	X	74.4	10.9	>= 81.5 mmhg
Pulse Rate	X	X	68.7	10.6	>= 75.5 bpm
CRP – C-reactive protein	X	X	3.06	6.16	>= 3.2 mg/l
IGF-1 - insulin-like growth factor 1	X		18.4	7.07	>= 22 nmol/l
Triglycerides (unfasted)	X	X	1.79	1.22	>= 2.2 mmol/l
HbA1c - Glycated Haemoglobin (ifcc standardised)	X	X	37.1	7.96	>= 39 mmol/mol hb
Total cholesterol	X	X	5.38	1.16	>= 6.1 mmol/l
HDL - high-density lipoprotein cholesterol	X	X	1.57	0.462	<= 1.2 mmol/l
Fibrinogen	X	X	2.78	0.595	>= 3.2 g/l
DHEAS - Dehydroepiandrosterone Sulphate	X		4.65	3.23	<= 2.2 µmol/l
Albumin	X		46.9	2.9	<= 45 g/l
HDL cholesterol ratio	X	X	3.71	1.34	>= 4.4

[38] After adjustment for Statins.
[39] Contains matched biomarkers with biomarkers present in waves 2,4,6, and 8 combined with 9 in the English Longitudinal Study of Aging to aid comparison with results from chapter 4.

HGB - Haemoglobin		X	136.95	13.92	>=146
Ferritin		X	137	176.82	>=10

3.5.4 Setting and spatial extent

This study considered proximal access to 20MN domains for residential locations across England for participants included in the nurse data in Understanding Society. In 2010, the year corresponding to when the data were collected for wave 2 in Understanding Society, England had an estimated population of 52.6 million people (*Revised Annual Mid-Year Population Estimates, UK - Office for National Statistics*, 2024). Distance measures for each domain were initially computed at the OA PWC level and later aggregated to the LSOA level before being linked to the ELSA data. LSOAs consist of multiple OAs and are designed to encompass populations ranging from 1,000 to 2,000 individuals and 400 to 1,200 households (Census 2021 Geographies - Office for National Statistics, 2021).

3.5.5 Operationalising the 20-Minute Neighbourhood

Twenty-minute neighbourhoods were operationalized as distances to features and domains that provided for the six functions (living, working, education, healthcare, commerce, and entertainment) initial descriptions of the 20MN concept outlined as necessary for basic service provision and a good quality of life (Moreno et al., 2021). Selection of the included domains was also guided by their regular representation in 20MN policies worldwide and their capacity to distinctly capture specific features not covered by other domains included in the study (Calafiore et al., 2022; Dunning et al., 2023; Olsen, Thornton, et al., 2022, pp. 20-; TCPA, 2021; Thornton et al., 2022). This resulted in the following 10 domains being selected: 1) Community Facilities; 2) Culture; 3) Education; 4) Eating and drinking; 5) Food Services; 6) Financial Services; 7) Greenspace and Recreation; 8) Health services; 9; Public Transport; and 10) Retail Services[40].

Key facilities and amenities from the Ordnance Survey (OS) Points of Interest (POI) dataset were then selected to represent access to each of the included domains. Social clubs, halls and community centres, libraries, and sport clubs/associations were included to represent the ***community facilities domain***. Historic buildings, historic structures, historical ships, museums, art galleries, cinemas, theatres and concert halls, places of worship represented the ***cultural domain***. Cafes, tea rooms and snack bars, pubs, and restaurants represented the ***eating and drinking domain***. First, primary and infant schools, further education, independent and preparatory schools, secondary schools, special schools and colleges, higher education, and other schools made up the ***education domain***. Cash points, banks, and post offices made up the ***financial services domain***. Supermarket chains, convenience stores, independent supermarkets, bakeries, butchers, frozen foods, grocers, farm shops and pick your own, herbs and spices, organic, health, gourmet and kosher foods, markets made up the ***food services domain***. Country and national parks, municipal parks and gardens, commons, picnic areas, playgrounds, gymnasiums, sports halls and leisure centres, sports grounds, stadiums and pitches, and allotments made up the ***greenspace and recreation domain***. Chemists or pharmacies and doctor's surgeries made up the ***health services domain***. Railway stations, tram, metro, light railway stations and stops, and bus stops made up the ***public transport domain***. General household goods, department stores, discount stores, shopping centres and retail parks indicated the ***retail domain***. All 10 domains were included

[40] Additional information relating to domain and feature selection is outlined in the overall introduction to the thesis and in Table 1

in models concurrently to control for overall level of access to 20MNs without combining distinctive domains to avoid the amalgamation of domains into a single index.

3.5.6 Measuring proximal access to the 20-Minute Neighbourhood Domains

All spatial data files were projected to the (EPSG:27700) coordinate reference system for the British National Grid using Easting and Northing coordinates and the sf package in R (Pebesma, 2018). All location data of features used to represent access to 20MN domains were taken from the Ordnance Survey Points of Interest Data (PointX & OS, 2025). Distances to domains were then calculated in two ways using Euclidian distance (straight line metres). Whilst Euclidean distances tend to underestimate true network distances (Oliver et al., 2007; Shahid et al., 2009), this approach has been shown to produce reliable distance values when focused solely on the nearest neighbour and offers computational benefits relative to network distances (Hua et al., 2018; Tatit et al., 2024).

Firstly, Euclidean (straight line) distances in metres were calculated between coordinates for participant postal code (PC) grid references and the nearest feature representing a 20MN domain for each of the 10 included domains. Secondly[41], distances were calculated in the same way, but using the coordinates of Output Area (OA) Population Weighted Centroids (PWC) as the starting point (rather than postcode grid reference). These OA distances were then aggregated at the Lower Super Output Area (LSOA) level, representing the average nearest distance to domains from PWCs across OAs at the LSOA level.

These distance values were then linked to the analytic sample so that each sample member had a distance measure to each of the 10 included 20MN domains from both their postcode and an average distance score for each domain across OA PWCs in the LSOA they

[41] This approach is outline din greater detail in chapter 4 as this is the main distance measure used there.

lived in. This approach enabled consideration to be given to whether the overall picture of access at the LSOA level produced similar results to more detailed individual measures calculated at the postcode grid reference level. It also allowed consideration to be given to the potential impact of neighbourhood definitions, the potential impact of the Modifiable Areal Unit Problem (MAUP) on the analysis, issues relating to ecological fallacy, and whether less restrictive and less identifiable data produced comparable results[42].

3.5.7 Covariates

Variables known to be associated with Allostatic Load and expected to relate to 20MNs such that they may confound any relationship between access to 20MN domains and AL were included in models in a block-wise fashion. The reasons for the inclusion of these covariates as potential confounders are outlined in detail in Table 13 below[43]. Following the approaches of related studies (Prior et al., 2018b; Ribeiro et al., 2018; Sarkar et al., 2013b), demographic covariates were added at model 2, area-based covariates were added at model 3, and lifestyle covariates were added in complete models (model 4)[44].

Demographic Covariates

Age was included as a continuous measure which also allowed for its inclusion in models stratified by age group. The sample was stratified into those aged 50 and above and those aged under 50 to aid comparison with the English Longitudinal Study of Aging analysis in chapter 4. Sex was included as a binary measure (0=female, 1=male). Ethnicity was included as a binary measure (0=Not white, 1=White) due to low counts of all groups other than the 'white' group. Evidence points to existing disparities in service access for ethnic groups and significant differences in AL score by race and ethnicity (Calafiore et al., 2022). Relationship

[42] As outlined in the overall introduction to this thesis.
[43] This reasoning is also relevant in the following chapter (chapter 4) where the same or similar covariates were included.
[44] These measures are outlined in detail below.

status was also included as a binary measure (0=In a relationship, 1= Single). Individual income was included in complete models as a continuous measure transformed using the inverse hyperbolic sin transformation due to being highly positively skewed.

Table 13: Outline of covariates included in models as confounders

Model/s	Covariate	Reasons for Inclusion as potential confounders
2-4	Age	Age was included as AL is theorised to represent disadvantages accumulated over time. Higher AL scores are also associated with age and older populations are less likely to live in urban areas (N. A. Lewis & Hill, 2023; ONS, 2020b; Piazza et al., 2019), where 20MNs are more likely to be present even without a specific policy to implement them (Dunning et al., 2023; Olsen, Thornton, et al., 2022).
2-4	Sex	Evidence of sex differences in AL (Juster et al., 2019; Kerr et al., 2020; Longpré-Poirier et al., 2022; Tampubolon & Maharani, 2018; van Deurzen & Vanhoutte, 2019). Evidence points to women being less likely to drive, to rely on public transport more, and to rely more on services closer to home, with all of these desired outcomes of 20MNs (Goel et al., 2023; *Public Space*, n.d.; RTPI, 2021; SUSTRANS, 2018; WBG, 2020).
2-4	Ethnicity	Ethnic differences may influence the sources, types, and severity of stress exposure as well as the biological pathways through which chronic stress responses lead to an accumulation of AL (Allen et al., 2019; Duru et al., 2012;

		Gilmore et al., 2022; Howard & Sparks, 2016; L. J. Richardson et al., 2021). For example, racial discrimination impacts physical and mental health outcomes perpetuating health inequalities (Berger & Sarnyai, 2015; Harrell et al., 2003). Ethnic segregation varies across England and is associated with higher unemployment, long-term illness, and exposure to pollution (Patias et al., 2023).
2-4	Partnership Status	Current and good quality relationships associated with better cardiovascular and inflammatory functioning (Holt-Lunstad et al., 2008), with relationship disruption associated with higher blood pressure and compromised functioning of immune and neuroendocrine systems (Rote, 2017), although mixed evidence of positive and negative health effects of marital status indicates importance of relationship quality (Allan et al., 2019; Memiah et al., 2022). Single people are more likely to live in urban areas and to meet physical activity guidelines (Druta et al., 2021; Fritsch et al., 2023; Pasanen et al., 2023; Puciato & Rozpara, 2021), but also evidence that people who live alone at greater risk of loneliness, social isolation, and higher inflammation (Davidsen et al., 2022; Perissinotto & Covinsky, 2014). The urban form may also impact personal relationships (Mouratidis, 2018).

2-4	Income	Wealth and income are recognized social determinants of health and earning or owning less than peer's can foster stress and anxiety, with greater wealth and income predictive of lower levels of AL (Cuevas et al., 2024; Daly et al., 2015). Evidence that income attenuates association between social economic position and AL completely (Robertson et al., 2015).
3-4	IMD Score	Living in deprived neighbourhoods associated with higher AL (Prior et al., 2018a; Ribeiro, Fraga, & Kelly-Irving, 2019). Evidence in Scotland highlighted that deprived areas had better access to 20MN domains (Olsen, Thornton, et al., 2022).
3-4	Urbanity	GUTS expects urban environments to promote feelings of unsafety (Brosschot et al., 2018). Access to 20MN more prevalent in urban versus rural areas and services closer on average within urban environments (Calafiore et al., 2022; Olsen, Thornton, et al., 2022).
4	Smoking status	Evidence smoking status mediates effects of social economic status on higher AL (Robertson et al., 2015). Smoking also linked with direct and indirect negative effects on individual biomarkers included within the AL construct (Gallucci et al., 2020). Population density and better access to healthcare associated with reduced odds of current smoking status (Caraballo et al., 2019). Proximity to tobacco outlets may

		also influence smoking outcomes including initiation and cessation (Valiente et al., 2021).
4	Alcohol spend (£)	Alcohol use has been associated with both higher and lower AL scores (Suvarna et al., 2020). Poorer quality built environments and alcohol outlet density associated with increased alcohol consumption (Bernstein et al., 2007; E. A. Richardson et al., 2015).
4	Vehicle Access	Evidence of negative associations between car use and cardiovascular disease and biomarkers relevant to AL, with evidence of health benefits for similar measures with more active travel modes (Panter et al., 2018; Patterson et al., 2020; Sugiyama et al., 2020). Car access can be an important mobility aid (Alliance, 2021), whilst the lack of car access can limit opportunities for employment and social engagement, with poorest households more likely to lack access (Brown et al., 2019; Mihaylova, 2021). Evidence from Liverpool highlights there may be people who experience low access to both services and cars in some low income areas (Calafiore et al., 2022). Low traffic neighbourhoods (LTNs), related to 20MNs, have also been linked with reduced noise pollution, itself a predictor of poorer health outcomes (Recio et al., 2016), as well as increases in active travel and reduced car ownership (Leach et al., 2024), and reduced levels of crime (Goodman & Aldred, 2021). Rural

		households more likely to own a car, increasing reach in terms of resource accessibility and activity spaces (*National Travel Survey 2021*, 2022).
4	Disability or long-standing illness	AL predicts and is predicted by disability and long-standing illness (Gallagher & Kate M, 2021). 20MNs aim to improve access to local amenities key for daily living within a walk, wheel, or cycle, with a focus on inclusive accessibility (Alliance, 2021; Living Streets, 2023). Disabilities and long-standing illnesses may influence accessibility, particularly simple proximal access measures that do not account for barriers, and are important to consider when considering boundaries for 20MNs (Dunning et al., 2023).
4	Housing tenure	Housing tenure may attenuate associations between social economic position and AL (Robertson et al., 2015). Renting associated with cardiometabolic risk factors and renters known to have poorer health outcomes (Mawhorter et al., 2023; Prior, 2021).

Area-based Covariates

IMD score was included as a continuous measure of deprivation, with values running from 0-100, where 0 indicates the least deprived LSOA and 100 indicates the most deprived LSOA. The IMD score is included as a covariate as, although it includes measures of proximal access within the barriers to housing and services domain which includes features included in the 20MN domains, the included measures are combined within a single measure in the IMD index, and only make up 9% of the weighted overall index (*English Indices of*

Deprivation 2019, 2019). This limited weight, combined with the multidimensional nature of the index, is expected to reduce the likelihood of multicollinearity issues in the models. Urbanity was also included as a binary measure (0=Rural, 1=Urban) based on the Rural Urban Classification (2011) of LSOAs in England and Wales (ONS, 2017).

Lifestyle Covariates

Smoking status (0=Never Smoker, 1=Ever Smoker), Household access to a vehicle (0=Has Access, 1=No Access), and Disability or long-standing illness status (0=No, 1=Yes) were all included as binary indicators in the lifestyle covariates block. Household spend in pound on alcohol within the last 4 weeks was included as a continuous measure and log transformed due to positive skew. Housing tenure was also included as a 3-level factor (0=Mortgage owner, 1=Owner Outright, 2=Renter) in the final block of confounding variables included.

3.5.8 Main Analyses

Multiple weighted-least squares (WLS) regression was used as the main statistical method to account for the complex survey design, with AL regressed on the measures of proximal access for the 10 included 20MN domains in model 1. Model 2 additionally controlled for demographic covariates, with area-based covariates added at model 3, and lifestyle covariates added at model 4, the complete model. To address survey design complexity and attrition at the nurse visit, all models incorporated the appropriate biomarker-specific weights. All models were run separately for the distance measures calculated from either the postcode grid reference or OA PWCs. Additionally, all models were run on a stratified sample of those aged 50 and above and those under 50. This was to allow for result comparison with the analysis in the third empirical study of this thesis and to assess whether different 20MN domains appeared more important at different stages of adult life.

To account for multiple testing, models were Bonferroni corrected on a hypothesis basis as outlined in Table 14 below, with 4 models run on the full sample and 8 models run on the stratified sample (4 models for the under/over 50 samples). Variance Inflation Factor (VIF) values were also assessed to check for multicollinearity among the predictors with all below 5, other than the food service domain, which was closer to 6, but still indicated acceptable collinearity. Whilst VIF values greater than 5 can indicate a cause for concern, values greater than 10 are typically used to indicate a problematic cut-point, so all domains were included (James et al., 2021).

Table 14: Hypotheses and model assessment

Hypotheses	**Assessed in Models**	**Bonferroni Correction for p values**
H1: Improved access to 20MN domains would be associated with lower AL	M1	p.value multiplied by 4 in full sample p.value multiplied by 8 in samples stratified by age
H2: Improved access to 20MN domains would be associated with lower AL over and above demographic characteristics	M2	
H3: Improved access to 20MN domains would be associated with lower AL over and above both demographic and area-based characteristics	M3	

H4: Improved access to 20MN domains would be associated with lower AL over and above demographic, geographical, and lifestyle characteristics	M4	
H5: There would be differences in associations between domain relevance between stratified samples (those aged under 50 and those aged 50 plus).	M1, M2, M3, M4	

3.6 Comparison of measures analysis

Distance measures were calculated using OA PWCs and postcode grid references as starting points when calculating straight line distances to the nearest feature representing each of the 10 included 20MN domains. Distances calculated at the OA PWC level were additionally aggregated at the LSOA level prior to being linked with the data to allow for comparison of results between Understanding Society and ELSA in chapter 4. Additionally, the two measurement approaches were compared using Pearson's correlations. A 'Total Rank Score' based on the sum of ranked coefficients of variation (CV), calculated as the standard deviation divided by the mean, for each domain and measure (PC or OA PWC) change in rank position was also calculated. This 'Total Rank Score' was calculated by first squaring the difference between the postcode coefficient of variation Rank and the LSOA CV Rank. This value was then added to the CV Difference Rank (how large the difference was between measures) to produce the final score. This approach assessed similarities and stability across the measurement approaches.

3.7 Results

Table 15 (below) shows the descriptive characteristics of the analytic sample (n=10,055). Demographic covariates were added at model 2. The sample was 95% white, 55% female, and 66% over the age of 60, with a mean age of 51 (SD: 16.7). Close to 57% of the sample were currently in employment, with 27% retired and 16% inactive in terms of their current economic activity. A little over half of the sample were in a relationship (57%), compared to being single, widowed or divorced (42%). A plurality of the sample had a degree or above as their highest qualification (36%), with 19% having A-levels or equivalent, 21% having GCSE's or equivalent, 11% having other, and 13% having none as their highest qualification. There were 32% with a monthly household income of between £0-2,000, 36% with more than £2,000-4,000, 19% with more than £4,00-6,000 and 13% with more than £6,000. Significant differences between the analytic sample (n=10,055) and the full sample (n=13,249, inclusive of the analytic sample) were not found overall between demographic measures. However, compared to those not in the analytic sample only (n=3,194), the analytic sample were more likely to be in employment, and less likely to be inactive or retired. They were also more likely to have a higher household income, to be between the ages of 20-59, to have a degree, and to be in a relationship than the full sample.

Table 15: Descriptive summaries of Covariates and Outcomes

		Overall
Demographic		
Sex	Female	55.00%
	Male	45.00%
Age	Mean (SD)	51.2 (16.7)
Current Economic Activity	In employment	56.90%
	Inactive/Other	15.70%
	Retired	27.40%
Ethnicity	Not White	5.30%
	White	94.70%
Highest Qualification	Degree	35.80%
	A Level	18.70%
	GCSE	21.10%
	other	11.20%
	None	13.30%
Partnership status	Married/In a	57.60%
	Single	42.40%
Household Income (IHS)	Mean (SD)	8.60 (0.826)
Household Income (Categories)*	£0-2,000	32.10%
	>£2,000-4,000	35.70%
	>£4,000-6,000	18.80%
	>£6,000	13.40%
Area-based		
IMD Score (0-100, 100 = most deprived)	Mean (SD)	19.7 (14.7)
Urbanity	Rural	21.6%
	Urban	78.4%
Lifestyle		
Smoking Status	Never smoker	74.5%
	Ever smoker	25.5%
Housing Tenure	Mortgage Owner	40.4%
	Owner	36.3%
	Renter	23.4%
Household access to vehicle	Has Access	86.6%
	No Access	13.4%
£ HH spent on Alcohol < 4 weeks (log)	Mean (SD)	2.92 (1.81)
Long-standing Illness/Disability	No	62.6%
	Yes	37.4%
Outcome		
Allostatic Load (including primary	Mean (SD)	3.46 (2.45)
Allostatic Load (for ELSA comparison, scale	Mean (SD)	2.51 (1.95)

Notes: * indicates variables presented as categorical measures in the table that were not included as categorical measures in models

Area-based covariates were added from model 3 onwards to account for area level confounders and to assess whether the proximal measures explained a relationship over and above IMD and urbanity levels. The mean IMD score for the sample was 20, indicating relatively low levels of deprivation, with 78% of the sample (n=10,055) living in an urban area and 22% living in a rural area. The analytic sample had significantly lower IMD scores (ie. lower deprivation) compared to those not in the analytic sample only (n=3,194), but overall, there were no significant differences between the full sample (n=13,459) and analytic sample (n=10,055).

The lifestyle covariates were added at model 4. The majority of the sample indicated they had never been a smoker (75%), and the mean household spend on alcohol over the last 4 weeks was £54. In terms of housing tenure, 40% were mortgage owners, 36% owned their homes outright, and 23% were in some form of rental accommodation. Close to 87% of the sample had access to a vehicle and 37% had a disability or long-standing illness. There were no significant differences between the full sample and analytic sample for lifestyle covariates overall. However, those not in the analytic sample were more likely to have a disability or long-standing illness, to spend less on alcohol, and not to have access to a car. Mean AL across the 15-biomarker measure (AL15) that included primary mediators was 3.46 (SD: 2.45). Mean AL for the 12 biomarkers measure[45] (AL12) was 2.51 (SD: 1.95). Figure 8 below highlights mean AL scores across the 4 waves for random samples of 100 participants.

[45] Included in the analysis for comparison with ELSA in chapter 4 and in order to assess the impact of biomarker selection on results as recommended for further exploration in Mcloughlin et al. (McLoughlin et al., 2020).

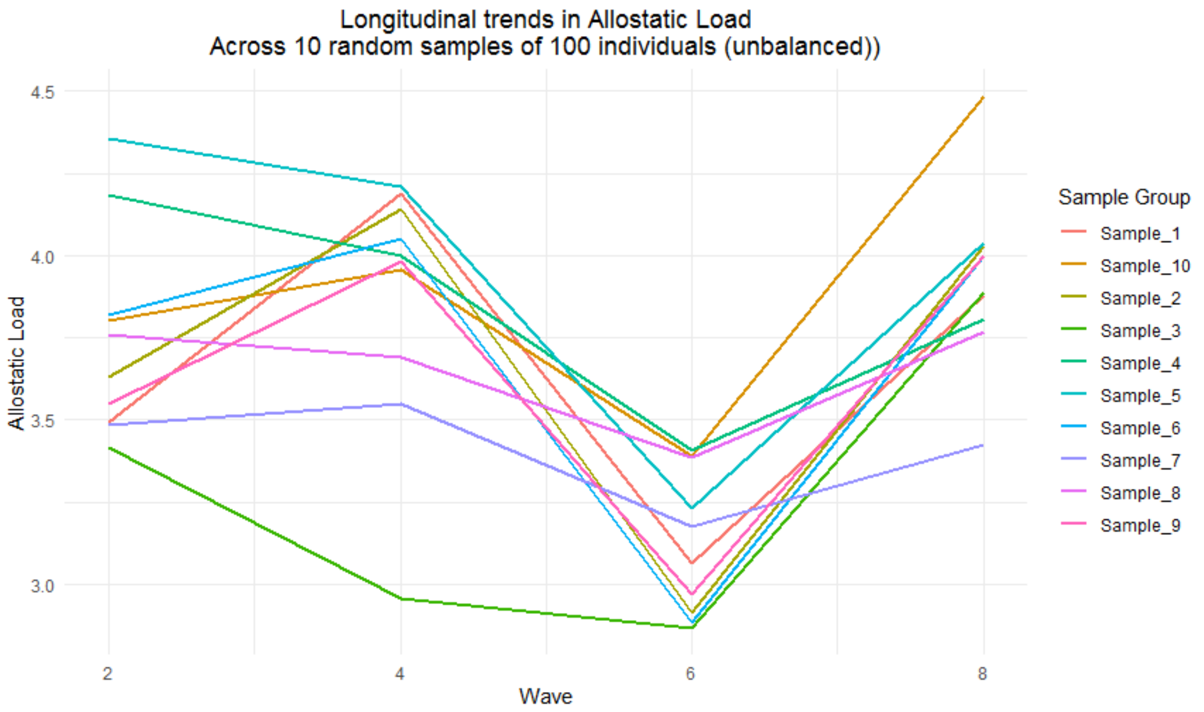

Figure 8: Longitudinal trends in mean Allostatic Load across 10 random samples of 100 individuals using unbalanced data in ELSA

3.7.1 Comparison of distance measures

The distributions of the different distance measures are presented by domain, Pearson correlation, Postcode Coefficient of Variation, LSOA CV, and difference between postcode coefficient of variation and LSOA CV below.

Table 16: Comparison of LSOA and Postcode mean distances to 20-minute neighbourhood domains

N = 10,055	Postcode mean (SD) in metres from grid reference	LSOA mean (SD) in metres from OA PWC	PC CV (SD/ mean)	LSOA CV (SD/ mean)	PC CV - LSOA CV
Public Transport	180 (210)	180 (126)	1.1666667	0.7	0.466667
Greenspace & Recreation	339 (329)	340 (237)	0.9705015	0.697059	0.273443
Culture	395 (293)	390 (210)	0.7417722	0.538462	0.203311
Eating & Drinking	477 (474)	472 (357)	0.9937107	0.756356	0.237355
Food Services	491 (663)	487 (565)	1.3503055	1.160164	0.190141
Education	514 (518)	509 (392)	1.0077821	0.770138	0.237645
Community Facilities	516 (513)	514 (403)	0.994186	0.784047	0.210139
Financial Services	517 (622)	514 (511)	1.2030948	0.994163	0.208931
Health Services	814 (995)	814 (916)	1.2223587	1.125307	0.097052
Retail Services	1950 (2130)	1950 (2100)	1.0923077	1.076923	0.015385

Note: PC = Postcode, CV=Coefficient of Variation calculated as SD/mean, LSOA=Lower Super Output Area, OA=Output Area, PWC=Population Weighted Centroid

The values in Table 16 above represent mean distances from postcode (PC) grid references of Understanding Society participants and mean distances from OA PWCS aggregated at the LSOA level to the nearest Ordnance Survey Maps' Points of Interest feature representing the 10 included 20MN domains. The table shows that, on average, people live closest to the public transport domain and furthest away from health services across both measurement approaches.

The variance is reduced with the aggregate approach, with the SD always reducing for the aggregated OA PWC distances compared to the postcode distances. The final 3 columns in Table 16 represent the magnitude of the difference between the measures, as an indicator of the extent to which finer scale variations are masked when aggregating values at the LSOA level. Formal significance tests indicated significant differences in the distributions of the approaches for every domain. However, the approaches offer comparable means theoretically with the mean of differences between distance values minimal (ranging from -1 to +5 metres, with differences calculated by domain as mean PC distances minus mean LSOA distances). The order of nearest domains is the same across approaches and, as the distance measures are considered as a continuous measure, these averaged differences are not expected to be meaningfully different within the analysis.

The discrepancy for the public transport measure (represented by the large value in the PC CV - LSOA CV column in Table 16) may be explained by the fact that almost all areas have a bus stop, and all OA PWCs are likely to have a bus stop closely located given they reflect the population density of an area. However, postcodes reflect actual locations and may or may not fall within or close to PWCs or bus stops, increasing the likelihood of errors being at the positive end of the tail for this domain (ie. where distances in the postcode measure have the potential to be much higher and distances using the aggregate measure are likely to be lower). The final column indicates that, although not entirely linear, there appears to be a general pattern in the data that shows that when access to domains is further away on average, the difference between the variability in the measures goes down (or less variance is lost). This is essentially a feature of how both measures are constructed, as if something is further away, it is more likely to cross an LSOA boundary, so the variation around the mean is likely to be less pronounced. Some of the more nuanced differences highlighted by the coefficient of variation (CV) are outlined below.

The CV is a ratio measure and is calculated by dividing the SD by the mean and helps to illustrate differences between the measurement scales. The CV normalizes variability relative to the mean, making it easier to compare relative dispersion across domains, with higher CVs indicating greater variability around the mean and values under 1 indicating a standard deviation smaller than the mean. Given that LSOAs are designed to have similar population sizes necessarily results in varied LSOA area sizes (and shapes) due to differences in population density, this high degree of variability around the mean is to be expected when comparing distances calculated for every area nationally. However, the standardization of the variability highlights interesting differences between the measures in terms of the distributions depending on the scale of the analysis being used.

For example, whilst the CV is greater at the postcode (compared to the LSOA) scale in all cases within domains (ie. postcode CV for retail versus LSOA CV for retail), the ranked order of domains by CV differs across scales (ie. the ranked order of postcode CV does not necessarily equal the ranked order of LSOA CV, as highlighted in table 17 below for the retail domain which has the 8th highest CV at the LSOA scale but the 6th highest CV at the postcode scale). Where the ranks differ, this indicates that the relative dispersion of values around the mean may be influenced by the scale of measurement more, reflecting potential disparities in proximal access may be more likely to be different at one scale or another. For example, despite public transport having the smallest mean distances across both scales, its CV ranks 7th at the postcode level and reduces to 3rd at the LSOA level indicating highly variable distances within the sample when factoring in postcode grid reference. Additionally, the difference between the two CV measures (ie. the actual value of the difference) is also the highest ranked difference for public transport. This suggests that access to public transport is highly varied at the local scale and that comparisons of access for this measure may be more sensitive to measurement scale. As such, although on average people live closest to the public transport domain, there is lots of variability around the average values, with these differences particularly evident at the postcode scale.

Table 17: Ranked Coefficients of Variation for LSOA and Postcode distance measures

Domain	**Mean Distance Rank^**	**PC CV Rank**	**LSOA CV Rank**	**CV Difference Rank**	**Total rank score***
Health Services	9	9	9	2	2
Food Services	5	10	10	3	3
Retail Services	10	6	8	1	3
Culture	3	1	1	4	4
Financial Services	8	8	7	5	6
Eating & Drinking	4	3	4	7	8
Community Facilities	7	4	6	6	8
Education	6	5	5	8	8
Greenspace & Recreation	2	2	2	9	9
Public Transport	1	7	3	10	14

* Total Rank Score = max((PC CV Rank - LSOA CV Rank)^2, PC CV Rank - LSOA CV Rank) + CV Difference Rank

^ = not included in Total rank score

CV Rank Change > 2

CV Rank Change > 1

CV Rank Change > 0

No CV Rank Change

Table 17 above assesses the extent to which the measures appear to share similar variance structures and compare which domains show the most stability across the measurement approaches (ie. that the approaches appear to capture similar relationships). To make this table, CVs were ranked 1-10, with 1 indicating the lowest CV, and 10 the highest (most dispersed). The absolute difference in values between the postcode CVs and LSOA CVs was also calculated and ranked, highlighting which measures had the biggest differences in CV. A total rank score to assess the stability of the measures was then calculated by subtracting LSOA CV rank from PC CV rank, squaring the value if it was below zero, and adding this value to the CV difference rank. Based on this scoring system, distances to health services were the most stable across approaches, which may be explained by the large average distance values to this domain.

The high rank for PC CV and LSOA CV shows the actual distribution of features representing the health domain (made up of general practitioners and chemists or pharmacies) are widely dispersed. Food services and retail showed the next greatest stability based on this approach, each scoring 3. For food services the entirety of the score came from the rank of the difference between CV scores, whereas retail combined differences across ranks. For example, access to food services showed the highest variability around the mean for both postcode and LSOA distances equalling a score of 0, meaning only the rank of the difference (3/10) was included in the total score. However, for retail there was greater variation around the mean at the LSOA level, with its rank at the LSOA scale 2 places higher and the magnitude of the difference between measures the lowest across all domains, meaning it also scored 3 using this approach. Generally, retail was least present in LSOAs, which may explain the lower CV at the postcode level for this measure due to most values being highly distant at this scale. Overall, the ranked CV's and total score highlight the potential that aggregation effects may influence results for some domains more than others.

Table 18: Main Spearman Correlations of Mean distances from Output Area Population Weighted Centroids and from Postcode Grid References to domains

20 Minute Neighbourhood Domain	Spearman Correlations with OA PWC distances	Postcode mean distances in metres (SD)	OA PWC mean distances in metres (SD)
Retail	0.960207354	1950 (2130)	1950 (2100)
Health Services	0.818122559	814 (995)	814 (916)
Food Services	0.716947571	491 (663)	487 (565)
Eating & Drinking	0.710351664	477 (474)	472 (357)
Financial Services	0.703384258	517 (622)	514 (511)
Community Facilities	0.698539174	516 (513)	514 (403)
Education	0.681632672	514 (518)	509 (392)
Culture	0.66461202	395 (293)	390 (210)
Greenspace & Recreation	0.623889257	339 (329)	340 (237)
Public Transport	0.456611224	180 (210)	180 (126)

Table 18 (above) shows Spearman correlations between the distance measures calculated from the postcode grid reference versus the LSOA aggregate of OA PWC distances in descending order. Spearman's correlations were used due to the non-normality of the data. The table shows strong correlations of ≥0.7 between the measures for retail, health, food, eating and drinking, and financial domains. Community facilities, Education, and Culture were also on the cusp of being strongly correlated. Greenspace and recreation and public transport measures were only moderately correlated between measurement approaches.

Table 19: Comparison of differences between OA PWC and Postcode distances in number of domains within/outside of 800-metres

20-Minute Neighbourhood Domain	800+ (OA PWC)	800+ (PC)	<800 (OA PWC)	<800 (PC)	OA PWC 800+ Over/ Underestimation (%)[46]
Community Facilities	1398	1446	8654	8606	-3
Culture	490	836	9562	9216	-41
Eating & Drinking	1138	1266	8914	8786	-10
Education	1288	1317	8764	8735	-2
Food Services	1213	1188	8839	8864	2

[46] Calculated as (**'800+ (OA PWC)'** – **'800+ (PC)'**)/ **'800+ (OA PWC)'***100

Greenspace & Recreation	441	489	9611	9563	-10
Health Services	2661	2708	7391	7344	-2
Public Transport	61	176	9991	9876	-65
Financial Services	1332	1290	8720	8762	3
Retail	6766	6807	3286	3245	-1

Table 19 (above) shows the breakdown of individuals living in areas that do not have access to domains within 800-metres and those that do. Distances calculated from postcodes were more likely to fall outside of the 800-metre threshold (commonly used to indicate the boundary of a 20MN) than OA PWC distances. However, this was not the case for retail and food service domains, where the number of people living more than 800-metres away from the domain was (marginally) larger at the aggregated OA PWC level. The final column calculates the extent to which mean OA PWC distances over or underestimate (relative to the postcode measure) how many people live further than 800-metres of a feature representing each domain, expressed as a percentage.

For example, the OA PWC approach underestimates the number of people living without public transport and cultural domain access within 800-metres by 65% and 41% respectively. The remaining domain counts are all within 10% of the postcode distance measure, suggesting the OA PWC distance measure provides a reasonable proxy for the postcode distance measure for these domains. Nevertheless, these descriptive results highlight that it is important to consider the effects of aggregation as the effects are not uniformly distributed by domain. As such, any potential differences between associations for public transport and cultural measures may be explained by these aggregation effects.

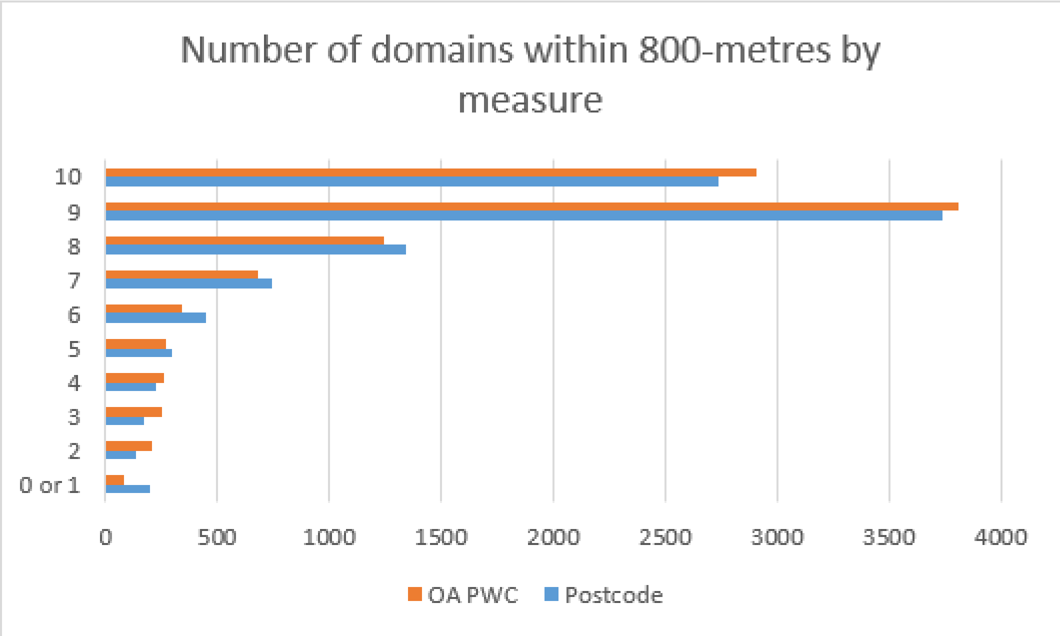

Figure 9: Count of Number of domains within 800-metres by postcode and Output Area Population Weighted Centroid

Figure 9 indicates the number of participants living in areas without access within 800-metres across all 10 domains for OA PWC and postcode distances. A score of 0 indicates an area that has no access to any domains within 800-metres, whilst a score of 10 indicates areas with access to all domains within 800-metres. When summing domain access in this way there is no uniform pattern across the distance measures. For example, the OA PWC approach suggests more areas with access within 800-metres to 10, 9, 4, 3, and 2 domains. On the other hand, the postcode distances show more participants have access to 0 or 1[47], 5, 6, 7, and 8 domains within 800-metres. However, differences likely fall within a single level, as both distance measures indicate between 77-79% of the sample live in areas with access to 8 or more domains within 800-metres. Close to 90% of the sample live in areas with access to 6 or more domains based on the postcode measure compared to 89% using the OA PWC measure,

[47] Domains at this level were combined due to counts under 10 across 0 and 1 domains.

indicating very little difference between the approaches overall when using an 800-metre threshold.

Table 20: Mean distances from Output Area Population Weighted Centroids and from Postcode Grid References to domains by covariates

					Mean Distances in metres to domains from OA PWC and Postcode Grid Reference									
Model [48]	Variable	Value Label	N	from	Community Facilities	Culture	Eating & Drinking	Education	Food Services	Greenspace & Recreation	Health Services	Public Transport	Financial Services	Retail Services
2	Job Status	In employment	5717	OA PWC	514	392	470	508	485	339	818	179	512	1910
2	Job Status	Inactive Other	1580	OA PWC	462	368	439	455	416	313	720	167	457	1700
2	Job Status	Retired	2755	OA PWC	543	397	497	542	530	358	862	188	550	2160
2	Highest Education	Degree	3596	OA PWC	533	391	475	521	531	356	881	188	557	2010
2	Highest Education	A Level	1882	OA PWC	502	392	472	501	479	336	798	176	504	1950
2	Highest Education	GCSE	2115	OA PWC	507	392	473	507	458	330	788	177	505	1890
2	Highest Education	other	1126	OA PWC	512	394	481	509	468	341	771	175	489	1890
2	Highest Education	None	1333	OA PWC	490	376	459	488	439	319	738	170	447	1890

[48] In the model column a * indicates a variable that is treated as continuous in models but presented as categorical in the table for interpretation purposes.

2	Sex	Female	5531	OA PWC	513	385	467	508	485	340	812	180	512	1940
2	Sex	Male	4521	OA PWC	514	395	480	510	488	340	818	180	516	1950
2	Ethnicity	Not White	537	OA PWC	378	307	331	340	262	275	442	154	315	1040
2	Ethnicity	White	9515	OA PWC	521	394	481	518	499	344	836	181	525	2000
2	Partnership Status	Married or In a relationship	5791	OA PWC	552	411	503	538	537	363	894	189	561	2070
2	Partnership Status	Single	4261	OA PWC	462	361	431	469	419	310	707	167	449	1780
2*	Income quantile	£0 to £2,000	3223	OA PWC	487	373	452	481	437	321	741	170	458	1860
2*	Income quantile	£2,000 to £4,000	3592	OA PWC	506	392	474	508	484	338	812	182	513	1960
2*	Income quantile	£4,000 to £6,000	1888	OA PWC	536	401	488	528	518	351	856	183	550	1940
2*	Income quantile	£6,000+	1349	OA PWC	565	409	495	551	568	377	939	194	598	2130
2*	Age Group	50+	5375	OA PWC	547	397	496	541	535	358	879	189	550	2110
2*	Age Group	Under 50	4677	OA PWC	476	382	446	472	432	319	740	169	472	1760

3&4	Urbanity	Rural	2166	OA PWC	835	466	761	903	1070	539	1810	287	1040	4560
3&4	Urbanity	Urban	7886	OA PWC	425	369	393	400	325	286	542	150	369	1230
3&4*	IMD Quantile (Rounded)	0 to 9	2513	OA PWC	564	451	496	506	492	346	818	190	544	2210
3&4*	IMD Quantile (Rounded)	9 to 16	2514	OA PWC	598	425	515	579	626	391	1010	199	649	2350
3&4*	IMD Quantile (Rounded)	16 to 26	2513	OA PWC	544	378	509	589	568	370	967	196	568	2110
3&4*	IMD Quantile (Rounded)	26 to 93	2512	OA PWC	349	305	371	361	261	254	464	134	294	1120
4	Smoking Status	Never smoker	7489	OA PWC	528	396	481	523	508	347	838	183	532	2010
4	Smoking Status	Ever smoker	2563	OA PWC	472	373	447	468	426	319	745	169	460	1760
4	Housing Tenure	Mortgage Owner	4059	OA PWC	512	400	472	505	470	334	785	176	503	1880
4	Housing Tenure	Owner	3645	OA PWC	562	406	504	550	554	373	920	196	582	2220
4	Housing Tenure	Renter	2348	OA PWC	440	346	425	451	412	299	701	163	427	1640

4	Disability	No	6288	OA PWC	515	391	472	505	490	340	815	179	515	1950
4	Disability	Yes	3764	OA PWC	511	387	474	514	481	340	814	181	511	1950
4	Vehicle Access	Has Access	8704	OA PWC	535	402	489	529	515	351	863	185	541	2040
4	Vehicle Access	No Access	1348	OA PWC	378	313	365	380	302	269	500	146	336	1320
4	Alcohol spend (£) quantile	£0 to £5	2582	OA PWC	480	375	456	479	436	319	723	170	464	1810
4	Alcohol spend(£) quantile	£5 to £30	2801	OA PWC	523	402	477	513	493	338	820	180	526	1970
4	Alcohol spend(£) quantile	£30 to £70	2206	OA PWC	529	398	492	535	524	359	874	186	543	2020
4	Alcohol spend(£) quantile	£70+	2463	OA PWC	524	384	468	511	500	348	851	184	526	1990
NA	Full sample for OA PWCS	Overall for OA PWCS	**10055**	OA PWC	514	390	473	509	487	340	815	180	514	1950
2	Job Status	In employment	5717	PC	521	400	481	515	499	341	824	181	522	1920

2	Job Status	Inactive or Other	1580	PC	457	368	440	463	410	308	719	165	458	1680
2	Job Status	Retired	2755	PC	540	400	492	539	520	354	849	188	540	2160
2	Highest Education	Degree	3596	PC	534	391	480	527	539	356	885	190	563	2010
2	Highest Education	A Level	1882	PC	511	404	478	507	484	335	790	180	511	1960
2	Highest Education	GCSE	2115	PC	516	399	474	507	462	329	791	176	503	1900
2	Highest Education	other	1126	PC	513	409	491	518	472	344	763	172	504	1860
2	Highest Education	None	1333	PC	482	374	464	494	432	312	738	170	434	1900
2	Sex	Female	5531	PC	515	389	473	514	489	338	813	180	517	1940
2	Sex	Male	4521	PC	519	402	483	513	492	340	816	181	517	1950
2	Ethnicity	Not White	537	PC	371	307	337	349	264	271	451	151	314	1040
2	Ethnicity	White	9515	PC	525	400	486	523	503	343	835	182	528	2000
2	Partnership Status	Married or In a relationship	5791	PC	558	419	516	546	544	365	894	194	570	2080
2	Partnership Status	Single	4261	PC	460	362	425	469	418	304	706	163	444	1770
2*	Income group	£0 to £2,000	3223	PC	476	373	444	478	421	305	728	162	445	1850

2*	Income group	£2,000 to £4,000	3592	PC	512	401	483	511	496	338	816	181	524	1950
2*	Income group	£4,000 to £6,000	1888	PC	539	392	504	525	533	358	856	185	550	1940
2*	Income group	£6,000+	1349	PC	594	435	508	590	585	396	956	216	622	2160
2*	Age Group	50+	5375	PC	550	403	497	544	538	359	875	192	550	2110
2*	Age Group	Under 50	4677	PC	478	386	456	479	437	316	745	167	478	1760
3&4	Urbanity	Rural	2166	PC	843	481	774	927	1080	535	1800	288	1040	4550
3&4	Urbanity	Urban	7886	PC	427	371	396	400	329	286	544	151	374	1230
3&4*	IMD Quantile (Rounded)	0 to 9	2513	PC	554	450	487	499	486	338	807	183	542	2210
3&4*	IMD Quantile (Rounded)	9 to 16	2514	PC	597	427	522	593	646	391	1010	203	654	2350
3&4*	IMD Quantile (Rounded)	16 to 26	2513	PC	563	390	522	596	558	371	962	201	563	2110
3&4*	IMD Quantile (Rounded)	26 to 93	2512	PC	352	313	379	367	272	257	479	135	308	1130
4	Smoking Status	Never smoker	7489	PC	530	400	488	528	514	347	840	186	539	2010

4	Smoking Status	Ever smoker	2563	PC	478	380	446	473	424	317	738	164	451	1760
4	Housing Tenure	Mortgage Owner	4059	PC	518	408	480	512	481	336	789	175	512	1890
4	Housing Tenure	Owner	3645	PC	565	408	510	546	547	372	916	201	583	2220
4	Housing Tenure	Renter	2348	PC	439	352	422	467	419	295	700	158	422	1630
4	Disability	No	6288	PC	515	397	476	511	494	341	811	180	523	1950
4	Disability	Yes	3764	PC	519	392	480	518	485	336	819	182	506	1940
4	Vehicle Access	Has Access	8704	PC	540	409	496	535	522	351	865	187	547	2050
4	Vehicle Access	No Access	1348	PC	365	306	357	375	288	263	486	139	322	1310
4	Alcohol spend(£) quantile	£0 to £5	2582	PC	475	380	459	483	447	316	724	172	465	1820
4	Alcohol spend(£) quantile	£5 to £30	2801	PC	526	408	482	525	491	332	810	176	529	1980
4	Alcohol spend(£) quantile	£30 to £70	2206	PC	543	409	489	535	531	367	884	186	550	2020

4	Alcohol spend(£) quantile	£70+	2463	PC	525	383	482	514	499	347	851	189	527	1980
NA	Full sample for postcodes	Overall for postcodes	**10055**	PC	517	395	478	514	491	339	814	180	517	1950

Table 20 (above) highlights the breakdown of proximal access measures by 20MN domain and covariates for OA PWCS and PC distances, with PC distances outlined in greater detail here (in text) as they offer the greatest measurement specificity (where participants actually lived within the LSOA). The sample under the age of 50 lived closer on average to all 20MN domains (570 metres versus 662 metres across domains). The lowest quantile for pounds (£0-£5) spent on alcohol lived closer to all 20MN domains on average (570), with average distances increasing linearly from quantiles 1-3 across domains. However, quantile 4 (£70+), the highest spenders on alcohol, had similar average distances to domains as quantile 2 (>£5-£30).

Those with a disability or long-standing illness had higher mean distances to 5/10 domains, with overall differences in means across domains for those with (618-metres) or without (620-metres) small across all domains. The non-white sample lived closer to all domains than the white sample, with mean distances across domains 386-metres for the non-white sample compared to 633-metres for the white sample. Across all domains, mean distances appeared to increase linearly with additional educational attainment whereby those with higher qualifications lived further away from domains on average.

Whilst the patterns were not uniform across individual domains (for example those with A Levels lived further from the cultural domain than those with a degree), those with no qualifications lived closer to all domains on average. A similar pattern was present for the measure of housing tenure, renters lived closer to all domains, followed by mortgage owners, with outright homeowners living furthest from all domains on average (apart from the cultural domain which was level with mortgage owners).

As IMD scores increased (indicating higher deprivation) average distances to domains decreased for quantiles 2-4. However, quantile 1 (indicating those living in the least deprived LSOAs) tended to have lower average distances than quantiles 2 and 3 to individual domains (other than culture). For income quantiles, those with the lowest incomes lived closer to all domains which increased by income group across all domains bar the cultural domain. Employment status followed a similar pattern with those unemployed living nearest to all domains, followed by those in employment, with those who had retired living furthest from all domains (apart from culture).

Those who were single lived closer to all domains on average than those who were married. Females lived closer to 7/10 domains, but overall mean differences to domains were small with females living an average of 617-metres from domains compared to 621-metres for males. People who admitted to ever being smokers lived closer on average to all domains than reported never smokers. Those without access to a car also lived closer to all domains than those with access to a car. Average distances to domains were roughly 3 times larger as in urban areas in rural areas, although the difference between distances to culture were the smallest of any domain with average distances 481-metres in rural areas compared to 371-metres in urban areas. This somewhat surprising proximity to cultural venues in rural areas is likely explained by the inclusion of places of worship within the features representing the cultural domain.

3.7.2 19Evidence for H1: Improved access to 20MN domains would be associated with a protective effect on AL

Evidence for H1 was assessed by model 1 only for both AL15 (including primary mediators) and AL12 (including biomarkers included in 4 waves of ELSA used in chapter 4). Across all domains there was limited evidence of a cross-sectional association between proximal access to 20MN domains and AL in either a positive (deleterious) or negative (protective) direction. However, living further away from both the 'eating and drinking' and 'retail services' domains was associated with higher AL in line with expectation that poorer proximal access to key amenities would be associated with higher (worse) AL. Beta estimates of an association were smaller when the AL15 measure was included as an outcome, indicating the inclusion of primary mediators diluted the association with the distance measure. There was also evidence against H1 as, contrary to expectation, living further away from the 'Greenspace and Recreation' and 'Public Transport' domains was associated with lower AL. Again, beta estimates for this association were smaller (closer to 0) for the AL15 construct compared to the AL12 construct for both measures.

3.7.3 Evidence for H2: Improved access to 20MN domains would be associated with a protective effect on AL over and above demographic characteristics

After including demographic confounders, only higher logged OA PWC distance to retail remained significantly associated with higher AL12 but not AL15. Adding the demographic covariates also made model-2 significant for the sample aged over 50 for AL12, as this association was not present for this sample in model-1. Evidence against H2 (ie. lower AL associated with increased distance) was maintained for the public transport domain for both the full sample and the sample under 50 for AL15 and AL12. However, evidence against H2 was only maintained for greenspace and recreation for AL12, with beta estimates attenuating very slightly.

3.7.4 Evidence for H3: Improved access to 20MN domains would be associated with a protective effect on AL over and above both demographic and area-based characteristics

When accounting for the area-based confounders, no new patterns (or domains) emerged. However, distance to retail regained significance for the full sample in AL15 and was maintained in AL12 for the full sample and the sample under 50. Additionally, distances to retail from postcode became significant for both AL12 and AL15 after accounting for area-based and demographic confounders. This association with postcode distances was significant for the full sample for both AL constructs and the sample aged 50 and above for AL15 only. Living further away from greenspace and recreation remained associated with lower AL for the sample under 50 for the AL12 construct but not AL15. However, conversely, living further away from the public transport domain remained associated with lower AL for the AL15 construct and not the AL12 construct.

3.7.5 Evidence for H4: Improved access to 20MN domains would be associated with a protective effect on AL over and above demographic, geographical, and lifestyle characteristics

When accounting for all confounders, distance to retail remained significantly associated with increased AL for both the AL15 and AL12 constructs in the full sample only, in line with H4. Contrary to H4, distance to the public transport domain remained associated with lower AL for the AL15 construct in the full sample and the sample under 50.

3.7.6 Evidence for H5: There would be differences in associations between domain relevance between stratified samples (those aged under 50 and those aged 50 plus).

Higher logged distances to eating and drinking were associated with higher AL in model 1 only of the stratified sample for those under the age of 50 when AL15 was included as an outcome, and both the full sample and the sample under 50 for AL12. Living further form retail was associated with higher AL in the full sample only for AL15 in models 1,3, and 4 and all models for AL12 for the full sample as well as models 2, 3, and 4 only for the sample over 50. Living further away from the public transport domain was associated with lower AL in the full sample and the sample under 50. However, living further away from greenspace and recreation was only associated with lower AL in the sample aged under 50 (for model 1 only for AL15 and models 1-3 for AL12).

3.7.7 Significant results (survived Bonferroni correction) AL15

Higher logged distances from OA PWCs to the ***eating and drinking*** domain were associated with higher AL15 in the sample under 50 for model 1 only ((<50) model-1, Beta (B):0.214, Standard Error (S.E.):0.08, p<0.007, Bonferroni corrected p-value (p.bonf)<0.043). Higher logged distances from OA PWCs to the ***greenspace and recreation*** domain were associated with lower AL15 in the sample under 50 for model 1 only ((<50) model-1, B:-0.231, S.E.:0.085, p<0.006, p.bonf<0.039). Higher logged distances from OA PWCs to the ***public transport*** were associated with lower AL15 in models 1-2 for the full sample ((FS) model-2, B:-0.189, S.E.:0.062, p<0.002, p.bonf<0.008), although when including area-based covariates this association did not survive correction ((FS) model-3, B:-0.152, S.E.:0.063, p<0.015, p.bonf<0.06) nor regain significance in complete models ((FS) model-4, B:-0.142, S.E.:0.062, p<0.023, p.bonf<0.092). However in the sample under 50 the significant association between public transport and AL15 was found in all models ((<50) model-4, B:-0.24, S.E.:0.087, p<0.006, p.bonf<0.036). Higher logged distances from OA PWCs to the ***retail services domain*** was associated with higher AL15 in all models other than model 2 for the full sample ((FS) model-4, B:0.111, S.E.:0.037, p.bonf<0.008). Higher logged distances to **retail services** from postcodes was not significantly associated with higher AL15 in models 1 and 2 but was close to significance after correction in models 3 and 4 for the full sample ((FS) model-4, B:0.15, S.E.:0.062, p<0.015, p.bonf<0.06) and was significantly associated with higher AL15 in model 3 only of the sample under 50 ((<50) model-3, B:0.24, S.E.:0.091, p<0.008, p.bonf<0.049).

3.7.8 Significant results (survived Bonferroni correction) AL12

Higher logged distances from OA PWCs to the ***eating and drinking*** domain were associated with higher AL12 in both the full sample (FS) model-1, B:0.202, S.E.:0.072, p<0.005, p.bonf<0.02) and the sample under 50 for model 1 only ((<50) model-1, B:0.318, S.E.:0.106, p<0.003, p.bonf<0.024). Higher logged distances from OA PWCs to the ***greenspace and recreation*** domain were associated with lower AL12 in the sample under 50 for models 1-3 ((<50) model-3, B:-0.295, S.E.:0.101, p<0.004, p.bonf<0.032). Higher logged distances from OA PWCs to the ***public transport*** was associated with lower AL12 in models 1 and 2 for the full sample ((FS) model-2, B:-0.228, S.E.:0.075, p<0.002, p.bonf<0.008) and the sample under 50 ((<50) model-2, B:-0.31, S.E.:0.107, p<0.004, p.bonf<0.032). Higher logged distances from OA PWCs to the ***retail*** domain was associated with higher AL12 in all models for the full sample ((FS) model-4, B:0.147, S.E.:0.045, p<0.001, p.bonf<0.004), and for the sample aged 50 and over ((50+) model-4, B:0.205, S.E.:0.062, p<0.001, p.bonf<0.008). Higher logged distances to the ***retail*** domain from postcodes was also associated with higher AL12 in models 3 and 4 only of the full sample ((FS) model-4, B:0.193, S.E.:0.076, p<0.011, p.bonf<0.044).

Table 21: Summary of beta estimates for significant results by domain, variable, and Allostatic Load measure

Beta estimates significant at P<0.05 after Bonferroni correction	AL12				AL15			
	M1	**M2**	**M3**	**M4**	**M1**	**M2**	**M3**	**M4**
Eating and drinking								
Logged mean distance (OA PWC) in kilometres to eating and drinking venues								
Full Sample	0.202							
Over 50 Sample								
Under 50 Sample	0.318				0.214			
Greenspace & recreation								
Logged mean distance (OA PWC) in kilometres to greenspace								
Full Sample								
Over 50 Sample								
Under 50 Sample	-0.336	-0.31	-0.295		-0.231			
Retail services								
Log of mean distances (OA PWC) kilometres to retail services								
Full Sample	0.126	0.116	0.151	0.147	0.098		0.114	0.111
Over 50 Sample			0.195	0.205				
Under 50 Sample								
Log of kilometres to Retail Services from postcode								
Full Sample			0.198	0.193				
Over 50 Sample								
Under 50 Sample							0.24	
Public transport								
Logged mean distance in kilometres (OA PWC) to public transport								
Full Sample	-0.257	-0.228			-0.188	-0.189		
Over 50 Sample								
Under 50 Sample	-0.351	-0.31			-0.283	-0.286	-0.254	-0.24

All models adjust for sampling design, with model 2 adjusting for demographic, model 3 additionally controlling area, and model 4 additionally controlling for lifestyle characteristics

Table 21 (above) summarise the beta estimates for significant (p<0.005 after Bonferroni correction of X4 for the full sample and X8 for the stratified sample) associations between proximal access to 20MN domains and both AL measures. These results are summarised below relative to the hypotheses they evidence or contradict. When distance measures were significant for postcode distances this is explicitly stated, otherwise the significant findings were all found only for the OA PWCS distances when aggregated at the LSOA level.

3.7.9 Non-significant domains

There were no significant associations between distances and AL for any models or AL constructions that survived Bonferroni correction for the: cultural; community facilities; financial services; food services; or health services domains.

3.7.10 Demographic Covariates

Age was associated with higher AL15 in complete models in all samples, with beta estimates showing a one unit increase in age on AL as having the strongest effect the sample under 50 (for full results for model covariates see Appendix A) [49], in line with previous studies that shows increases between the ages of 20-60 before levelling off (Crimmins et al., 2003; Maier, 2014). Compared to having a degree as highest qualification moving between levels to lower qualifications was increasingly associated with higher AL, with other producing beta estimates on a par with A-levels or equivalent. Having ***A-Levels or equivalent*** was associated with higher AL15 in the full sample and the sample over 50, but not the sample under 50, ***GCSE's or equivalent*** were associated with higher AL15 in all samples and represented the largest increase in Beta estimates between levels, having no qualification was

[49] Sections 3.7.10-3.7.12 summarise results found in Appendix A.

associated with the highest AL. Being male was associated with higher AL15 in the full sample and the sample under 50 but not the sample aged 50 and above. Compared to being in employment, only inactivity was significantly associated with higher AL15 and only in the sample under 50. Being single was associated with lower AL15 in the full sample but not the samples stratified by age. Binary ethnicity and the (inverse hyperbolic sin of) household income measure were not significantly associated with AL in complete models in any sample.

3.7.11 Area-based Covariates

Higher IMD scores indicating greater deprivation were associated with higher AL in complete models for all samples, but urbanity was not significant in any model. However, it was retained in models due to the context it provided for the distance measures which varied widely between the urban and rural settings.

3.7.12 Lifestyle Covariates

Having a disability or long-standing illness was associated with higher AL in complete models in all samples, with logged increases in alcohol spend associated with lower AL in all samples. Compared to being a mortgage owner, renting was only significantly associated with higher AL in the sample aged 50 and above. Similarly, being an outright owner was associated with a protective effect relative to mortgage owners only for the sample aged 50 and above. Neither car access nor smoking status was significantly associated with AL in complete models. However, again these were maintained due to the theoretical confounding they sought to explain.

3.8 Sensitivity analysis

As a sensitivity check, backward stepwise regression was applied to the basic model including logged mean distances to all 10 domains. The reduced model retained six domains, including: community services, eating and drinking, greenspace and recreation, public transport, financial services, and retail. Higher logged distances to community services and retail were significantly associated with higher allostatic load, while higher logged distances to financial services were significantly associated with lower allostatic load, supporting the robustness of the key associations identified in the full model.

3.9 Discussion

The primary aim of this chapter was to assess whether there was evidence of a cross-sectional association between proximal access to 20MN domains and AL and to explore which domains were the most salient[50] relative to AL. It achieved this by fitting weighted linear regression models to examine relationships between distances to ten distinctive 20MN domains and two simple risk score approaches to calculating AL. The sample was weighted using the nursing blood weight to more accurately reflect the population of interest and to reduce sampling bias. All 10 distance measures were also included within a single model to control for overall 20MN access within the estimated associations. This approach sought to isolate the independent effect on AL of distances to individual domains whilst accounting for potential correlations between them. Secondary aims were to consider whether any associations were maintained over and above the individual characteristics of the sample, with demographic, area-based, and lifestyle confounders added in a block-wise fashion to models 2, 3, and 4 respectively. Variables expected to predict Allostatic Load and to have a relationship to 20MN domains such that they may confound any relationship between access to 20MN domains and AL were included in these models[51]. Thirdly, to assess whether

[50] With salience considered associations that maintained significance ($p<0.05$) after Bonferroni correction for multiple testing.
[51] A more detailed description of how these variables are expected to act as confounders is found in the overall introduction to this thesis in Table 13.

associations between AL and access to 20MN domains were modified by age the sample was stratified into those aged below 50 and those aged 50 and above[52].

The findings in this chapter indicate that the retail domain appeared the most salient domain relative to AL[53]. For example, living further away (having higher logged distances) from features representing the retail domain was associated with higher AL in the full sample for OA PWC distances aggregated at the LSOA level. In some instances, this was also the case for both the sample under 50 and, more often, the sample over 50. These associations were maintained across all models for the full sample after accounting for potential demographic, area-based, and lifestyle confounders offering some weight to their relationship being more than correlational.

Whilst the addition of the confounders (in blocks) tended to attenuate estimates, the addition of IMD and urbanity at model 3 amplified the association between logged mean distances to retail and AL, with beta estimates increasing by 40% (0.081 to 0.114) between model 2 and model 3 for the OA PWC measure and significance being attained at the postcode level with the inclusion of this contextual detail. This amplification of the estimate may be explained by the inclusion of urbanity which accounts for the large differences in average distances to retail between urban (1.2-km) and rural (4.6-km) areas, even though urbanity itself was not significantly associated with AL. As such, this model better accounts for geographical context when assessing any apparent association between distance to retail

[52] This split was also to facilitate result comparisons in the following chapter (3) which uses data from the English Longitudinal Study of Aging, a nationally representative sample of the non-resident adult population of England aged 50 and above.
[53] With salience here reflecting significant associations ($p<0.05$) that survived Bonferroni correction for multiple testing in any model.

and AL, particularly given the wide differences between the urban and rural settings for this domain.

When AL12 was included as an outcome, postcode distances also retained significance for the retail domain in all models of the full sample, but not for AL15. This suggests there is some sensitivity to biomarker selection between these AL constructs, but interestingly in this case, the AL measure without primary mediators and fewer included biomarkers appeared more strongly associated with proximal access. This may indicate that underlying associations are not driven by the stress response and relate more directly to the secondary outcomes included within the AL construct. However, although significance was not maintained at the postcode level for AL15, the complete model came close to significance after Bonferroni correction for multiple testing ($p<0.015*4=p.bonf<0.075$) for this AL construct, and was significant in model-3 only for the sample under 50, the only time at which this domain appeared salient for this age group. As such, the general picture of the two constructs is the same, even if formal significance is not shared completely across the models.

The maintenance of significance in complete models for distances to the retail domain, and the amplification of the estimate with the addition of the area-based covariates, suggests this domain may be a useful indicator of areas that face broader socio-environmental stressors or areas offering environmental characteristics that support physical activity and social engagement. For example, that further distances to this domain are associated with higher AL may suggest that the included features indicate areas that face a special form of isolation over and above the effects of neighbourhood deprivation, relative to their urban or rural form.

Whilst the included measures within the retail domain do not themselves seem to inherently offer spaces that might typically be associated with a sense of community or healthy outcomes[54], they are all features that are most likely to be present on high streets or close to densely populated areas. Given that high streets offer opportunity spaces for communities to come together with the offer of places to meet, shop, and be entertained, living in areas with larger average distances to the retail domain may indicate areas that lack access to the spaces that serve this purpose of drawing people in and/or promote car use over active travel modes (Fernandez et al., 2024; Healthy High Streets, 2018).

More abstractly, the distance from this domain may serve as a proxy for places where a sense of decline has had a broader impact on local community wellbeing, with the distance also potentially an indicator of empty high streets that may present visual signals of decline that may trigger feelings of unsafety (RSPH, 2018). However, further consideration needs to be given to whether this association is related to the stress response, given the estimates for AL12 models, the measure that did not include primary mediators, appeared more stable. For example, proximity to retail may encourage active travel and increased physical activity (Saelens & Handy, 2008; Wu et al., 2016), with more direct links to secondary outcome biomarkers included within the AL construct (Friel et al., 2024; Jarrett et al., 2012; Laverty et al., 2013; Sarkar et al., 2013a), and not involve the stress pathway. Nevertheless, any effect on the stress response is likely to be small and cumulative, and both AL constructs encouraged similar conclusions. Namely, that proximity to retail did appear to have a cross-sectional relationship with AL.

[54] General household goods, department stores, discount stores, shopping centres and retail parks indicated the retail domain.

Other than distances to retail services, only distances to the public transport domain remained significant in complete models[55]. However, the association with public transport was not in the hypothesized direction, with further distances to this domain associated with higher AL. In this instance, AL15 remained significant in more complete models rather than AL12. Access to public transport was expected to indicate connectivity to employment opportunities, social connections with friends and family, and essential health-promoting amenities like schools, parks, libraries, and healthcare facilities (Mihaylova, 2021). That the association was in the opposite direction to expectation may indicate that proximity to the public transport domain as it was constructed here, which is dominated by the bus stops feature which make up the vast majority of this domain, is actually an indicator of proximity to busy roads than access to quality public transport, with quality not assessed here. Proximity to busy roads is more likely to increase exposure to air and noise pollution, themselves predictors of stress and AL in the literature, which may explain the maintained significance in the AL15 measure but not the AL12 measure (Leach et al., 2024; Recio et al., 2016; Thomson, 2019; Tonne et al., 2016).

There is also no assessment of the quality-of-service provision incorporated in this measure, such as whether the stops could be considered high-frequency stops (have five or more services per hour), a potential factor encouraging active travel choices (Olsen, Thornton, et al., 2022). This mixed evidence highlights that future research into 20MNs should look to include a variety of measures of quality for this domain. This also appears particularly important for the public transport domain. However, this is a complex task, particularly at a national level as it likely involves considering what, where, and when

[55] In the sample aged under 50, and at $p<0.1$ in complete models of the full sample.

services can be accessed from and to, mode of transport, travel times and costs, and individual barriers and constraints to use (Nie et al., 2024).

The beta estimates for the AL15 measure were closer to 0 than for the AL12 measure. As such, there was again evidence of sensitivity to biomarker selection relative to public transport, although in contrast to the retail domain AL15 retained significance in more complete models rather than AL12. Despite differences in formal significance, the overall conclusions from the estimates pointed to a relationship in the same direction for both AL constructs, supporting evidence in the AL literature that a latent AL factor can often be reliably identified regardless of which biomarkers or subsystems are included (Wiley et al., 2016). In this sense, similarly to Mcloughlin's findings regarding different constructions having only limited influence on result interpretation, these result support the versatility of the AL construct in terms of biomarker selection (McLoughlin et al., 2020).

3.10 Strengths and Limitations

This study was the first to investigate cross-sectional health effects associated with proximal access to 20MN domains relative to AL in a nationally representative sample. By including two measures of AL including differing biomarkers, it contributes to the AL literature by exploring the effects of biomarker selection on results. It also considered the effects of distance at two scales, from individual postcodes and the mean of distances across OA PWCs aggregated at the LSOA level. This approach made it possible to compare individual proximal access with an aggregate measure that can be calculated using less restrictive data access due to its use of less identifiable data. The distance measures for domains were highly correlated[56] (>0.7) or moderately-highly correlated (>0.6) for all domains other than the public transport domain, which was only moderately correlated

[56] Using Pearson's correlations

(>0.4), indicating similar underlying spatial patterns being captured and the utility to this approach. However, even though this measure was only moderately correlated both measures produced comparable results, suggesting they measured a shared aspect of proximal access.

Descriptive statistics highlighted evidence in line with previous 20MN studies that found better proximal access to 20MN domains in areas that were more deprived, with distances aggregated by individual characteristics often expected to represent disadvantage indicating lower average distances to almost every domain (Calafiore et al., 2022; Olsen, Thornton, et al., 2022). This approach also allowed for assessment of the effect of proximal access at both a specific level and an aggregate level, helping to consider potential impacts of the MAUP, an ever-present issue in spatial analysis that reflects the fact that the results of analysis can vary depending on the spatial scale or unit of aggregation used. By identifying whether the effects of distance were consistent across scales and correcting for multiple testing I sought to improve the robustness of the study findings. Whilst not surviving Bonferroni correction in complete models for any domain, the postcode measure to distance was close to formal significance relative to retail ($p<0.06$) after correction, suggesting close alignment for this domain in particular between the measurement approaches. Beta estimates for both measures were also consistent across domains in complete models for the full sample, albeit not obtaining significance for any other domains when using postcode level distances. Whilst the measures are conceptually slightly different, as the aggregate measure represents broader structural asymmetries in access to resources and the localized scale situates the nearest feature as of primary importance, the shared variance and similar results suggest both measures for this domain do represent a common dimension of proximal access. Just as AL can be composed and constructed differently but capture similar underlying processes.

Another strength of the analysis was the inclusion of 10 distinct 20MN domains within single models which allowed for wider spatial processes to be controlled for when assessing the effects of proximal access to specific domains. The decision to keep them separate prevented masking of underlying processes that may take place when combining scores together into a single indicator whilst accounting for greater complexity than focusing on individual domains allows (M. A. Green et al., 2018). A wide variety of individual-level confounders were also controlled for which helped to isolate the effects of proximal access on AL by seeking to ensure observed associations were not confounded by factors commonly included in neighbourhood effects (Jivraj, Murray, et al., 2019), AL (Johnson et al., 2017), and 20MN literatures (Calafiore et al., 2022; Dunning et al., 2023). This approach sought to avoid the ecological fallacy (assuming that relationships observed at the aggregate level apply to all individuals within a group), by measuring the effects of proximal access at the individual level. For example, even when assessing associations with the aggregate measure of distance, the measure reflected individual associations with a broader assessment of local physical access to 20MN domains.

A limitation of this study is that the measures of proximal access were calculated using data that was temporally misaligned, leading to the potential misalignment of exposure and health outcome. Even though it was expected that the net result of grouping features by domain would lead to minimal differences between time-points, changes in the built environment between the data collection times may still have influenced results, particularly in areas where infrastructural changes took place at greater speeds[57]. The distances were also

[57] Greater detail relating to this particular limitation is given in the strengths and limitations section in Chapter 4 of this thesis.

calculated in straight line metres (using Euclidean distance) rather than actual network distance and did not factor in potential physical barriers such as busy roads, topology, or pavement access that may help or hinder practical accessibility. Whilst a wide-range of confounders were adjusted for, residual confounding remains likely due to the distal relationship between exposure (proximity to X domain) and outcome (AL). For example, diet and exercise were not adjusted for at the individual level and neighbourhood-level sociodemographic characteristics were also not considered, all potentially things AL and 20MNs may both influence and be influenced by (Calafiore et al., 2022; Olsen, Thornton, et al., 2022; Robinette et al., 2016).

The quality of domains was also not considered, meaning proximal access was uniformly considered based solely on the presence or absence of features. However, it is probable that quality maters. For example, the quality of greenspace is known to be important in terms of health outcomes as the presence of greenspace does not mean it is considered safe, the presence of a park does not mean it is not damaged, and the presence of a sports centre does not mean it is well resourced (Hoffimann et al., 2017; Nguyen et al., 2021). This omission may explain the limited findings of beneficial associations relating to proximity and some associations operating against expectation, such as the public transport and the greenspace and recreation domains (where proximity was sometimes associated with higher AL). Future research should look to include an assessment of quality within proximity measures. Additionally, presence does not indicate use, and the primacy given to the household location as the context of influence ignores the potential role of the environment around places of work or educational settings (Ribeiro, Tavares, et al., 2019).

This relates to the Uncertain Geographic Context Problem, which recognizes that the presence of specific amenities doesn't necessarily expose anybody to anything or indicate for how long they have bene exposed (Kwan, 2012). Future research would benefit from including subjective measures that allow assessment of the actual use of included features or domains. It may also be beneficial to consider broader aggregate effects than the LSOA level, such as by using hot-spot analysis that can account for geographical clustering that appears to be spatially patterned[58]. The included covariates were also all treated as confounders, whereas it is possible that some of these measures may also moderate or mediate any relationship between proximal access and 20MNs. However, due to the inclusion of 10 domains as separate measures, formal interaction terms were not tested, and baseline models were run without covariates. By stratifying the sample by age group, the study sought to address potential interactions between age and proximal access. This stratification allowed for the exploration of whether the relationship between access to 20MN domains and Allostatic Load varied across different age groups. Given that life stage may influence both exposure to neighbourhood environments and physiological stress responses, this was an important consideration.

A further limitation relates to the use of the nurse data of Understanding Society. The use of this sample means there may be the potential for collider bias in the findings, with disengaged individuals (who may experience higher levels of chronic stress) being less likely to participate in the nurse component of Understanding Society, leading to missing blood sampling data for this socially and culturally disengaged group (E. Walker, 2024). While weighting for nurse visits may help to account for some of this missingness, remaining bias

[58] Chapter 4 includes hot-spot clusters of resource density to assess this.

could reflect this subset of more socially and culturally engaged participants, whose access patterns and associated relationships with AL may not fully represent the broader population.

3.11 Conclusions

Whilst interest in 20MN policies has blossomed post COVID-19 (Pozoukidou & Chatziyiannaki, 2021), no studies have explored potential health effects of living in areas with better access to 20MNs. This study addressed this gap and explored the relationship between proximal access to 10 commonly included 20MN domains and a 15 component AL (including primary mediators) and a 12 component AL (excluding primary mediators).

It achieved this by describing the distribution of access by potentially confounding sociodemographic characteristics. Descriptive statistics showed that individual indicators of deprivation, such as low income, were fairly linearly patterned as being nearer distances to domains. This agrees with evidence in the literature where it was found in analyses of Scotland and Liverpool that deprived areas had better access to 20MN domains (Calafiore et al., 2022; Olsen et al., 2023). As such, this study again recognises the importance of finding ways to incorporate measures of quality in future research looking at 20MNs.

It then considered associations between measures of direct and aggregate proximal access and two AL constructs in linear regression models. There was limited evidence of cross-sectional associations with any of the included domains. However, access to retail appeared to be a salient domain relative to AL across both distance measures, with higher distances to retail associated with higher AL in line with expectation that improved proximal access to the key amenities for daily living would be beneficial to AL. Contrary to expectation, living closer to the public transport domain was associated with higher AL. This likely reflects the dominance of bus stops in this domain that may make it an indicator of busy roads and the lack of consideration given to quality of provision, which is particularly relevant for this domain.

4 Longitudinal associations between 20-Minute Neighbourhoods and Allostatic Load in older age groups (Chapter 4)

4.1 Introduction

The COVID-19 pandemic fueled interest in the idea of 20-minute neighbourhoods (20MN) as a "new urban planning utopia" amongst mayors, planners, politicians, liberals and socialists alike (Pozoukidou & Chatziyiannaki, 2021), albeit with some push-back further down the line (BBC, 2023). The general rise in the popularity of the 20MN concept has been built on the simplicity of the idea that improved proximal access to key local amenities will reduce the need for carbon-intensive transport (Capasso Da Silva et al., 2020), encourage active travel (Kamruzzaman, 2022), and transform local economies and infrastructural environments, with wide-ranging benefits for the environment, health, and social cohesion (AlWaer & Cooper, 2023; Logan et al., 2022; Maizlish et al., 2017; Thornton et al., 2022). However a key tenet of the 20MN framework that has been underexplored is that areas should be inclusively designed as places for all ages and should "respond to the needs of everyone in the community [in order to] have the greatest potential to create opportunities for people to work, relax, exercise and thrive" (Our Place, 2021).

Given that 28% people in the UK were over the state pensionable age in 2020, and more than 50% of the UK Population are likely to be over 50 by 2041 (ONS, 2020a), older populations represent a key group to consider when assessing the effects of 20MNs across the life-course. Ass older people are more likely to wish to 'age in place', are less likely to move addresses over time (Pelikh et al., 2020), and are more likely to rely on local services for their daily needs

(Maresova et al., 2023; Padeiro et al., 2021), the neighbourhood context is most likely to be the key contextual influence on the activities and experiences of this population[59]. However, to my knowledge, only one study to date has explored access to 20MNs amongst older age populations specifically (Dunning et al., 2023). Importantly, they note that as older populations tend to have more diverse mobility needs, a simplistic focus on 20-minute thresholds that are uniformly applied regardless of underlying population demographics may not lead to equitable outcomes. They also show that a reduction in walking speed reduced access scores for all of the demographic groups assessed in their analysis. This leads them to ask an important question about whether the maximum active travel speed used to create 20MN thresholds should reflect the average mobility of residents, or those with limited mobilities. This question also points to a potential benefit of focusing on distance itself, rather than distance abstracted as time. However, the focus of this sole study on age and the 20MN was on the impact of reduced walking speed on calculated accessibility scores rather than any downstream impact of the resultant reduced accessibility score. This is similar in much of the literature assessing 20MNs, with few studies assessing 20MN as an exposure against any outcomes, health or otherwise.

4.2 20-Minute Neighbourhoods

Twenty-minute neighbourhoods are typically conceptualised as areas that provide access to most of people's daily needs within a short distance of their homes that is preferably accessible through walking, wheeling, or cycling (SUSTRANS, 2020). When using the 20MN framing (rather than 15-minute-cities for example), a common distance threshold estimated is around 800-metres from households to a given amenity (CIHT, 2015). This distance is selected as it is expected to take roughly 10 minutes each way at an average walking speed, with 10-minutes

[59] An important consideration in the face of the UGCoP outlined in the introduction to this thesis.

walking time considered the typical threshold that would put people off walking or wheeling in the general population.

Operationalising 20MNs typically involves selecting specific amenities to act as indicators of access to given domains or themes that are deemed to be essential to meet most of people's daily needs (Calafiore et al., 2022; Lima & Costa, 2023; Logan et al., 2022, Olsen, Thornton, et al., 2022; Thornton et al., 2022). The selected amenities are then used to represent domains, with a number of common domains existing in the literature, building on Carlos Moreno's six functions that services should provide for in a well-rounded 20MN, including: commerce; education; entertainment; healthcare; living; and working (Moreno et al., 2021). However, there is no uniform approach to constructing 20MNs and the selection of essential amenities that fall under a given over-arching domain varies throughout the literature, with amenities in one approach to constructing a 20MN not necessarily representing the same domain in another operationalisation. As such, this study considers a suite of distinctive domains found across the literature[60]. Whilst a number of studies have explored the operationalisation of 20-minute neighbourhoods (Thornton et al., 2022), few have explored the impact living in a 20MN might have on any of the outcomes proponents of the concept argue it seeks to address.

4.3 Ageing and 20-minute neighbourhoods

As already alluded to, the literature surrounding 20MNs and older populations specifically is sparse at best, despite the recognised importance of local neighbourhoods for this group (Bosch-Farré et al., 2020). However, there has been a global push to create age-friendly environments that facilitate "active ageing by optimizing opportunities for health, participation

[60] Outlined below and in the introduction of this thesis.

and security in order to enhance quality of life as people age" which has been driven by the dual demands of urbanisation and demographic ageing (WHO, 2007). The World Health Organization (WHO) has declared healthy ageing as a priority and, akin to the six needs Carlos Moreno identified in early descriptions of 20MN, identifies six determinants of active ageing including: behavioural; economic; health and social services; personal; physical environment; and social (Dunning et al., 2023; WHO, 2007). As such, there is a burgeoning related literature surrounding healthy ageing that offers insights into why 20MNs may be particularly relevant for older populations (Vasunilashorn et al., 2012).

In the UK, demographic changes that will see the expansion of older populations relative to their younger counterparts (*Our Ageing Population | The State of Ageing 2023-24 | Centre for Ageing Better*, 2023), alongside individual preferences of older people to stay in their own homes as they age (*Housing | State of Ageing in 2020 | Centre for Ageing Better*, 2020), and the costs to governments associated with the provision of institutional care (Bloom et al., 2015), has led to policies geared towards supporting 'Ageing in place' for many decades (Department of Health and Social Care, 2024). These policies are designed to support older people to remain living in their own homes as long as possible, with the expectation that this will both save governments money and increase individuals' autonomy over their daily lives (Grimmer et al., 2015). Policies supporting ageing in place also highlight that connections to place and a sense of home will be stronger when people have lived in areas for longer, with the expectation that this will improve wellbeing, support healthy ageing, and delay functional decline (Webber et al., 2023). The widespread desire of individuals to remain in place, and the strong connection to the local area this fosters, identifies the local neighbourhood as the key contextual areal unit likely to influence the health of older populations over time, albeit the 'neighbourhood' is itself a nebulous concept (Lu & Diab, 2023).

Similarly, the concept of 'active ageing' recognises that, in order to 'age in place', people need exposure to opportunities for health, community participation, and the maintenance of wellbeing that often include aspects outside of the home. This includes supporting people to stay socially active, to engage in different aspects of professional and family life, and to engage in community and leisure activities (Lak et al., 2021). As such, "enabling older people to live independent, active and fulfilling lives requires coordinated effort that spans national and local government policy areas, mobilises all sectors of society, and involves all health and care disciplines" (Hendry, 2017). Literature highlights that the home extends beyond the bricks and mortar buildings where people live, with neighbourhoods and communities recognised as being crucial in terms of understanding the health, wellbeing, and the potential for an improved quality of life for people as they age (Dobner et al., 2016). Outdoor mobility is also seen as a fundamental feature of healthy ageing, with regular physical activity in old age associated with reductions in the onset of chronic diseases, the maintenance of functional abilities, and improved quality of life (Chodzko-Zajko et al., 2009; Clarke & Gallagher, 2013).

Given the central role that neighborhoods play in promoting active living and facilitating ageing in place, the 20MN offers a suitable lens through which to evaluate how local access to essential services, social spaces, and opportunities for physical activity may influence health for an older population. For example, the 20MN concept emphasizes equitable access to the amenities and opportunities necessary for daily life should be provided within a short walk, wheel or cycle form home. This may be particularly salient for older populations who tend to face more mobility challenges than other age groups and for whom reduced access to private transport may be or may become a concern over time (Qin et al., 2020). Changes such as these as people age increase the risk of social isolation which is itself associated with poorer health outcomes and higher AL (Brooks et al., 2014; Cené et al., 2022; Saxbe et al., 2020b). Conversely, by improving access to key services and fostering opportunities for social interaction and independence, neighbourhoods designed with 20MN principles may help to alleviate chronic stressors (or prevent feelings of unsafety to use the terminology of the Generalised Unsafety Theory of Stress (GUTS) (Brosschot et al., 2018)) and their physiological impacts, as measured by AL (Read & Grundy, 2014).

4.4 Allostatic Load

Allostatic load has been described as a "weathering on physiological functioning resulting from repeated and prolonged exposure to stressors" (Prior et al., 2018b, p. 26), "as the cost of chronic exposure to fluctuating or heightened neural or neuroendocrine response resulting from repeated or chronic environmental challenge" (McEwen & Stellar, 1993b, p. 2093) (p.-2093), and as "the wear and tear on regulatory systems caused by chronic or frequent stress" (Saxbe et al., 2020a, p. 469). 'Stress' here, is perceived as anything that threatens the healthy functioning of an individual's ability to achieve 'allostasis', with Broschott et al.'s GUTS pointing to feelings of unsafety as the primary determinant of the stress response (Brosschot et al., 2017, 2018).

'Allostasis' refers to an active process whereby organisms adapt by evaluating and responding to challenges in their environment in order to maintain and achieve physiologic stability or 'homeostasis'. On the other hand, homeostasis refers to the "the mechanisms that maintain stability within the physiological systems and hold all the parameters of the organisms internal milieu within limits that allow an organism to survive", or the point at which chemical imbalances caused by stress responses that have caused allostatic states return to the normal set-points necessary for survival (Koob & Le Moal, 2001). Allostasis then, refers to the process that maintains these systems in balance by adapting the parameters of physiological systems to cope with chronic demands beyond the limits or the set-points of homeostasis (McEwen, 2005). In this sense, the process of allostasis involves the maintenance of physiologic stability through the adaptation of the normal homeostatic range. However, the need to constantly adapt, when stressors are multiple, recurring, or long lasting, can lead to long-term dysregulation of the body's ability to recover from stressors, be they social, environmental, or perceived (Read & Grundy, 2014).

Achieving allostasis involves the body's physiologic stress response system made up of: the sympathetic nervous system; the hypothalamic-pituitary-adrenal (HPA) axis within the neuroendocrine system, and; the immune system (Chandola et al., 2019b; Clark et al., 2007; Guidi et al., 2021; Read & Grundy, 2014). If a threat is detected, this system plays a vital role in survival by allowing the body to prioritise adaption to a stressful situation caused by the environment by altering the parameters of control beyond the bounds of homeostasis, resulting in an allostatic state (McEwen, 2005). An allostatic state reflects a "stabilised new level of activity far from homeostatic equilibrium [and] a state of chronic deviation of the regulatory systems from their normal state of operation with establishment of a new set point" (Koob & Le Moal, 2001). As such, when the stress response is activated, primary mediators such as cortisol or other chemical messengers both promote adaptation to stressful events and contribute to AL when they become dysregulated due to long-term activation of the stress response (Carbone, 2020a), which represents the cumulative burden of allostatic states.

Allostasis allows the body's systems to handle acute challenges and adapt effectively, but when this process becomes excessive or dysregulated, it leads to allostatic overload. This ongoing process, in turn, leaves a mark or markers within the body and the concept of AL seeks to capture and measure both the extent and the cumulative effects of these markers (McEwen, 2017). As such, the theory of AL is premised on the understanding that the body's repeated adaptation to challenges to re-establish stability, known as allostasis, can lead to an impaired capacity to respond to future challenges and a "failure to properly downregulate stress response systems" (Wiley et al., 2017, p.-1). This means that, over time, stressors may accumulate in the body, increasing the biological risk of ill-health.

A benefit of using this measure is that a range of studies have consistently shown its association with poorer mental and physical health outcomes and that it is positioned as a precursor to such outcomes (Karlamangla et al., 2002; T. Seeman et al., 2010). Studies have also shown that the composite measure has more predictive power when compared to evaluating individual biomarkers separately (Castagné, Garès, Karimi, Chadeau-Hyam, Vineis, et al., 2018). Because AL involves a three-stage stress mediation pathway affecting multiple organs and systems, it is typically operationalised as a composite multi-system index of biomarkers. However, the included biomarkers in the composite measure may vary as there is no consistent method of operationalisation (Johnson et al., 2017). As such, the biomarkers included in AL are not uniform and the methods to combine them into an overall construct also vary, despite recent efforts to define a consensus (McCrory et al., 2023).

Whilst it has been constructed in a variety of ways, previous research has shown that "the same latent factor representing allostatic load may be identified even if the underlying set of biomarkers varies" evidencing its comparability even when its construction varies (Prior et al., 2018b). A further potential benefit of using the measure is that different levels of exposure to a wide range of stressors can be captured in the measurement of AL. Studies have consistently found higher allostatic load to be predictive of mortality and a range of poorer health outcomes irrespective of the biomarkers used in the composite measure. This indicates the theory of AL's versatility to different modes of operationalisation and its utility in identifying people at risk of poorer health outcomes prior to their presentation as chronic conditions (Juster et al., 2010).

Building on these findings, and to address the gap in the 20MN literature relating to assessment of health outcomes, this chapter considers the associations between varying levels of proximal access to 20MN domains and health for older populations, using a measure of chronic stress, AL, as an outcome. It describes the distribution of existing access to common domains typically included in 20MN policies in locations that have implemented them and assesses whether access to these domains is associated with AL in the English Longitudinal Study of Ageing (ELSA). AL is selected as an outcome due to its position as a mediator of neighbourhood deprivation effects on health outcomes (Prior et al., 2018a) and it's utility as a predictor of health outcomes in advance of their presentation as chronic conditions. As such, AL can both reveal pathways that lead to poor health and indicate targets for proactive intervention (Read & Grundy, 2014).

4.5 Aims and Objectives of this study

To support the broader aims of the thesis, this chapter uses the ELSA[61] to address the following aims:

1. Outline the 10 domains and features included as indicators of 20MN access.
2. Calculate distances to each domain and link these summary measures to the biomarker waves 2, 4, 6, and 8 combined with 9[62].
3. Describe the distribution of access to domains within the ELSA dataset.
4. Explain the associations between distance to domains and Allostatic Load.
5. Consider whether adjusting for medication in the construction of Allostatic Load influences the interpretation of results.

4.6 Research Questions & Hypotheses

To support the research aims of the thesis, this chapter asks the following research questions (presented below with their accompanying hypotheses):

1. Is there longitudinal evidence of an association between distances to 20MN domains and AL and which domains appear to be the most salient in this relationship?

[61] A representative sample of the non-resident adult population aged 50 and above and their partners in England.
[62] As the biomarker sample was collected across waves 8 and 9.

Hypothesis 1: Improved access to 20MN domains would be associated with lower AL.

2. Are these relationships independent of an individual's demographic characteristics?

   Hypothesis 2: Improved access to 20MN domains would be associated with lower AL over and above demographic characteristics.

3. Are these relationships independent of an individual's area-based characteristics?

   Hypothesis 3: Improved access to 20MN domains would be associated with lower AL over and above both demographic and area-based characteristics.

4. Are these relationships independent of an individual's lifestyle characteristics?

   Hypothesis 4: Improved access to 20MN domains would be associated with lower AL over and above demographic, area-based, and lifestyle characteristics.

5. Does adjusting for medication in the construction of AL influence the findings?

   Hypothesis 5: Accounting for medication in AL would not influence the interpretation of results.

6. How do these associations vary by urbanicity and car access?

Hypothesis 6: There would be differences in salient associations between urban and rural areas and the sample with and without access to cars.

4.7 Methods

4.7.1 Participants – The English Longitudinal Study of Ageing

The current study used data from the ELSA, a nationally representative panel study for English adults aged 50 and above. Data is collected every two years in ELSA, with nurse visit waves taking place every four years at waves 2, 4, 6, and 8 between 2002-2019. However, waves 8 and 9 were also treated as a single wave in this analysis as half of the nurse sample data were collected at wave 9 for this collection period. Refreshment sampling also took place using participants previously included in the Health Survey for England (HSE). This took place in ELSA in waves 3, 4, 6, 7 and 9 over the time period of the included waves and created a total potential sample of 27,188 which reduced to 17,393 with the removal of participants without complete data for the included covariates and to 14,100 with the inclusion of the nurse blood weight. Nurse waves include an in-person assessment to collect data on physical functioning, anthropometrics, and blood samples for the assessment of biomarkers which were used in the calculation of summary AL risk scores (outlined below). More information on biomarker collection is available in the waves 2, 4, 6, 8 and 9 nurse wave user guide (ELSA, n.d.).

4.7.2 Setting and spatial extent

This study considered proximal access to 20MN domains for Output Area (OA) Population Weighted Centroids (PWCs) aggregated at the Lower Super Output Area (LSOA) level in England, which covers 50,301 square miles, for participants with biomarker data for any of waves: 2 (2004-2005); 4 (2008-2009); 6 (2012-13); and; 8 (2016-2017) combined with 9 (2018-19) in the English Longitudinal Study of Ageing (ELSA) (Study Documentation, 2024). Distance measures were first calculated at the OA PWC level for each domain before aggregation at the LSOA level when they were linked with the ELSA data. LSOAs represent groups of OAs, with an intended population range of between 1,000-2,000 individuals and between 400 and 1200 households (*Census 2021 Geographies - Office for National Statistics*, 2021).

4.7.3 Defining 20-Minute Neighbourhood Domains

To capture 20MNs, individual Ordnance Survey (OS) points of interest (POI) features (such as allotments, playing fields, and parks) were first categorised into overarching domains (such as greenspace and recreation) based on evidence from the literature (PointX & OS, 2025)[63]. Domains were selected if they were commonly included in existing 20MN policies in cities and nations seeking to implement them and were distinctive of other included domains. This resulted in 10 domains (made up of the POI features listed in brackets) being included in models: **Community Facilities** (social clubs, halls and community centres, libraries, and sport clubs/associations); **Culture** (historic buildings, historic structures, historical ships, museums, art galleries, cinemas, theatres and concert halls, places of worship); **Eating and drinking** (Cafes, tea rooms and snack bars, pubs, and restaurants); **Food services** (supermarket chains, convenience stores, and independent supermarkets, bakeries, butchers, frozen foods, grocers, farm shops and pick your own, herbs and spices, organic, health, gourmet and kosher foods, markets); **Greenspace and recreation** (country and national parks; municipal parks and gardens, commons, picnic areas, playgrounds, gymnasiums, sports halls and leisure centres, sports

[63] The POI data utilised reflected data available in 2021.

grounds, stadiums and pitches, allotments); **Health** (chemists/pharmacies, doctor's surgeries); **Education** (first, primary and infant schools, further education, independent and preparatory schools, secondary schools, special schools and colleges, higher education, and other schools); **Public transport** (railway stations, tram, metro, light railway stations and stops, and bus stops); **Financial services** (cash points, banks, post offices), and; **Retail** (general household goods, department stores, discount stores, shopping centres and retail parks). These domains were selected to represent the broad range of services and amenities commonly considered as key to daily activities and essential living in existing 20MN policy frameworks. Improved access to 20MNs is theorised to improve neighbourhood cohesion and being a place for all ages, provide health benefits from increased physical activity due to enhanced opportunities for active travel, and to create a sense of security derived from thriving places. To assess this, access to domains was measured in a variety of ways, as outlined below.

4.7.4 Measuring Access to 20MN Domains

A variety of approaches were used to measure access to each domain, with measures constructed including: indicators of binary (yes/no and within 800-metres/not within 800-metres) access, proximal access (in straight-line metres using Euclidean distance), and density of access using Local Indicators of Spatial Association (LISA) and hot-spot analysis to identify clusters of high or low density counts of resources (X. Li, 2021). Each of these measures were then aggregated at the LSOA level to assess whether different aspects of access to 20MN domains were related to AL, assessed through multiple linear regression (MLR) and p-values of less than 0.05 after Bonferroni correction on a hypothesis basis. Whilst a variety of measures were calculated, the focus of most measures incorporated distance (or proximal access), due to the importance of this aspect in particular to the 20MN framework. These measures are outlined in detail below.

4.7.5 Simple access (based on presence/absence)

This measure assessed whether an LSOA had access to a given domain or not based on the presence or absence of at least one POI feature representing the domain. To calculate this measure, a binary score was calculated for each domain, with the value of 1 assigned when at least one feature representing a domain was present within a given LSOA. For example, if a 'Post Office' was present in an LSOA, that LSOA would be assigned a value of 1 for the financial services domain this feature was included to represent. These scores were then summed to create an overall domain mix score at the LSOA level.

This measure gives no consideration to distance or time and assumes all features equally indicate access to the domain they represent. This measure made it possible to assess whether complete 20MNs (with all 10 domains) existed at the LSOA level, without delving into detail at a finer scale (such as the household level). It serves as a comparison to the proximal access measures by evaluating whether the mere presence of a domain is sufficient to capture any relationships identified in models including measures that do account for proximity. Figure 10 below outlines the distribution of overall access to 20MN domains at the LSOA level. However, models including the simple access measures treated domains separately, rather than as an overall mix score, so as to be able to assess the salience of individual domains in any relationship with AL (M. A. Green et al., 2018).

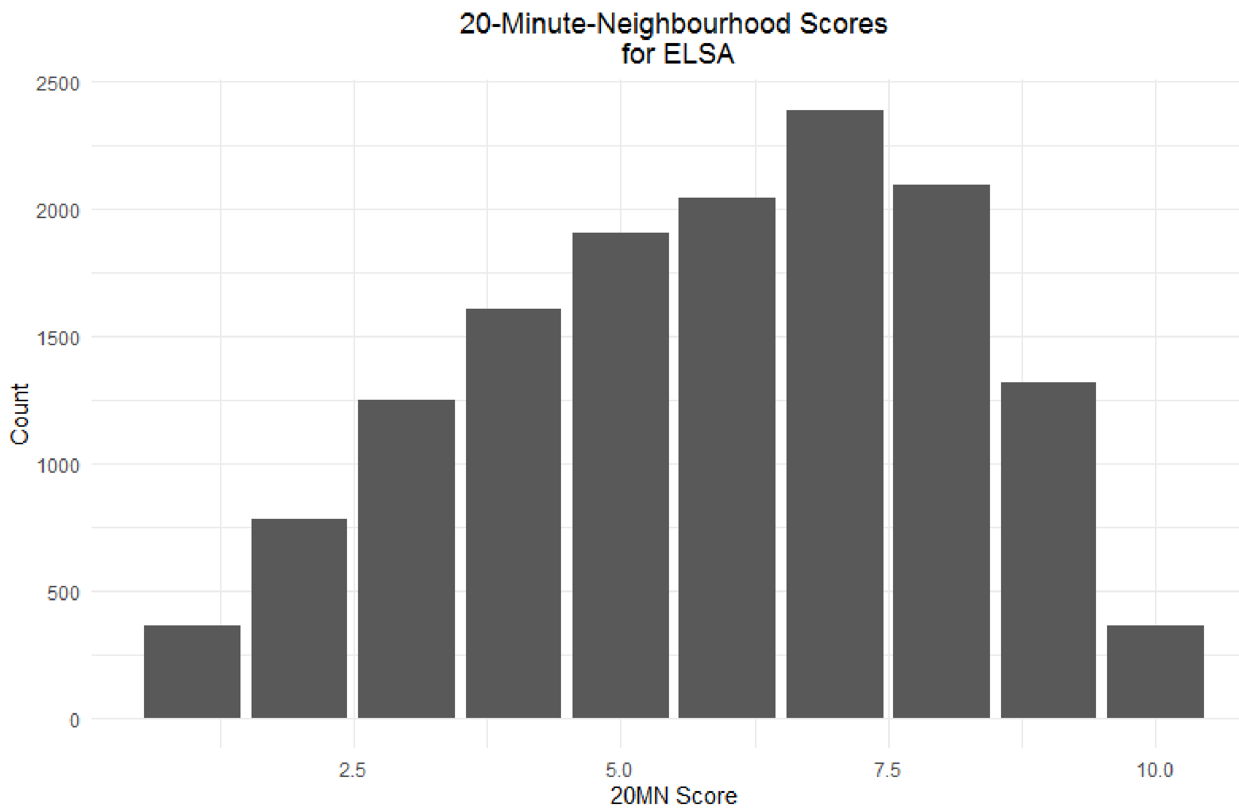

Figure 10: 20-minute neighbourhood scores in ELSA (0-10)

Figure 10 shows that, within the sample and across all time-points: 358 (3%) of sample members lived within LSOAs with access to 1 domain; 773 (6%) had access to 2 domains; 1,225 (9%) had access to 3 domains; 1,582 (12%) to 4 domains; 1,877 (14%) to 5 domains; 2,006 (15%) to 6 domains; 2,335 (17%) to 7 domains; 2,058 (15%) to 8 domains; 1,287 (10%) to 9 domains; and; 352 (3%) to 10 domains. This highlights that, even at the LSOA level, very few LSOAs can offer a complete 20MN. LSOAS with scores of 10 are most likely to include domains not typically present in other LSOAS, such as retail and health services.

4.7.6 Access measured by continuous distance (proximal access)

To add an element relating to time and to explore whether distances to domains were important in any relationship between 20MN and AL (over and above their presence within an area) a continuous measure of distance to each domain was first calculated. Distances were calculated in straight line metres between all Output Area (OA) Population Weighted Centroids (PWC), and the nearest feature of each included domain. These distances were then converted to kilometres by dividing values by 1,000 prior to their inclusion in models. Whilst typically 20-minute neighbourhoods begin at the household scale, chapter 3 highlighted that distances calculated from OA PWCs and aggregated at the LSOA level provided a useful proxy for most domains. They also allowed for assessment of broader proximal access across a local area.

Greater variation of access across LSOAs was captured by first calculating proximal access measures at the OA PWC level and aggregating these at the LSOA level. OAs are made up of between 40-250 households and 100-625 people, with LSOAs typically containing between 4-5 OAs (ONS, 2025). This approach ensured that every OA PWC had a nearest distance value to every domain type, even when a feature representing a particular domain was not present within an individual OA or LSOA, limiting boundary effects. This also meant distance measures of access to domains across an LSOA reflected the position where populations tended to live in the OA[64], but was not restricted to pre-defined administrative boundaries until aggregation at the LSOA level. Nearest distance was selected based on Tobler's first law of Geography that states that everything is related to everything else but near things are more related than distant things (Bjorholm et al., 2008).

As an example, the domain of 'Retail', is made up of any of the following POI features: 'department stores'; 'discount stores'; 'general household goods stores'; and 'shopping centres and retail parks'. Distances were calculated between an OA PWC and the nearest of any of these

[64] Although population weighted averages were not calculated, bot OA's and LSOAs are designed to have similar population levels.

POI features, with the LSOA score taking the mean of the nearest domain scores across the OAs contained within it. Average proximity is then assumed to be an indicator of improved access to the overarching domain of retail at the area level when mean LSOA distances were lower. This approach ensured that all OA PWCs had a distance score to the nearest domain regardless of which sub-domain feature type is nearest. The same feature can therefore be the nearest facility for multiple OA PWCs. Given the lowest level areal link to the ELSA data used was LSOA, a single LSOA includes all distances from OA PWCs to nearest domain features across all the OAs that make up the larger LSOA. This is illustrated in Table 22 below, with example data only.

Table 22: Illustrative example of LSOA mean distance scores

Example OA Code	Example LSOA Code OA comes from	Example LSOA Code Where Feature Comes from	Feature Type	Domain	Minimum Distance (metres)	LSOA Mean Distance
OA1	LSOA1	LSOA1	Department Stores	Retail	535	Mean distance from OA PWCs to domain = 560 metres
OA2	LSOA1	LSOA2	Shopping Centres And Retail Parks	Retail	506	
OA3	LSOA1	LSOA1	Department Stores	Retail	657	
OA 4	LSOA1	LSOA1	Department Stores	Retail	567	
OA5	LSOA1	LSOA4	Shopping Centres And Retail Parks	Retail	615	
OA6	LSOA1	LSOA4	Shopping Centres And Retail Parks	Retail	542	
OA7	LSOA1	LSOA4	Shopping Centres And Retail Parks	Retail	363	
OA8	LSOA1	LSOA1	Department Stores	Retail	696	

This approach produced similar mean scores compared to calculating nearest distance measures from postcode addresses in the Understanding Society data in chapter 3. Whilst these differences were statistically significantly different from postcode measures in Understanding Society, they were not meaningfully different, with differences in mean distance scores to domains under 5-metres across the 10 domains. However, the standard deviations in the aggregate distances were reduced. This approach did not rely on setting a-priori distance thresholds in the overall continuous access measure for each domain. This was important as reductions in walking speed have been found to reduce 20MN access scores across demographic groupings in the only study looking at access to 20MN in older populations (Dunning et al., 2023). As such, this approach created an overall measure of proximal access to each domain that did not assume equal walking speeds in order to isolate the effect of distance to the nearest feature representing a given domain through direct assessment of proximal access itself[65].

4.7.7 Access measured by categorical distance thresholds

A categorical distance measure using predefined thresholds was also calculated to assess whether specific distance bands indicated different relationships with AL. This approach allowed different levels of proximal access to be compared to assess whether different distance thresholds were important, as 20MN thresholds in the literature vary. For example, they may differ between 15-minute city and 20MN framings and can be calculated as network or Euclidean distances. This measure was calculated by categorising the distances in metres between OA PWCS and domains into 4 groups, with 1 indicating access within (but not including) 200-metres, 2 indicating access between 200 to within (but not including) 400, 3 indicating access between 400 to within (but not including) 600, 4 indicating access between 600 to within (but not including) 800, and 0 indicating access 800-metres and over. The 800-metre plus group was considered as the reference group due to the relevance of the 800-metre threshold in the 20MN literature. This was then aggregated at the LSOA level as a mean value to create an ordinal-continuous measure which was additionally rounded to the nearest factor level to retain a defined 5 level factor (categorical) structure. Where a given level had a mean value of .5 this was rounded up.

[65] Network distances were not applied to improve computational efficiency and were justified by the effectiveness of Euclidean distance for first order neighbours, as outlined in the introductory chapter and empirical chapter 3 of this thesis.

4.7.8 Binary measure of OAs with/without access to a domain within 800-metres

As 800-metres is classically considered a cut-off point for a 20MN, a measure of the proportion of OA PWCs lacking access within this threshold was also calculated for each domain. This was calculated based on the proportion of OA PWCS within an LSOA that did not have access to a given domain within 800-metres. This created a range from 0-1, with 0 indicating that an LSOA has access to a given domain within 800-metres of population centres across all OA PWCS within it, and 1 indicating no OA PWCS have access within 800-metres. However, due to sparse data points between 0 and 1 and clustering at 0 and 1 values, the variable was coded as a binary measure with all areas containing at least one OA without 800-metre access coded as 1.

4.7.9 Local Indicators of Spatial Association (LISA) Hot-Spot Clusters

This measure used hot-spot analysis to calculate whether an LSOA is surrounded by LSOAs with similar values in a manner that appears geographically patterned and in a manner that would not be expected at random given the overall distribution of features (Anselin, 2020). Measures were calculated using the ‘rgeoda’ package and the approach outlined in the package documentation (X. Li, 2021). Additional detail on LISA and hot-spot analysis is also available in the online ‘GeoDa: An Introduction to Spatial Data Science’ (Anselin, 2020).

These measures sought to capture whether living in areas that offer more widely dispersed access, or more widely dispersed scarcity, were associated with AL. To assess clustering, the count of features representing domains was first aggregated at the LSOA level. These values were then compared with the values of neighbouring areas using queen contiguity weights for first order neighbours. Queen continiguity weights are calculated based on the values of neighbouring LSOAs, with first order neighbours any LSOA with a border touching any part of the LSOA under consideration (second order neighbours would expand this relationship to the borders of first order neighbours). These local values are then compared proportionally, relative to the overall average counts, or the sum of all feature counts across all LSOAs.

This allowed assessment of whether a given LSOA and its neighbours represent high-high, low-low, high-low, low-high, or non-significant spatial clustering (relative to the domain mean) based on the counts of features representing each domain. Each LSOA then has a cluster classification for each 20MN domain, defined as 0 = Not significant, 1=High-High, 2=Low-Low, 3=Low-High, and 4=High-Low. Where the relationship is not significant, neighbouring LSOAs do not show significant geographical clustering of domain counts that appears significantly different (using pseudo-significance testing) from what might be expected at random, given the overall average. High-High clusters indicate LSOAs that do show significant geographical clustering of high counts of a given domain (within an LSOA and its neighbours). For example, LSOAs with high counts of features representing the retail domain, neighboured by other LSOAs that have high counts of features representing the retail domain in a way that seems to be geographically patterned. Low-Low LSOAs indicate areas with low counts surrounded by areas with low counts. Low-High relationships indicate areas that appear to be outliers, with low counts surrounded by at least one neighbouring LSOA with high counts in a manner that appears spatially patterned, with towns in rural areas perhaps most likely to be captured by this cluster. High-low relationships indicate the reverse of this and may reflect town centres serving rural areas. The reference group for the measures of clustering was areas defined as non-significant clusters which in each case was the largest category.

4.7.10 Additional data preparation detail

A classification spreadsheet was created using the OS Maps Points of Interest data, which classifies all POI's into overarching groups and sub-groups. Sub-groups were labelled to aid with feature selection and features were then assigned to reduced groupings or domains based on their representation of access to aspects commonly captured in the 20MN literature. With domains ascribed, an R script linked to this classification file was used to break down the large POI file into domains prior to calculating distances to speed up computation between every OA PWC and every nearest domain (based on the nearest feature representing the domain). This was necessary due to each file being large. For example, the POI file had more than 3.5-million rows and the OA PWC file had more than 180,000 rows. Structuring the data in this way made it quicker to process distances between all OA PWCs and different domains and allows for adaptations to be made to the design of what is included or excluded from the 20MN domains so that a given 20MN typology can be easily adapted if desired[66]. Given that 20MN are not uniformly designed, the idea of this approach was to make it feasible for new typologies to be outlined and created in a single spreadsheet that is carefully structured to produce relevant files for use in creating descriptive statistics, mapping, and analysis. However, this analysis focused on key domains included across typologies rather than comparing existing typologies as a first step towards explaining which 20MN domains appear most salient relative to AL.

[66] In addition, during processing, relevant shapefiles and analysis files are created that are specific to different typologies through the inclusion of an additional logic column that assigns a score for domain access by a given parameter at the LSOA level. This may be a score of 1 if any of the features of a given domain are present, or a score of 1 if at least X number of features are present, for example, but can be adapted for any scenario with a suitable ifelse() statement.

4.7.11 Outcome: Allostatic Load

An overall Allostatic Load index was constructed using 12 biomarkers to assess cumulative physiological dysregulation. Nine biomarkers were selected following the approaches of Richards et al. and Read and Grundy (Read & Grundy, 2014; Richards et al., 2023). Additionally, three further biomarkers were included based on their common usage in other measures of AL in the literature and, more restrictively, their availability at every included biomarker wave (waves 2, 4, 6 and 8 with 9) in the ELSA dataset[67]. This restriction precluded the inclusion of some of the most commonly included biomarkers (such as BMI and waist-hip-ratio), as well as any primary mediators reflecting the HPA-Axis or neuroendocrine response (such as Insulin-like growth factor 1 (IGF-1), cortisol, dehydroepiandrosterone (DHEAS), or Cortisone), despite their availability in some waves of the dataset. The included biomarkers were: Systolic Blood Pressure (SBP); Diastolic Blood Pressure (DBP); Pulse Pressure; Cholesterol; Triglycerides; Glycosylated haemoglobin (HbA1c); Ferritin; C-Reactive Protein (CRP); High-density lipoprotein (HDL); haemoglobin (HgB); Glucose, and; Fibrinogen. The included biomarkers represented dysregulation of the cardiovascular, metabolic, and immune systems, but were summed to create a total index of 0-12. Figure 11 below highlights the distribution of Allostatic Load in ELSA.

[67] As well as their availability in Understanding Society.

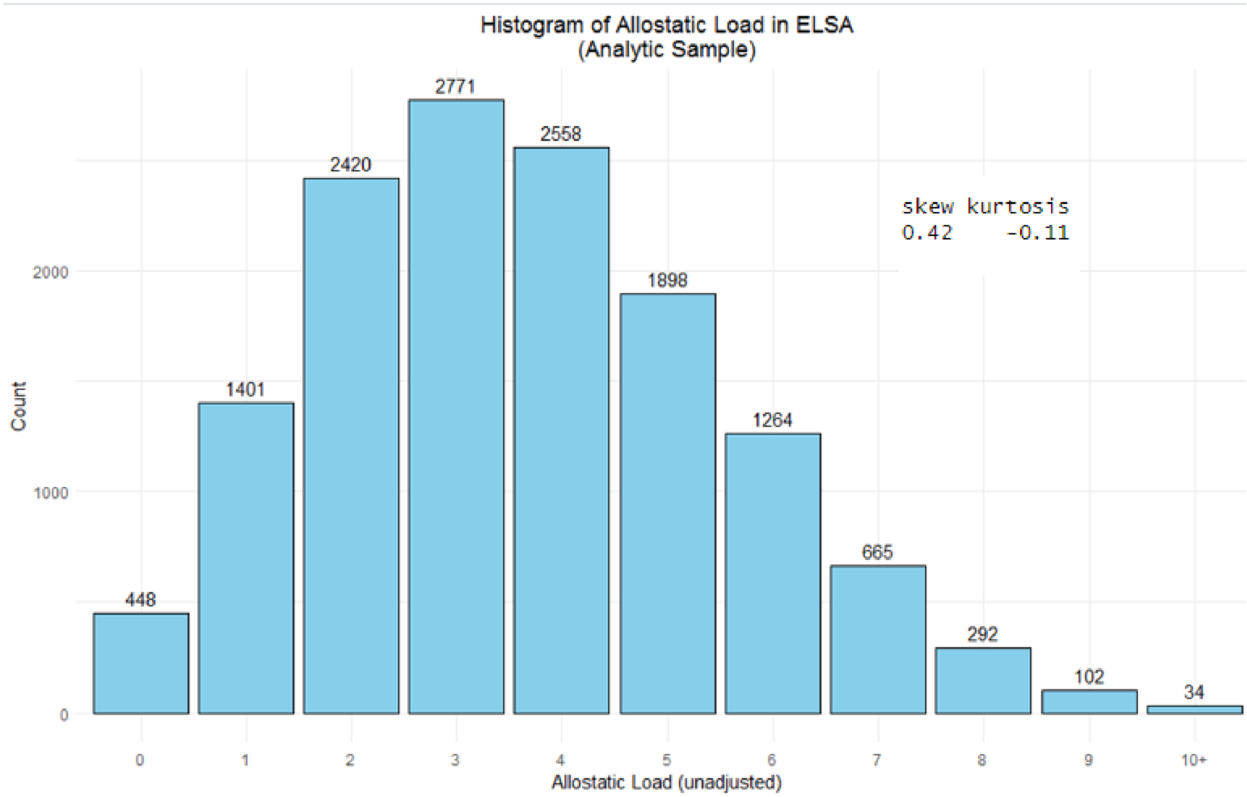

Figure 11: Histogram of unadjusted Allostatic Load in ELSA (Analytic Sample)

A total AL score was calculated as the number of biomarkers that fell within the quartile of the sample distribution typically considered as the risk factor for each individual biomarker. This was the top 25% of values for each of the included biomarkers in this instance other than HDL, where the lowest quartile indicated the risk factor. This involved first creating binary indicators for each included biomarker, with 1 indicating risk and 0 indicating values falling outside the risk quartile cut-off. Risk values were determined based on the sample distribution, with the primary approach to calculation involving calculating risk cut-off points at baseline (wave 2), as outlined in Table 23 below. These risk cut-off values were then used as risk thresholds across all subsequent waves to define binary risk scores at each time point (rather than re-calculating risk thresholds at each time-point based on the remaining sample). These values were then summed for the included biomarkers to create a total possible score of 0-12 at each wave.

Following recommendations in the literature, an additional measure accounting for medication use was also included in the main analysis to compare the extent to which results varied based on these two approaches to calculating AL (McLoughlin et al., 2020). Medication was adjusted for by assigning risk values for: DBP and SBP if participants used blood pressure lowering medication; Fibrinogen if they used anticoagulants; Triglycerides if they used lipid lowering medication; HbA1c if they used diabetes medication; and including the second highest quartile as a risk value for CRP if blood pressure, cholesterol or diabetes medications were taken following Read & Grundy (2014). These two measures were constructed to assess the extent to which variations in construction impacted result interpretation and following evidence that medication adjustment within AL constructs was underexplored (McCrory et al., 2023; McLoughlin et al., 2020). Figure 12 below highlights the distribution of Allostatic Load when adjusting for medication in ELSA.

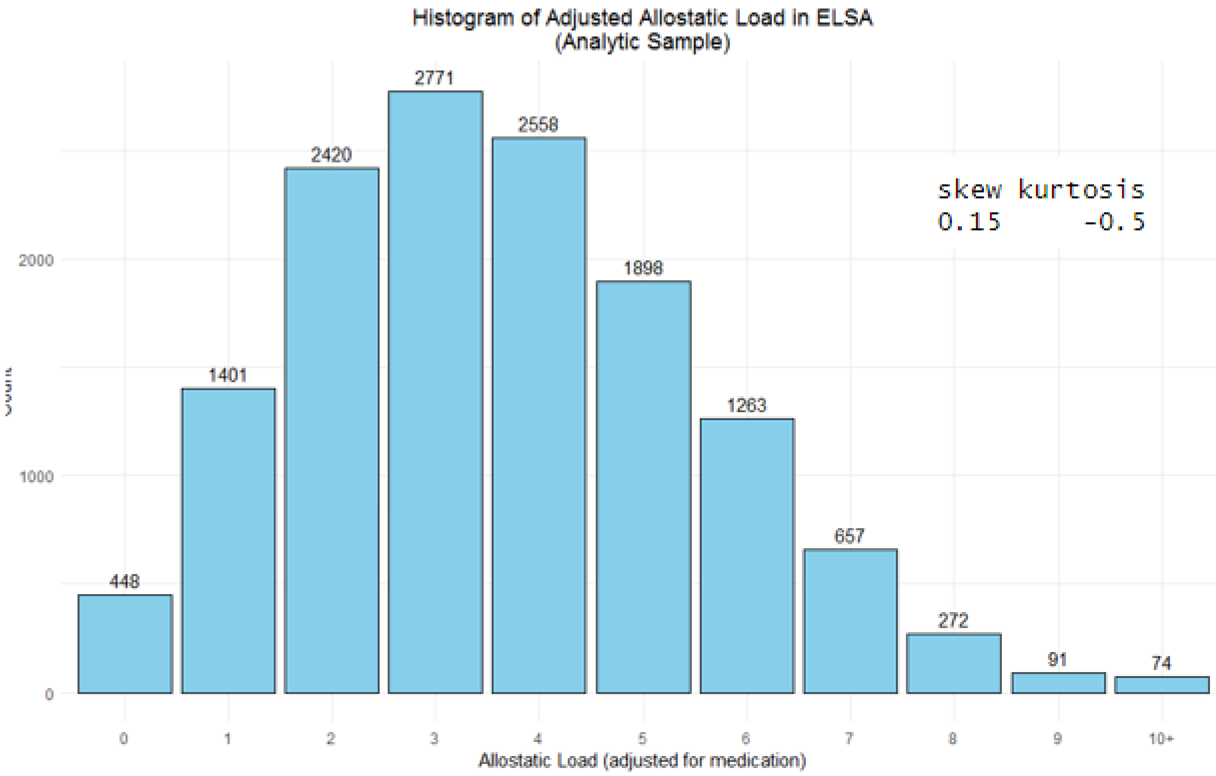

Figure 1: Histogram of Allostatic Load adjusted for medication use in ELSA (Analytic Sample)

Table 23: Cut-off values for biomarkers

System	Biomarker	Wave-2 Risk Cut-off values	Cut-Points calculated on sample of 27,188. Lower band of upper quartile used as threshold.
Cardiovascular	DBP Diastolic Blood Pressure	>81	Missing = 2,426**
Cardiovascular	SBP Systolic Blood Pressure	>144	Missing = 2,426**
Cardiovascular	Pulse Pressure	>67.5	Missing = 2,426*
Cardiovascular	Hgb- Haemoglobin	>16	Missing = 6817*
Cardiovascular	Cholesterol	>6.4	Missing = 6551*
Cardiovascular	HDL – High Density Lipoprotein	<1.3	Missing=6,452*
Immune	CRP C-Reactive Protein	>3.7	Missing = 6,554**

Immune	Fibrinogen	>3.6	Missing = 7,191**
Metabolic	Triglycerides	>2	Missing = 6,551**
Metabolic	HbA1c Glycosylated haemoglobin	>5.6	Missing = 6,852**
Metabolic	Glucose	>5.3	Missing = 15,402*
Metabolic	Ferritin	>172	Missing = 6550*
* Treated as 0 values ** Treated as 0 values unless use of medication indicated risk factor			

4.7.12 Covariates

Covariates were selected to control for individual characteristics that could confound the relationship between the 20MN domain access measure and AL by acting as predictors of AL, given existing relationships identified in the literature[68]. Covariates were grouped into demographic, area-based, and lifestyle groupings and were added to primary models in blocks as outlined below.

4.7.13 Demographic covariates (Included from Model 2 onwards)

Measures included in demographic models (Model 2), were gender, ethnicity, employment, highest qualification, age, and total net wealth. Gender (0=male, 1=female); ethnicity (0=white, 1=not white); whether in paid employment within the last 7 days (0=No, 1=Yes); partnership status (0=Married/in a relationship, 1=Single/Widowed/Divorced); and highest qualification (0=O-level/equivalent or below, 1=Higher than O-level), were included as binary measures. Age and net total wealth (benefit unit Level) were included as continuous measures. Age was centred on the mean and net total individual wealth was log transformed (+1) due to being highly positively skewed. Additionally, to the demographic factors, wave was included as a 4-level factor centred at wave 2 (0=wave 2, 1=wave 4, 2=wave 6, 3=waves 8 & 9).

[68] This is outlined in Table 13 in empirical chapter 3 of this thesis.

4.7.14 Area-based Covariates (Included from Model 3 onwards)

Binary measures included whether the respondent remained at the same address as the previous wave (0=No, 1=Yes) and urbanity level. Urbanity level was assessed based on the 2011 rural urban classification of LSOAs (ONS, 2017). Whilst this classification breaks down rural and urban into 8 sub-groups, this was collapsed into a binary measure (0=Rural, 1=Urban), with any RUC11 classifications containing the word 'urban' considered to be an indicator of an urban LSOA, and any RUC11 code containing the word 'rural' indicating a rural LSOA. Neighbourhood deprivation was controlled for with IMD treated as a continuous measure (0-100, with 100 representing the most deprived area).

4.7.15 Lifestyle Covariates (Included in Model 4, the complete model)

Housing tenure (0=Owner outright, 1=Mortgage owner, 2=Renter), frequency of transport use (0=Never, 1=Sometimes, 2=Never), alcohol intake (0=Weekly, 1=Monthly/Once or twice a year, 2=Not at all within the last 12 months), and difficulty of walking a quarter of a mile (0=No difficulty, 1=Some/Much difficulty, 2=Unable to do this), were treated as 3 level factors. Access to a car (0=No, 1=Yes) and current smoking status (0=No, 1=Yes) were included as binary measures.

4.8 Statistical Analyses

Statistical analyses were conducted using RStudio with the 'dplyr' package used to produce summary tables, lme4 (Bates et al., 2015) and lmerTest (Kuznetsova et al., 2017) packages were used for multi-level modelling and the gtsummary (Sjoberg et al., 2021) and broom packages used for reporting outputs (D. Robinson et al., 2024). Descriptive statistics are presented as frequencies (for categorical measures) and means with standard deviations (for continuous measures). Descriptive statistics are presented for the analytic sample by wave and presented as separate tables by the block of covariates they represented, with demographic measures added at model 2 (Table 24), geographic measures added at model 3 (Table 25), and lifestyle covariates added at model 4 (Table 26). All models were weighted using wave specific blood weights that adjust for both design and conditional non-response, helping to ensure that participants who provided biomarker data better represent the population (ELSA, n.d.).

Access to 20MN domains was captured in a number of different ways, as outlined above, with 20MN domain scores assigned to LSOAs and linked to each ELSA wave. Unfortunately, the geographic data was not available across multiple years, so although the data is assigned to each wave, it is assumed that the major substance of domain presence within the LSOAs did not change over the time-period, even if individual features changed. Assigning the scores at each wave allowed for the inclusion of subjects who had moved house between waves and for the inclusion of the measure of address change as a covariate in the main analysis. A little under 5% (n=668) of the analytic sample had changed address from the previous wave across all waves.

A random intercept multi-level regression was used to assess associations between access to 20MN domains and AL and to account for the non-independence of individuals due to the repeated measures design. A random slope for wave was not included because the panel data were unbalanced, with many individuals contributing data at only one or two time points. This resulted in insufficient within-person variation to estimate random slopes reliably. Four models, plus a null model, were calculated to assess the extent to which estimates of association between 20MN access and AL were attenuated by individual characteristics. Models were clustered within individuals to account for baseline differences in AL by adding a random effect (random intercept) for individual identifiers, with the null model assessing how much of the variation in AL scores was within and between individuals. To test for the potential for shared neighbourhood environment effects on AL, 3-level models were additionally run with individual identifiers nested within LSOA or MSOA boundaries. However, variation at these levels represented less than 3% of the variance in AL and did not significantly improve the models, so the simpler models clustered within individuals are reported. Prior to fitting the multilevel models, a simple linear model was run to test for multi-colinearity using Variance Inflation Factor (VIF) scores, with all values generally falling between 1-5, indicating some collinearity but no serious multi-collinearity problems. The retail and food services domains had a VIF value over 5 but under 10 was deemed acceptable[69].

4.9 Results

Tables 24-26 show the descriptive characteristics of the analytic sample (all waves=14,084). Table 24 shows the demographic covariates, added from model 2 onwards. This is presented by wave in the table but the sample is described here at the wave 2 (n=5027) baseline, with changes by the final wave outlined in brackets (n=2,192). At baseline, the sample was 54% (51%) female, 99% (98.5%) white, and had a mean age of 66 (71). A little more than 64% (79%) of the sample had not been in paid employment within the last 7 days, 66% (56%) had O-level or below as their highest qualification. Mean total net (non-pension) wealth was 299,000 (465,000), although this had a large standard deviation of 403,000 (552,000). Significant differences between the analytic sample and the full sample were not found for wealth, nor highest qualification. However, they were found for: wave, with those with data available for later waves less likely to

[69] This may be explained by the inclusion of ATM's in the financial services domain which are likely to be located in or nearby to supermarkets which were included in the food services domain.

appear in the analytic sample; gender, with the full sample more likely to be female; ethnicity, with the full sample more likely to include participants who were not white; employment, with the full sample less likely to have been in paid employment within the last 7 days, and; age, with the full sample mean marginally older, although rounded means were 67 for both samples.

Table 24: Demographic Covariates (Model 2)

	2 (N=5027)	4 (N=3870)	6 (N=2995)	8 (N=2192)	Overall (N=14084)
Female					
Male (reference group)	2314 (46.0%)	1773 (45.8%)	1481 (49.4%)	1066 (48.6%)	6634 (47.1%)
Female	2713 (54.0%)	2097 (54.2%)	1514 (50.6%)	1126 (51.4%)	7450 (52.9%)
Age (Years)					
Mean (SD)	65.5 (9.27)	66.5 (9.46)	67.0 (8.43)	70.6 (7.40)	66.9 (9.04)
In Paid Employment (last 7 days)					
No (reference group)	3225 (64.2%)	2521 (65.1%)	2039 (68.1%)	1733 (79.1%)	9518 (67.6%)
Yes	1802 (35.8%)	1349 (34.9%)	956 (31.9%)	459 (20.9%)	4566 (32.4%)
Ethnicity					
White (reference group)	4979 (99.0%)	3819 (98.7%)	2951 (98.5%)	2160 (98.5%)	13909 (98.8%)
Not white	48 (1.0%)	51 (1.3%)	44 (1.5%)	32 (1.5%)	175 (1.2%)
Highest Qualification					
O-level/equiv or below (reference group)	3306 (65.8%)	2228 (57.6%)	1781 (59.5%)	1226 (55.9%)	8541 (60.6%)
Higher than O-level	1721 (34.2%)	1642 (42.4%)	1214 (40.5%)	966 (44.1%)	5543 (39.4%)
Total net (non-pension) wealth					
Mean (SD)	299000 (405000)	354000 (632000)	378000 (711000)	465000 (552000)	357000 (571000)
Partnership Status					
Married/In Relationship	3696 (73.5%)	2817 (72.7%)	2177 (72.6%)	1542 (70.2%)	10232 (72.6%)
Single/Widowed/Divorced	1335 (26.5%)	1056 (27.3%)	823 (27.4%)	654 (29.8%)	3868 (27.4%)

Table 25: Area-based Covariates (Model 3)

	2 (N=5027)	4 (N=3870)	6 (N=2995)	8 (N=2192)	Overall (N=14084)
IMD Score (0-100)					

	2 (N=5027)	4 (N=3870)	6 (N=2995)	8 (N=2192)	Overall (N=14084)
Mean (SD)	17.0 (12.6)	16.9 (12.5)	18.0 (13.3)	17.2 (12.9)	17.2 (12.8)
Urbanity					
Rural	1295 (25.8%)	1016 (26.3%)	801 (26.7%)	615 (28.1%)	3727 (26.5%)
Urban	3732 (74.2%)	2854 (73.7%)	2194 (73.3%)	1577 (71.9%)	10357 (73.5%)
Same Address					
No	251 (5.0%)	155 (4.0%)	142 (4.7%)	120 (5.5%)	668 (4.7%)
Yes	4776 (95.0%)	3715 (96.0%)	2853 (95.3%)	2072 (94.5%)	13416 (95.3%)

Table 25 (above) outlines the area-based covariates included from model 3 onwards, again broken down across waves and described here at baseline (and final included wave in brackets). At baseline, 74% (72%) of the sample lived in urban areas. The mean IMD score was 17.3 (17.2) with a standard deviation of 12.6 (12.9) and 95% (94.5%) of the sample were still living at the same address as they had been at the previous wave. Significant differences between the analytic sample and the full sample were not found for living in built-up areas nor whether they were still living at the same address. However, they were found for IMD score, with the full sample having a marginally higher mean score indicating higher deprivation areas (although this still fell between 17-18, as with the analytic sample).

Table 26 (below) outlines the lifestyle covariates included in the complete model 4, broken down by wave and described at baseline (and final included wave). Nearly 87% (89%) of the sample were not current smokers, 66% (79%) owned their own home outright, and 64% (62%) had drunk alcohol at least weekly. Over 77% (75%) had no difficulty walking a quarter of a mile and 74%

(70%) were married or in a relationship. Significant differences between the analytic sample and the full sample were found for: housing tenure, with the full sample less likely to own their own home outright or be a mortgage owner, and more likely to rent; having access to a car, with the full sample less likely to have access to a car; having difficulty walking a quarter of a mile, with the full sample more likely to have difficulty; being a current smoker, with the full sample more likely to include current smokers.

Table 26: Lifestyle Covariates (Model 4)

	2 (N=5031)	4 (N=3873)	6 (N=3000)	8 (N=2196)	Overall (N=14100)
Current Smoker					
No	4367 (86.8%)	3443 (88.9%)	2518 (83.9%)	1944 (88.5%)	12272 (87.0%)
Yes	664 (13.2%)	430 (11.1%)	482 (16.1%)	252 (11.5%)	1828 (13.0%)
Housing Tenure					
Owner outright	3325 (66.1%)	2725 (70.4%)	2078 (69.3%)	1743 (79.4%)	9871 (70.0%)
Mortgage Owner	1130 (22.5%)	721 (18.6%)	540 (18.0%)	203 (9.2%)	2594 (18.4%)
Renting	512 (10.2%)	378 (9.8%)	357 (11.9%)	234 (10.7%)	1481 (10.5%)
Other	64 (1.3%)	49 (1.3%)	25 (0.8%)	16 (0.7%)	154 (1.1%)
Public Transport Use					
Never	1371 (27.3%)	2360 (60.9%)	1861 (62.0%)	1370 (62.4%)	6962 (49.4%)
Often	980 (19.5%)	776 (20.0%)	576 (19.2%)	388 (17.7%)	2720 (19.3%)
Sometimes	2680 (53.3%)	737 (19.0%)	563 (18.8%)	438 (19.9%)	4418 (31.3%)
Alcohol Use (<12 months)					
Weekly	3225 (64.1%)	2493 (64.4%)	1904 (63.5%)	1352 (61.6%)	8974 (63.6%)
Not at all in the last 12 months	443 (8.8%)	358 (9.2%)	322 (10.7%)	255 (11.6%)	1378 (9.8%)
Monthly/Once or twice a year	1363 (27.1%)	1022 (26.4%)	774 (25.8%)	589 (26.8%)	3748 (26.6%)
Ability to walk ¼ mile					
No Difficulty	3890 (77.3%)	3017 (77.9%)	2255 (75.2%)	1644 (74.9%)	10806 (76.6%)
Some/Much Difficulty	848 (16.9%)	640 (16.5%)	533 (17.8%)	375 (17.1%)	2396 (17.0%)
Unable to do this	293 (5.8%)	216 (5.6%)	212 (7.1%)	177 (8.1%)	898 (6.4%)

Table 27: Mean Allostatic Load scores for different constructions of AL for the analytic sample

	2 (N=5027)	4 (N=3870)	6 (N=2995)	8 (N=2192)	Overall (N=14084)
Allostatic Load (Each wave measures + medication) ***Wave 2 cut-points*** Mean (SD)	3.79 (2.10)	3.97 (2.06)	4.73 (2.04)	5.54 (1.99)	4.31 (2.15)
Allostatic Load (Each wave measures) ***Wave 2 cut-points*** Mean (SD)	3.44 (1.97)	3.21 (1.85)	3.97 (1.84)	4.70 (1.77)	1.95)

Table 27 (above) outlines the results of the differently constructed measures of Allostatic Load across waves. When AL was calculated using risk quartile cut-offs calculated at wave 2, mean AL was 3.44 at wave 2, and 3.79 after adjustment of risk values (for SBP, DBP, CRP, TGs, HbA1C, and Fibrinogen), with adjustments made based on medication use following the approach of Read and Grundy (Read & Grundy, 2014). Whether medication was accounted for or not, the mean AL score for the sample increased at each wave, apart from between waves 2 and 4 when medication was not adjusted for.

Table 28: Descriptives of features by domain at the LSOA level for analytic sample

Domain	Feature	Count	% Sample LSOAs		Mean Minimum Distance		SD Distance	IQR Distance	Mean # Features per LSOA (SD)
Community Facilities	Halls and community centres	3028	**54.1**	39.79	656	670	1780	309-672	1.54 (SD 0.9)
	Libraries	431		8.26		418	278	257-514	1.05 (SD 0.23)
	Social clubs	929		15.08		539	2185	245-490	1.24 (SD 0.56)
	Sports clubs and associations	687		11.59		603	1434	315-623	1.2 (SD 0.49)
Culture	Art galleries	232	**66.2**	3.61	446	248	192	126-312	1.3 (SD 0.78)
	Cinemas	105		1.78		321	290	128-426	1.19 (SD 0.45)
	Historic buildings	842		10.19		1043	4824	238-735	1.67 (SD 1.12)
	Historic structures	4509		35.93		470	1248	239-517	2.53 (SD 3.38)
	Museums	166		3.03		343	302	160-468	1.11 (SD 0.39)
	Places of worship	6841		58.22		389	568	236-454	2.37 (SD 2.01)
	Theatres and concert halls	151		2.42		261	153	149-328	1.26 (SD 0.74)
Eating & Drinking	Cafes, snack bars and tea rooms	4150	**62**	30.1	583	446	1206	200-457	2.78 (SD 3.97)
	Pubs	5555		47.13		606	1816	270-611	2.38 (SD 2.77)
	Restaurants	3500		28.62		461	653	205-516	2.47 (SD 3.24)
Education	First, primary and infant schools	2732	**55.4**	45.18	639	644	1677	327-671	1.22 (SD 0.46)
	Further education	128		2.38		399	230	281-464	1.08 (SD 0.38)
	Higher education	62		0.81		543	643	225-440	1.55 (SD 1.6)
	Independent and preparatory schools	253		4.5		725	1505	285-792	1.13 (SD 0.46)
	Secondary schools	563		10.72		483	442	309-515	1.06 (SD 0.25)
	Special schools and colleges	250		4.72		739	2768	281-621	1.07 (SD 0.28)
	Bakeries	1028	**65.9**	13.73	586	449	631	165-456	1.51 (SD 1.24)

Food Services	Butchers	762		11.71		649	1361	185-592	1.31 (SD 0.67)
	Convenience stores and independent supermarkets	5938		55.59		497	1032	217-467	2.16 (SD 1.83)
	Frozen foods	239		4		345	410	168-370	1.21 (SD 0.53)
	Grocers, farm shops and pick your own	801		11.89		819	978	165-1312	1.36 (SD 1)
	Herbs and spices	14		0.28		1667	1386	1135-1727	1 (SD 0)
	Markets	75		1.39		397	582	139-408	1.09 (SD 0.33)
	Organic, health, gourmet and kosher foods	378		5.55		906	3624	143-571	1.37 (SD 0.78)
	Supermarket chains	1029		17.46		569	2556	230-484	1.19 (SD 0.48)
Greenspace & Recreation	Allotments	2067	**78.7**	29.9	409	375	773	190-366	1.4 (SD 0.82)
	Commons	838		6.5		1144	3545	316-1133	2.6 (SD 3)
	Country and national parks	104		1.9		718	601	323-843	1.11 (SD 0.34)
	Gymnasiums, sports halls and leisure centres	1803		24.87		394	1357	198-372	1.46 (SD 0.88)
	Picnic areas	84		1.49		1246	1152	456-1785	1.14 (SD 0.45)
	Playgrounds	5047		57.49		369	1261	193-360	1.77 (SD 1.16)
	Sports grounds, stadia and pitches	3903		46.65		416	579	210-420	1.69 (SD 1.01)
Health	Chemists and pharmacies	1578	**33.1**	24.38	896	757	1525	368-754	1.31 (SD 0.68)
	Doctors surgeries	1280		21.68		949	1823	383-1092	1.19 (SD 0.51)
Public Transport	Bus stops	50357	**98.1**	98.02	251	252	1555	117-199	10.37 (SD 8.54)
	Railway stations, junctions and halts	297		5.77		275	360	101-287	1.04 (SD 0.19)

	Tram, metro and light railway stations and stops	49		0.83		163	81	106-239	1.2 (SD 0.51)
Financial Services	Banks	1091	**56.8**	8.3	616	398	328	210-452	2.65 (SD 2.45)
	Cash points	4477		48.18		520	1497	258-502	1.88 (SD 1.88)
	Post offices	1400		25.62		868	1688	326-1131	1.1 (SD 0.34)
Retail	Discount stores	279	**10.5**	3.39	1851	1381	1222	610-1631	1.44 (SD 0.9)
	Department stores	241		3.92		1613	1447	632-2047	1.43 (SD 0.82)
	General household goods	233		3.65		2118	3137	809-2818	1.29 (SD 0.68)
	Shopping centres and retail parks	274		4.34		1728	1657	733-2051	1.27 (SD 0.61)

4.9.1 Distribution of features and domains

Descriptive statistics relating to the distribution of features and domains are presented in Table 28 above, reflecting the areas where the analytic sample live, rather than the overall picture for England. Counts are presented for features in the table, however, any feature is treated as equally reflective of access to a given domain so they are summed and outlined by domain here. There were 5,075 features representing the community facilities domain, found in 2,682 LSOAs (54.1% of the LSOAS present in the analytic sample). There were 12,847 features representing the cultural domain, found in 3,280 LSOAS (66.2%). The 13,205 eating and drinking features were located in 3,073 LSOAS (62%). Access to the education domain was represented by 3,994 features in 2,745 LSOAS (55.4%). The food services domain was made up of 10,264 features in 3,265 LSOAS (65.9%).

There were 13,847 features representing greenspace and recreation in 3,898 LSOAS (78.7%). The health domain was made up of 2,858 features in 1,640 LSOAS (33.1%). The most prevalent features reflected access to the public transport domain with 50,703 features found in 98% of LSOAs present in the analytic sample. There were also 6,968 financial services features in 2,814 LSOAS (56.8%) and 1,027 retail features in 520 LSOAS (10.5%). A weakness with this approach is the different counts of features within domains. For example, there are 3,028 halls and community centres in the areas where the analytic sample live and only 431 libraries. Access to the community facilities domain is more likely to represent access to halls and community centres. For public transport the discrepancy is even more stark, with bus stops making up 99% of the features used to create the domain. However, because the POI data was only available at a single time-point, it was preferred to create overarching domains reflecting similar services deemed essential in many 20MN typologies.

Mean minimum distances at the LSOA level were calculated by grouping minimum distance scores from OA PWCS to each domain at the LSOA level, and summarizing these mean LSOA distances by domain. These values were then divided by 1,000 to reflect changes in kilometres, rather than metres and, due to being highly positively skewed, these scores were log transformed (+1) prior to their inclusion in models. For the overall sample, public transport was typically well served close to PWCs as you would expect with a mean distance of 251-metres, although it had a large standard deviation (SD:1542), perhaps due to the positively skewed data and the presence of outliers. However, outliers were retained as they reflected natural, or actually existing, variability in distances (Gress et al., 2018; Villanova, 2023). Mean distances (and standard deviations) were: 656-metres (1971) for community facilities; 446-metres (1464) for cultural venues; 583-metres (1695) for eating and drinking venues; 639-metres (1741) for educational facilities; 586-metres (1631) for food services; 409-metres (1400) for greenspace and recreation; 896-metres (1875) for health services; 616-metres (1645) for financial services, and; 1,851-metres (2156) for retail services.

Table 29: Access measures by domain (Analytic sample)

Group	Variable	Description	Level/Measure	N=14,100
	Logged distance	Logged mean distance in kilometres to community facilities	Mean (SD)	6.11 (0.603)
		Community Facilities distance score (reference = >800-metres)	4	1129 (8.1%)
		0 to <200 metres mean distance to community facilities	0	1338 (9.7%)
	Distance thresholds	200 to <400 metres mean distance to community facilities	1	4767 (34.4%)
		400 to <600 metres mean distance to community facilities	2	4469 (32.3%)
		600 to <800 metres mean distance to community facilities	3	2150 (15.5%)
community facilities	Binary 800-m+	At least 1 OA lacks access to Community Facilities within 800-metres	Mean (SD)	0.363 (0.481)
	Binary Presence	Presence of community facilities within the LSOA	Mean (SD)	0.552 (0.497)
		LISA hotspot cluster of Community Facilities - Not significant	Not significant	11162 (80.6%)
		LISA hotspot cluster of Community Facilities - High-High	High-High	1263 (9.1%)
	Hot Spot	LISA hotspot cluster of Community Facilities - High-Low	High-Low	626 (4.5%)
		LISA hotspot cluster of Community Facilities - Low-High	Low-High	596 (4.3%)
		LISA hotspot cluster of Community Facilities - Low-Low	Low-Low	206 (1.5%)
	Logged distance	Logged mean distance in kilometres to Cultural Venues	Mean (SD)	5.88 (0.505)
		Cultural domain distance score (reference = 800-metres+)	4	475 (3.4%)
		0 to <200 metres mean distance to cultural venues	0	2117 (15.3%)
	Distance thresholds	200 to <400 metres mean distance to cultural venues	1	5894 (42.5%)
		400 to <600 metres mean distance to cultural venues	2	4081 (29.5%)
		600 to <800 metres mean distance to cultural venues	3	1286 (9.3%)
Culture	Binary 800-m+	At least 1 OA without access within 800-metres of Cultural Venues	Mean (SD)	0.253 (0.435)
	Binary Presence	Presence of Cultural venues within the LSOA	Mean (SD)	0.674 (0.469)
		LISA hotspot cluster of Cultural venues - Not significant	Not significant	10932 (78.9%)
		LISA hotspot cluster of Cultural venues - High-High	High-High	1757 (12.7%)
	Hot Spot	LISA hotspot cluster of Cultural venues - High-Low	High-Low	121 (0.9%)
		LISA hotspot cluster of Cultural venues - Low-High	Low-High	530 (3.8%)
		LISA hotspot cluster of Cultural venues - Low-Low	Low-Low	513 (3.7%)
	Logged distance	Logged mean distance in kilometres to eating and drinking veneues	Mean (SD)	6.02 (0.634)
		Eating and drinking distance score (reference = 800-metres+)	4	903 (6.5%)
		0 to <200 metres mean distance to Eating and drinking facilities	0	1910 (13.8%)
	Distance thresholds	200 to <400 metres mean distance to Eating and drinking facilities	1	4941 (35.7%)
Eating and drinking		400 to <600 metres mean distance to Eating and drinking facilities	2	4293 (31.0%)
		600 to <800 metres mean distance to Eating and drinking facilities	3	1806 (13.0%)
	Binary 800-m+	At least 1 OA lacks access to Eating and drinking facilities within	Mean (SD)	0.320 (0.466)
	Binary Presence	Presence of Eating and drinking facilities within the LSOA	Mean (SD)	0.631 (0.483)
	Hot Spot	Eating and drinking LISA hotspot cluster - Not significant	Not significant	12626 (91.1%)

		Eating and drinking LISA hotspot cluster - High-High	High-High	236 (1.7%)
		Eating and drinking LISA hotspot cluster - High-Low	High-Low	113 (0.8%)
		Eating and drinking LISA hotspot cluster - Low-High	Low-High	345 (2.5%)
		Eating and drinking LISA hotspot cluster - Low-Low	Low-Low	533 (3.8%)
	Logged distance	Logged mean distance in kilometres to education facilities	Mean (SD)	6.11 (0.577)
		Education distance score (reference = 800-metres+)	4	878 (6.3%)
		0 to <200 metres mean distance to Education facilities	0	893 (6.4%)
	Distance thresholds	200 to <400 metres mean distance to Education facilities	1	5437 (39.2%)
		400 to <600 metres mean distance to Education facilities	2	4754 (34.3%)
		600 to <800 metres mean distance to Education facilities	3	1891 (13.7%)
Education	Binary 800-m+	At least 1 OA lacks access to Education facilities within 800-metres of	Mean (SD)	0.310 (0.462)
	Binary Presence	Presence of Educational facilities within the LSOA	Mean (SD)	0.568 (0.495)
		Education LISA hotspot cluster - Not significant	Not significant	11968 (86.4%)
		Education LISA hotspot cluster - High-High	High-High	645 (4.7%)
	Hot Spot	Education LISA hotspot cluster - High-Low	High-Low	699 (5.0%)
		Education LISA hotspot cluster - Low-High	Low-High	500 (3.6%)
		Education LISA hotspot cluster - Low-Low	Low-Low	41 (0.3%)
	Logged distance	Logged mean distance in kilometres to financial services	Mean (SD)	6.06 (0.696)
		Financial services distance score (reference = 800-metres+)	4	1121 (8.1%)
		0 to <200 metres mean distance to Financial services	0	1714 (12.4%)
	Distance thresholds	200 to <400 metres mean distance to Financial services	1	5579 (40.3%)
		400 to <600 metres mean distance to Financial services	2	3812 (27.5%)
		600 to <800 metres mean distance to Financial services	3	1627 (11.7%)
financial services	Binary 800-m+	At least 1 OA lacks access to Financial services within 800-metres of	Mean (SD)	0.312 (0.463)
	Binary Presence	Presence of financial services within the LSOA	Mean (SD)	0.573 (0.495)
		Financial Services LISA hotspot cluster - Not significant	Not significant	12586 (90.9%)
		Financial Services LISA hotspot cluster - High-High	High-High	199 (1.4%)
	Hot Spot	Financial Services LISA hotspot cluster - High-Low	High-Low	421 (3.0%)
		Financial Services LISA hotspot cluster - Low-High	Low-High	349 (2.5%)
		Financial Services LISA hotspot cluster - Low-Low	Low-Low	298 (2.2%)
	Logged distance	Logged mean distance in kilometres to food services	Mean (SD)	5.96 (0.754)
		Food services distance score (reference = 800-metres+)	4	1113 (8.0%)
		0 to <200 metres mean distance to Food services	0	2757 (19.9%)
Food services	Distance thresholds	200 to <400 metres mean distance to Food services	1	5483 (39.6%)
		400 to <600 metres mean distance to Food services	2	3279 (23.7%)
		600 to <800 metres mean distance to Food services	3	1221 (8.8%)
	Binary 800-m+	At least 1 OA lacks access to Food services within 800-metres of	Mean (SD)	0.275 (0.446)
	Binary Presence	Presence of food services within the LSOA	Mean (SD)	0.657 (0.475)

		Food services LISA hotspot cluster - Not significant	Not significant	12602 (91.0%)
		Food services LISA hotspot cluster - High-High	High-High	195 (1.4%)
	Hot Spot	Food services LISA hotspot cluster - High-Low	High-Low	364 (2.6%)
		Food services LISA hotspot cluster - Low-High	Low-High	260 (1.9%)
		Food services LISA hotspot cluster - Low-Low	Low-Low	432 (3.1%)
	Logged distance	Logged mean distance in kilometres to greenspace	Mean (SD)	5.75 (0.533)
		Greenspace distance score (reference = 800-metres+)	4	120 (0.9%)
		0 to <200 metres mean distance to Greenspace	0	2966 (21.4%)
	Distance thresholds	200 to <400 metres mean distance to Greenspace	1	7116 (51.4%)
		400 to <600 metres mean distance to Greenspace	2	2954 (21.3%)
		600 to <800 metres mean distance to Greenspace	3	697 (5.0%)
Greenspace & recreation	Binary 800-m+	At least 1 OA lacks access to Greenspace within 800-metres of PWC	Mean (SD)	0.180 (0.384)
	Binary Presence	Presence of greenspace and recreation within the LSOA	Mean (SD)	0.794 (0.404)
		Greenspace LISA hotspot cluster - Not significant	Not significant	10123 (73.1%)
		Greenspace LISA hotspot cluster - High-High	High-High	2109 (15.2%)
	Hot Spot	Greenspace LISA hotspot cluster - High-Low	High-Low	247 (1.8%)
		Greenspace LISA hotspot cluster - Low-High	Low-High	677 (4.9%)
		Greenspace LISA hotspot cluster - Low-Low	Low-Low	697 (5.0%)
	Logged distance	Logged mean distance in kilometres to health services	Mean (SD)	6.44 (0.797)
		Health Services distance score (reference = 800-metres+)	4	3360 (24.3%)
		0 to <200 metres mean distance to Health Services	0	647 (4.7%)
	Distance thresholds	200 to <400 metres mean distance to Health Services	1	3683 (26.6%)
		400 to <600 metres mean distance to Health Services	2	3582 (25.9%)
		600 to <800 metres mean distance to Health Services	3	2581 (18.6%)
Health	Binary 800-m+	At least 1 OA lacks access to Health services within 800-metres of	Mean (SD)	0.500 (0.500)
	Binary Presence	Presence of Health services within the LSOA	Mean (SD)	0.331 (0.471)
		Health services LISA hotspot cluster - Not significant	Not significant	12335 (89.0%)
		Health services LISA hotspot cluster Low-High - High-High	High-High	105 (0.8%)
	Hot Spot	Health services LISA hotspot cluster High-Low - High-Low	High-Low	862 (6.2%)
		Health services LISA hotspot cluster Low-High - Low-High	Low-High	435 (3.1%)
		Health services LISA hotspot cluster lLow-Low - Low-Low	Low-Low	116 (0.8%)
	Logged distance	Logged mean distance in kilometres to public transport	Mean (SD)	5.10 (0.500)
	Hot Spot	Public Transport LISA hotspot cluster - Not significant	Not significant	9840 (71.0%)
	Hot Spot	Public Transport LISA hotspot cluster - High-High	High-High	2283 (16.5%)
public transport	Hot Spot	Public Transport LISA hotspot cluster - High-Low	High-Low	131 (0.9%)
	Hot Spot	Public Transport LISA hotspot cluster - Low-High	Low-High	610 (4.4%)
	Hot Spot	Public Transport LISA hotspot cluster - Low-Low	Low-Low	989 (7.1%)
	Distance thresholds	600 to <800 metres mean distance to Health Services	Mean (SD)	0.0203 (0.0787)

	Binary 800-m+	At least 1 OA lacks access to Public Transport within 800-metres of	Mean (SD)	0.0821 (0.274)
	Binary Presence	Presence of public transport within the LSOA	Mean (SD)	0.984 (0.126)
retail	Logged distance	Logged mean distance in kilometres to retail	Mean (SD)	7.25 (0.884)
	Distance thresholds	Retail distance score (reference = 800-metres+)	4	9605 (69.3%)
		0 to <200 metres mean distance to Retail	0	100 (0.7%)
		200 to <400 metres mean distance to Retail	1	920 (6.6%)
		400 to <600 metres mean distance to Retail	2	1550 (11.2%)
		600 to <800 metres mean distance to Retail	3	1678 (12.1%)
	Binary 800-m+	At least 1 OA lacks access to Retail within 800-metres of PWC	Mean (SD)	0.833 (0.373)
	Binary Presence	Presence of retail within the LSOA	Mean (SD)	0.0998 (0.300)
	Hot Spot	Retail LISA hotspot cluster - Not significant	Not significant	12737 (91.9%)
		Retail LISA hotspot cluster - High-High	High-High	104 (0.8%)
		Retail LISA hotspot cluster - High-Low	High-Low	470 (3.4%)
		Retail LISA hotspot cluster - Low-High	Low-High	542 (3.9%)

4.9.2 Measures of access to domains

Table 29 (above) indicates the various measures of access calculated for each domain. The (exponentiated) logged distance values indicate that, on average, people lived closest to public transport (164 metres); greenspace and recreation (314m); cultural venues (358m); food services (388m); eating and drinking venues (412m); financial services (428m); education (450m); community facilities (450m); health services (626); and retail (1408m). The threshold distances indicate that the sample LSOAs did not have access within 800-metres of PWCs to features representing the: retail (69%); health services (24%); community facilities (8.1%); financial services (8.1%); food services (8.0%); eating and drinking (6.5%); education (6.3%); cultural (3.4%); and greenspace and recreation (0.9%) domains[70]. LISA hot-spot clusters were based on counts of features representing domains. They indicated the highest percentage of significant clusters was found in the public transport domain (29%); greenspace and recreation (27%); cultural venues (21%); community facilities (19%); education (14%); health services (11%); financial services (9%); food services (9%); eating and drinking venues(9%), and retail (8%).

4.9.3 Multilevel models predicting changes in Allostatic Load over time

Prior to the main analysis, a two-level null model was run in order to calculate the Intraclass Correlation Coefficient (ICC), by including a random effect for personal identification number. This approach partitions the variance in the error term to indicate how much of the variation of AL scores is within or between individuals (Cernat, 2024). This was run for AL risk scores that were adjusted and unadjusted for medication. For the unadjusted measure, 29% of the variation in AL was accounted for by the between person variation compared to 39% when medications are adjusted for. Although these estimates differ due to the varying nature in which AL was

[70] Due to low counts over 800-metres, the public transport domain is not presented here.

constructed and the underlying samples included, they each indicate that there is considerable variability in AL within individuals over time. Whilst persistent between-person differences account for some of the variation in the AL burden, individual changes in Allostatic Load accounted for more of the overall variation in AL scores over time. Overall, the ICC results indicate that both between-person differences and within-person changes over time are critical components of variation in AL. This supports the use of multi-level-modelling (MLM) for this analysis as MLM explicitly models the hierarchical structure of the data, captures individual-specific trajectories in AL, and accounts for the correlated nature of repeated measures within individuals such that unobserved heterogeneity across individuals is controlled for.

4.9.4 Model Results

Results are presented for models that adjusted for medication use when constructing AL relative to the hypothesis the model responded to. All models were run on the full sample (FS), rural sample (RS), urban sample (US), sample with access to a vehicle (HC), and sample without access to a vehicle (NC), for participants who had complete data across all included covariates, with weighting applied using longitudinal weights for the nurse blood sample. Results are presented for associations which survived Bonferroni correction as outlined in table 30 below. Full results are available in Appendix B.

4.9.5 H1: Is there longitudinal evidence of an association between distances to 20MN domains and AL and which domains appear to be the most salient in this relationship? (model 1)

Hypothesis 1: Improved access to 20MN domains would be associated with a protective effect on AL.

Supportive of H1

Only the access measures to food services supported Hypothesis 1 (H1) in uncontrolled models. Higher logged distances were associated with higher AL in the full sample (B:0.198, S.E.:0.069, p<0.004, p.bonf<0.016), the rural sample (B:0.34, S.E.:0.105, p<0.001, p.bonf<0.008), and the sample with access to a vehicle (B:0.225, S.E.:0.072, p<0.002, p.bonf<0.016). Living in an LSOA with at least 1 OA that lacked access to food services was also associated with higher AL in the rural sample only (B:0.555, S.E.:0.183, p<0.002, p.bonf<0.016).

When distance to food services was treated as a 5-level categorical variable, those living without access to food services within 800-metres were considered as the reference group (level 0). Here, living in the nearest category (0-<200-metres) was not significantly associated with lower AL in any sample after Bonferroni correction. Living in level 2 areas (200 to <400-metres) was associated with lower AL in the full sample (B:-0.391, S.E.:0.125, p<0.002, p.bonf<0.008), the rural sample (B:-0.69, S.E.:0.204, p<0.001, p.bonf<0.004), and the sample with access to a vehicle (B:-0.386, S.E.:0.128, p<0.003, p.bonf<0.016). This was also repeated at level 3 (400-<600-metres) for the full sample (B:-0.367, S.E.:0.118, p<0.002, p.bonf<0.008), the rural sample (B:-0.493, S.E.:0.155, p<0.001, p.bonf<0.009), and the sample with access to a vehicle (B:-

0.358, S.E.:0.12, p<0.003, p.bonf<0.024). However, level 4 was not significant (600-<800-metres).

Contrary to H1

There was also evidence against H1, whereby living closer to domains was significantly associated with lower AL. Higher logged distances to the **financial services** domain was associated with lower AL in the full sample (B:-0.202, S.E.:0.067, p<0.002, p.bonf<0.008) and the rural sample (B:-0.276, S.E.:0.098, p<0.005, p.bonf<0.04). When treated as 5 level factor, those living without access to financial services within 800-metres were considered as the reference group (level 0). Living in level 1 (0-<200-metres) was associated with higher AL in the full sample only (B:0.394, S.E.:0.141, p<0.005, p.bonf<0.020). Living in level 2 areas (200 to <400-metres) was associated with higher AL in the rural sample only (B:0.645, S.E.:0.2, p<0.001, p.bonf<0.008). Living in level 3 areas (400-<600-metres) was associated with higher AL for the full sample (B:0.331, S.E.:0.109, p<0.002, p.bonf<0.008), the rural sample (B:0.415, S.E.:0.15, p<0.006, p.bonf<0.048), and the sample with access to a vehicle (B:0.313, S.E.:0.11, p<0.004, p.bonf<0.032). However, level 4 was not associated (600-<800-metres).

Two other domains went against expectation, with living in a LSOA with at least one OA further than 800-metres from a **cultural venue** associated with lower AL in the full sample (B:-0.172, S.E.:0.061, p<0.005, p.bonf<0.020). Living in an area that was between 600-<800-metres of the **health domain** was also associated with higher AL (relative to those living 800-meters or further away) in the rural sample (B:0.361, S.E.:0.126, p<0.004, p.bonf<0.032).

4.9.6 H2: Are these relationships independent of an individual's demographic characteristics? (model 2)

Hypothesis 2: Improved access to 20MN domains would be associated with a protective effect on AL over and above demographic characteristics.

Supportive of H2

After accounting for demographic covariates higher logged distances to food services remained significantly associated with higher AL in the full sample (B:0.182, S.E.:0.068, p<0.007, p.bonf<0.028), the rural sample (B:0.314, S.E.:0.103, p<0.002, p.bonf<0.016), and the sample with access to a vehicle (B:0.207, S.E.:0.071, p<0.004, p.bonf<0.032). Living in an LSOA with at least 1 OA that lacked access to food services also remained associated with higher AL in the rural sample only (B:0.575, S.E.:0.178, p<0.001, p.bonf<0.008). However, only living in level 2 areas (200 to <400-metres) remained significantly associated with lower AL when distance was considered as a factor for the full sample (B:-0.34, S.E.:0.123, p<0.006, p.bonf<0.024) and the rural sample (B:-0.663, S.E.:0.197, p<0.001, p.bonf<0.008) but no longer for the sample with access to a vehicle.

Contrary to H2

After accounting for demographic covariates those living in a low-low hot-spot cluster of eating and drinking services was additionally contrary to H2. This cluster represented low access to the eating and drinking domain and was associated with lower AL in the sample without access to a vehicle (B:-0.738, S.E.:0.257, p<0.004, p.bonf<0.032). Living in an area that was between 600-<800-metres of the health domain remained associated with higher AL (relative to those living 800-meters or further away) in the rural sample (B:0.332, S.E.:0.122, p<0.006, p.bonf<0.048).

Higher logged distances to the financial services domain remained associated with lower AL in the full sample (B:-0.17, S.E.:0.065, p<0.009, p.bonf<0.036) but was no longer significant in the rural sample.

4.9.7 H3: Are these relationships independent of an individual's area-based characteristics? (model 3)

Hypothesis 3: Improved access to 20MN domains would be associated with a protective effect on AL over and above both demographic and area-based characteristics.

Supportive of H3

After additionally accounting for area-based covariates there were no changes in significant associations. Higher logged distances to food services remained significantly associated with higher AL in the full sample (B:0.181, S.E.:0.068, p<0.008, p.bonf<0.032), the rural sample (B:0.315, S.E.:0.103, p<0.002, p.bonf<0.016), and the sample with access to a vehicle (B:0.205, S.E.:0.071, p<0.004, p.bonf<0.024). Living in an LSOA with at least 1 OA that lacked access to food services also remained associated with higher AL in the rural sample only (B:0.592, S.E.:0.178, p<0.001, p.bonf<0.008). Living in level 2 areas (200 to <400-metres) remained the only level significantly associated with lower AL when distance was considered as a factor for the full sample (B:-0.326, S.E.:0.125, p<0.009, p.bonf<0.036) and the rural sample (B:-0.659, S.E.:0.197, p<0.001, p.bonf<0.008).

Contrary to H3

After additionally accounting for area-based covariates those living in a low-low hot-spot cluster of eating and drinking services remained associated with lower AL in the sample without access to a vehicle (B:-0.756, SE:0.259, p<0.004, p.bonf<0.032). Living in an area that was between

600-<800-metres of the health domain remained associated with higher AL (relative to those living 800-meters or further away) in the rural sample (B:0.337, S.E.:0.122, $p<0.006$, p.bonf<0.048). Higher logged distances to the financial services domain remained associated with lower AL in the full sample (B:-0.166, S.E.:0.066, $p<0.012$, p.bonf<0.048).

4.9.8 H4: Are these relationships independent of an individual's lifestyle characteristics? (model 4)

Hypothesis 4: Improved access to 20MN domains would be associated with a protective effect on AL over and above demographic, area-based, and lifestyle characteristics.

Supportive of H4

After additionally accounting for lifestyle covariates there were no changes in significant associations. Higher logged distances to food services remained significantly associated with higher AL in the full sample (B:0.172, S.E.:0.068, p<0.012, p.bonf<0.048), the rural sample (B:0.313, S.E.:0.103, p<0.002, p.bonf<0.016), and the sample with access to a vehicle (B:0.198, S.E.:0.071, p<0.006, p.bonf<0.048). Living in an LSOA with at least 1 OA that lacked access to food services also remained associated with higher AL in the rural sample only (B:0.578, S.E.:0.178, p<0.001, p.bonf<0.008). Living in level 2 areas (200 to <400-metres) remained the only level significantly associated with lower AL when distance was considered as a factor for the full sample (B:-0.315, S.E.:0.125, p<0.011, p.bonf<0.044) and the rural sample (B:-0.658 S.E.:0.198, , p<0.001, p.bonf<0.008).

Contrary to H4

After additionally accounting for lifestyle covariates those living in a low-low hot-spot cluster of eating and drinking services remained associated with lower AL in the sample without access to a vehicle (B:-0.758, S.E.:0.258, p<0.003, p.bonf<0.024). Living in an area that was between 600-<800-metres of the health domain remained associated with higher AL (relative to those living 800-meters or further away) in the rural sample (B:0.334, S.E.:0.122, p<0.006, p.bonf<0.048). However, higher logged distances to the financial services domain did not quite survive

Bonferroni correction in the complete model for any sample, with the full sample closest to significance (B:-0.163, S.E.:0.066, $p<0.013$, p.bonf<0.052).

Table 30: Comparison of significant results for AL with/without medication adjustment

	AL unadjusted for medication				AL Adjusted for medication			
Domains and Variables	**1**	**2**	**3**	**4**	**1**	**2**	**3**	**4**
Culture								
At least 1 OA without access within 800-metres of Cultural Venues								
Full Sample (n=14,100)	-0.182	-0.17	-0.17	-0.168	-0.172			
Has Car (n=12,467)	-0.179	-0.167	-0.167	-0.166				
Urban Sample (n=10,373)	-0.201	-0.19	-0.19					
Eating and drinking								
Low-Low LISA hotspot cluster of eating and drinking venues								
No Car (n=1,624)	-0.713	-0.736	-0.735	-0.713		-0.738	-0.756	-0.758
Education								
High-Low LISA hotspot cluster of education venues								
No Car (n=1,624)	0.799	0.724	0.729	0.703				
Financial services								
0 to <200 metres mean distance to financial services								
Full Sample (n=14,100)					0.394			
200 to <400 metres mean distance to financial services								
Rural Sample (n=3727)					0.645			
400 to <600 metres mean distance to financial services								
Full Sample (n=14,100)					0.331			
Has Car (n=12,467)					0.313			
Rural Sample (n=3727)					0.415			
Logged mean distance in kilometres to financial services								
Full Sample (n=14,100)					-0.202	-0.17	-0.166	
Rural Sample (n=3727)					-0.276			
Food services								
200 to <400 metres mean distance to food services								
Full Sample (n=14,100)	-0.358	-0.364	-0.356	-0.354	-0.391	-0.34	-0.326	-0.315
Has Car (n=12,467)	-0.333	-0.336	-0.331	-0.33	-0.386			
Rural Sample (n=3727)	-0.626	-0.623	-0.618	-0.624	-0.69	-0.663	-0.659	-0.658
400 to <600 metres mean distance to food services								
Full Sample (n=14,100)					-0.367			
Has Car (n=12,467)					-0.358			

Rural Sample (n=3727)					-0.493			
At least 1 OA lacks access to food services within 800-metres of PWC								
Rural Sample (n=3727)		0.44	0.451	0.453	0.555	0.575	0.592	0.578
Logged mean distance in kilometres to food services								
Full Sample (n=14,100)		0.163	0.159	0.159	0.198	0.182	0.181	0.172
Has Car (n=12,467)					0.225	0.207	0.205	0.198
Rural Sample (n=3727)					0.34	0.314	0.315	0.313
Greenspace & recreation								
Low-High LISA hotspot cluster of Greenspace venues								
No Car (n=1,624)	0.894	0.874	0.875	0.886				
Health								
600 to <800 metres mean distance to Health Services								
Rural Sample (n=3727)	0.374	0.335	0.339	0.346	0.361	0.332	0.337	0.334
Public transport								
400 to <600 metres mean distance to Public Transport								
Urban Sample (n=10,373)	-0.692	-0.692	-0.692	-0.677				
High-Low LISA hotspot cluster of Public Transport								
Rural Sample (n=3727)	1.984	2.111	2.096	2.023				

Table 31: Differences between significant findings for un/adjusted AL in Model 4

Domain	Adjusted AL*	Unadjusted AL*
Community Facilities		
Culture		
Eating & Drinking		
Education		Living in a high-low cluster relative to non-significant clusters (NC){+}
Food-Services	At least 1 OA within the LSOA lacking access to Food services within 800-metres of PWC (FS) {-}; living within 0-<200m (FS), 400-<600m (RS), and 400-600m (FS & RS) of the food services domain relative to the group living more than 800-metres {-}; at least 1 OA without access to food services within 800-metres of PWCs (RS){+};	Living within 200-<400-metres of food services relative to the group living more than 800-metres (FS, RS, HC){-}
Financial Services	Higher logged distances (kilometres) to financial services (FS & RS){-};	
Greenspace & Recreation		Living in a low-low cluster relative to non-significant clusters (NC){+}
Health		Living within 600-<800m of health services relative to the group living more than 800-metres (RS){+}.
Public Transport		Living within 400 to <600m of Public Transport; Living in a high-low cluster of public transport stops relative to non-significant clusters (RS){+}
Retail	proportion of OA's without access to retail services within 800-metres of PWCs (FS){-}.	

*Differences in significance levels in model 4
(FS)–Full sample; (RS)–Rural Sample; (HC)–Has access to a car/vehicle; (NC)-No car/vehicle access
{+} Associated with higher AL; {-} associated with lower AL

4.9.9 H5: Does adjusting for medication in the construction of AL influence the findings? (models1-4)

Hypothesis 5: Accounting for medication in AL would not influence the interpretation of results.

Table 30 (above on pages 221-222) outlines significant results across models when medication was or was not adjusted for. Table 31 (above on page 223) outlines the results that were different. The differences are described below.

Supportive of H5

The findings outlined above in H1-H4 were supported for the cultural, eating and drinking, food services, and health services domains generally, although significance varied for the models and samples when AL was not adjusted for medication. These differences in significance and further domain differences are outlined below under the contrary to H5 section.

Contrary to H5

Significant when AL was adjusted for medication (but not when unadjusted)

The association between categorical food service proximity was present in model 1 across different distance categories (0–200m (FS), 200–400m (RS), 400–600m (FS, RS, and HC) for food services only when accounting for medication. Logged distance to financial services appeared significant in model 1 (FS and RS), and in models 2, and 3 (FS) when medication was adjusted for. When treated as a categorical measure, the 200-<400 and 400<600-m categories were also significantly associated with higher AL (relative to the 800m+ group) in model 1 only, and only when medication was adjusted for.

Significant when AL was unadjusted for medication (but not when adjusted)

In line with the expectation that improved access, as the measures sought to indicate, would be associated with lower AL (or vice versa), living in a low-high cluster of access to greenspace was associated with higher unadjusted AL in all models for the sample without access to a car when unadjusted AL was included as an outcome (model-4, B:0.886, S.E.:0.288, p<0.002, p.bonf<0.016).

Contrary to expectations, living in an LSOA containing at least 1 OA without access to cultural venues was associated with lower AL in all models of the full sample and the sample with access to a vehicle (model-4, B:-0.168, S.E.:0.054, p<0.002, p.bonf<0.008), and models 1-3 in the urban sample (model-3, B:-0.19, S.E.:0.069, p<0.006, p.bonf<0.048). Living in a high-low cluster of access to education was associated with higher unadjusted AL in all models for the sample without access to a car when unadjusted AL was included as an outcome (model-4, B = 0.703, SE = 0.232, p < 0.003, p.bonf < 0.024), but not in any models when accounting for medication. Logged distance to public transport (400–600m) was significant in Models 1–4 for the urban sample (model-4, B:-0.677, S.E.:0.225, p<0.003, p.bonf<0.024), but not in any models when accounting for medication. Similarly, the High-Low LISA cluster of public transport in the rural sample was significant across Models 1–4 (model-4, B:2.023, S.E.:0.697, p<0.004, p.bonf<0.032) but was not significant when AL construction accounted for medication.

4.9.10 H6: How do these associations vary by urbanicity and vehicle access?

Hypothesis 6: There would be differences in salient associations between urban and rural areas and the sample with and without access to a vehicle.

The evidence did not support this hypothesis.

Urban Sample

There were no significant associations for any domains in the urban sample when accounting for medication. The potential reasons for this are outlined in the discussion section below.

Rural Sample

Significant associations in the rural sample matched the domains that were found to be significant for the full sample.

Has vehicle access

Significant associations in the sample with access to a car matched the domains that were found to be significant for the full sample.

Does not have access to a vehicle

There were no significant associations for any domains in the sample without access to a vehicle when accounting for medication. The potential reasons for this are outlined in the discussion section below.

4.10 Sensitivity Analysis

As a sensitivity check, backward stepwise regression was applied to the basic model including logged distances to all 10 domains. The reduced model retained four domains including: financial services, food services, culture, and eating and drinking, with all but the latter remaining significant after backwards stepwise regression, supporting the robustness of the main associations found in the full model.

4.11 Discussion

The primary aim of this chapter was to assess whether there was evidence of a longitudinal association between proximal access to 20MN domains and AL and to explore which domains were the most salient relative to AL. This was achieved using MLM to account for the repeated measures design and to account for within-individual variation over time. A random effect (random intercept) for individual identifiers was included to model initial levels of AL for each participant, allowing the effects of domain access to be disentangled from baseline differences. However, measures of access to domains were tied to a single LSOA code across waves due to this data only being available from a single time-point. As such, domain access scores from LSOA x at timepoint 1 are the same as at timepoint 2, 3 and 4.

Secondary aims were to consider whether associations were maintained over and above the individual characteristics of the sample, with demographic and lifestyle confounders added in a block-wise fashion to models. The included demographic and lifestyle characteristics were selected to help address self-selection issues by accounting for characteristics that might influence both an individual's choice of neighbourhood and their AL (Lamb et al., 2020). The sample was also weighted using the nursing blood weight for each included biomarker wave to more accurately reflect the population of interest and to reduce sampling bias (*Study Documentation*, 2024).

Tertiary aims were to consider whether associations between AL and access to 20MN domains were modified by particular contextual factors. To achieve this, associations were assessed relative to those living in urban or rural areas and, separately, for those with or without car access for both unadjusted and adjusted AL for all models. This involved stratifying the analytic sample 'urban/rural' and 'car access/no car access' status, and running separate models within each stratum to examine differences in relationships between variables across these contexts. Bonferroni corrections for multiple testing were made on a hypothesis basis by multiplying p-vales by 4 (based on running 4 models), which was doubled for the stratified samples (i.e. multiplied by 8).

The findings in this chapter indicate that across all measures, distances to food services appeared the most salient domain relative to AL. For example, continuous indicators of those living further away from food services (made up of features typically considered to offer access to healthier foods and/or food at affordable prices (Olsen, Thornton, et al., 2022)) were consistently associated with higher AL across the different proximity measures, including after accounting for relevant socio-demographic and lifestyle covariates. This finding supports (and may be explained by) evidence from elsewhere in the literature, such as an analysis of ProjectPlan in Melbourne and Adelaide in Australia, which found that 20MN residents visited fruit and vegetable retailers and walked to food services more often than those not living in 20MNs (Oostenbach et al., 2024). Elsewhere, fruit and vegetable consumption has been found to be associated with lower levels of AL (Dimitratos et al., 2021; Macit & Acar-Tek, 2020; Zhang et al., 2023) and physical activity as being predictive of a protective effect on AL, whilst stress itself can lead to changes in food consumption patterns and reduced physical activity (Scott et al., 2012), which may all help to explain this finding if proximal access to food services promotes these form of healthy behaviours (Forrester et al., 2019; Tsatsoulis & Fountoulakis, 2006). These associations were generally maintained in the rural sample and the sample with access to a vehicle, although there was a large degree of overlap between these samples, with 93% of those living in rural areas having access to a vehicle. However, there were no significant findings for the urban sample or the sample without access to a car for this measure[71].

When access to food services was considered as a factor, the evidence indicated that living nearer to food services was associated with lower AL (relative to those living more than 800-metres from food services), although living at level 2 (between 200 and under 400-metres) of food services only appeared protective of AL for the full sample and the rural sample beyond model 1. Plausible explanations for this nuance may be that the 200-400-metre threshold may be the ideal distance to promote walking to this service and sufficient physical activity being encouraged, with physical activity associated with lower AL (Bu & Li, 2023). Whilst this is speculative, that living within the nearest distance band did not show the relationship as strongly offers it some credence. Additionally, that the 600-800-metres threshold was not significant in any models may indicate that 600-metres is seen as a barrier for accessing this domain through an active mode in an older population, if physical activity mediates this relationship. However, this was not formerly tested and would be an interesting pathway to explore between the built environment and the stress pathway in future research.

These findings highlight the value of considering different thresholds when considering the effect of access to 20MN domains, especially when considering more specific needs of certain populations. However, applying these thresholds also demonstrates the MAUP, a common concern in any spatial analysis, given that the thresholds considered may produce somewhat differing results with the same data due to how they are aggregated or where thresholds are set to and from (Chen et al., 2022; Kwan, 2012). Nevertheless, the findings

[71] Possible reasons for the lack of significant findings across domains in the urban sample outlined in greater detail below.

here were not contradictory in terms of interpretation, beyond the loss of significance in some models, with nearer distances consistently associated with lower AL scores (a protective effect).

This is not to say that living closer to food services (or any domain) has a causal relationship with AL. However, the results perhaps point to a bi-directional relationship as the included features represented food services typically expected to offer healthier food choices at more affordable prices (Stone et al., 2024), that may be present in lower AL scores, just as unhealthy food environments can contribute to chronic disease risk factors (F. Li et al., 2009; Suvarna et al., 2020; van Erpecum et al., 2022). Interestingly this association was evident even though BMI was not included within the AL construct, as is commonly the case, offering some weight to the idea that proximity to these services might influence perceptions of environmental safety and security, in line with the GUTS. For example, that the proximity of resources (food services specifically) may signal feelings of safety that inhibit the stress-response. However, these findings also indicate that it may be interesting to explore the built environment around features representing food services in greater detail, whether to explore common morphometric properties (Sarkar et al., 2013c, 2015), or the underlying demographic features common across these areas, that might explain this apparent relationship in greater detail (D. C. Lee et al., 2018).

For example, given that this domain is primarily driven by where supermarkets and convenience stores are located (as they make up 68% of the features representing this domain), these findings may reflect that supermarkets select into areas with lower levels of deprivation and make decisions based on “sales per square foot, not local community need” (Wylie, 2015), perhaps compounding the effects of underlying inequalities. In addition, the inclusion of measures such as bakeries, delis, and organic, health, gourmet and kosher foods may point to this domain being an indicator of areas where gentrification has taken place (Elldér, 2024). However, that these associations were maintained over and above the individual demographic and lifestyle covariates, and the built-in control of LSOA boundaries (ensuring areas shared similar population sizes), offers robustness to the findings in terms of access to food services having a protective effect on AL.

With regards to the 20MN framework, the food services findings highlight the importance of the food services domain and suggests its inclusion in the majority of 20MN policies in practice is warranted. These findings also point to useful policy approaches in the literature implemented in response to identifying areas with poor quality access to food services. For example, the Portland Plan implemented the “Healthy Retail Initiative” to increase access to healthy and culturally relevant food by recruiting a range of healthy food providers, creating community gardens, and establishing community agriculture cooperatives (Pozoukidou & Chatziyiannaki, 2021).

Somewhat contrary to expectation, improved access to specific domains was not always associated with a protective effect relative to AL when a significant association was present. For example, living in areas closer to financial services was associated with higher AL in some models, including complete models in the full sample when medication was adjusted for in the AL construct. However, this could indicate an association confounded by selection effects, a common issue in neighbourhood effects research (Jivraj, Murray, et al., 2019; Lamb et al., 2020). This refers to the idea that groups with shared attributes may be more likely to live in certain neighbourhoods due to “residential mobility choices made by households within a restricted choice set” (Hedman & van Hamm, 2011), and as such, preexisting individual characteristics may be causing any association if selection effects are not properly controlled for. This finding may indicate that individuals with higher AL are more likely to live in areas that are closer to financial services. Or, as in the case of supermarkets and certain food services selecting into areas of lower deprivation, this may reflect that the features included to indicate access to financial services tend to be located in areas with higher levels of socioeconomic disadvantage, a known correlate of AL at the individual- (Johnson et al., 2017; Robertson et al., 2014) and neighbourhood- levels (Ribeiro, Fraga, Kelly-Irving, et al., 2019). For example, post offices were included in this domain, and may represent a feature where deliberate government policies have seen them located in deprived areas to compensate for a lack of access to other banking facilities (Macintyre et al., 2008). Nevertheless, that these associations were maintained in models accounting for within-individual changes addresses some of the common concerns of self-selection issues into neighbourhoods (Lamb et al., 2020).

4.12 Urban and Rural differences

Interestingly, there was a lack of significant findings in the urban sample for every measure and model other than a single threshold (400 to <600-metres) of public transport when to accounting for medication. Moreover, the inclusion of whether or not individuals lived in an urban or rural area did little to improve models. This is unexpected given that Broschott et al. highlight the urban context as one that may be sufficiently alienating such that the stress response is always at least partially released as the “environment offers limited or absent communication with strangers” and “tends to be largely the property of unknown others (strangers, companies, impersonal public authority)” (Brosschot et al., 2018).

These findings may reflect the methods used to calculate proximity. For example, LSOAs are designed to be roughly equal in population size, with a resident population between 1,000-3,000 individuals (*Census 2021 Geographies - Office for National Statistics*, 2021). As such, urban LSOAs cover a smaller spatial extent (a smaller total area[72]) due to their greater population density. Owing to this heightened population density, urban areas also generally have a greater variety of both domains and features accessible within shorter distances (AlWaer & Cooper, 2023), where the closest option may not always be the preferred or chosen option, making its presence less apparent and limiting its potential to be considered as an exposure.

For example, given that improved access to food services was consistently associated with reduced AL in the rural sample, full sample, and sample with vehicle access but not in the urban sample, this may indicate that the distance measures as constructed do not accurately reflect exposures in an urban context. In more rural areas, single features may actually represent multiple functions in response to lower population density and greater distances between available services. Such multi-purpose facilities may better foster sociality and cohesion, through their situation as the natural (or only) meeting points for residents who might otherwise be isolated due to distance or limited transport options, with greater salience to the stress-pathway (Goodwin-Hawkins et al., 2021). In this sense, features in rural areas may carry additional social and functional significance that is far less pronounced in urban settings. This relationship is perhaps highlighted by the findings, or lack thereof, within the US across almost all domains.

[72] Area size of LSOAs is available in metres-squared and can be divided by 1,000,000 to obtain the area coverage in kilometres-squared(*2011 Census Geography Boundaries (Lower Layer Super Output Areas and Data Zones) - UK Data Service CKAN*, 2024).

There was also a second aspect relating to the methods used to calculate proximity that may have contributed to the lack of significant findings in the urban sample. To construct the distance measures, only the nearest straight line Euclidean distance (ED) to domain features was considered, rather than network distance or radial buffers. The lack of significant findings in the US may also indicate that this approach specifically is not as well suited in areas with greater resource density. Nevertheless, this approach to distance calculation was preferred due to the computational benefits of this approach which was important in order to assess 20MN domain access measures nationally. The use of ED has been shown to offer comparable results to network distances when used over smaller distances, with evidence highlighting ED measures produce the most accurate results relative to distances when only first order neighbours (or when k-nearest neighbours (KNN) = 1) are considered (Oliver et al., 2007; Tatit et al., 2024)). Given that distances from OA PWCs were additionally aggregated at the LSOA level rather than being directly linked via postcode grid references for participants, and measures were calculated for both urban and rural settings, only first order neighbours were considered. The Understanding Society analysis outlined that this approach to calculating distance measures was a useful proxy when postcodes were unavailable as, even though there were significant differences in the distributions of these two measures, the mean values were theoretically comparable.

4.12.1 Vehicle access and no vehicle access sample differences

For the most part, stratifying the sample by car access and no car access did not lead to major differences in the findings, perhaps due to the smaller sample size (n=1,624) of those with no access to a vehicle and the majority of those without access to a vehicle also being found in the urban sample (with just 16% of the sample without access to a vehicle living in a rural area). However, some findings pointed to specific domains being more salient for those without car access. For example, living in a low-low cluster of eating and drinking venues was significantly associated with lower AL for the sample with no car access. This association was not present in model 1 but remained significant until model 4 after attaining significance at model 2.

This may reflect either a health benefit tied to the prohibitive nature of greater distances to features such as pubs, restaurants, or cafes that may be associated with increased AL. Conversely, having no car and living further from this domain may necessitate more active forms of travel, with associated benefits for lower AL. However, these scenarios remain speculative as it is not possible to determine which of these scenarios is the most plausible from these results. The inclusion of subjective measures would have been particularly valuable here to help understand how individuals engage with and perceive their local environment. Future research should aim to incorporate such measures, including perceptions of accessibility, satisfaction with available services, and actual usage patterns, in combination with objective measures, to provide a more nuanced assessment of access to 20-minute neighbourhoods.

4.12.2 Strengths and Limitations

This study was the first to investigate longitudinal health effects associated with proximal access to 20MN domains relative to AL in a nationally representative sample. It was also the first to explore this relationship amongst an older population where proximal access to local resources is likely to be the most salient, due to the fact that mobility issues become more prevalent as people age (Dunning et al., 2023), and because greater access to resources locally has been shown to increase active living (Clarke & Gallagher, 2013), which in turn promotes health and wellbeing as people age (Bosch-Farré et al., 2020). It is also one of relatively few studies to both assess the extent of 20MN provision and the effect of living in this type of area, with the majority of the literature focusing on constructing 20-minute neighborhoods to assess their distribution but not their effect. To my knowledge, it is only the second analysis to consider 20MNs nationally, with the first being focused on Scotland (Olsen, Thornton, et al., 2022).

The study also considered the impact of adjusting for medication use within the AL construct, confirming previous findings in the literature suggesting this did not tend to alter the overall conclusions of the analysis (such as by turning negative associations into positive ones). The study also used MLM with a random intercept included for individual identifiers to account for unobserved baseline differences to better isolate the effects of proximal access to 20MN domains. This is important as past research has shown that the relationship between stressors and AL is "is not uniform for all individuals but depends on many other factors, such as experience and available coping resources" (van Deurzen et al., 2016).

This study also had several limitations, although in some instances these also encourage potential avenues for improved future research. As is common in analysis using spatial data, the MAUP is always a present concern as this remains an unresolved problem (Tuson et al., 2019). The MAUP reflects the fact that the exact same data may lead to different results and conclusions based on scale and zoning effects (Parenteau & Sawada, 2011). Scale effects occur based on changes in the geographic units used, such as when aggregating data at the OA, LSOA, or city level. On the other hand, zoning effects relate to how and where boundaries are defined, such as using network buffers (that create a boundary factoring in actual barriers) versus radial buffers (that create a uniform boundary around a central point).

As the Dunning et al. study highlighted, accessibility to services decreased faster than expected when mobility issues and reduced walking speeds were considered indicating the threshold for calculating access measures ought to take account of accessibility ‘for whom’ (Dunning et al., 2023). However, in the present study, distances were first calculated from each OA PWC to each nearest domain feature. This approach sought to minimize boundary effects in the distance calculations until the moment of aggregation, which was necessary in order to link the data to the ELSA sample. For example, the mean values at the LSOA level reflected differences in access to domains from every OA PWC contained within the LSOA to every domain, irrespective of where the feature representing the domain was located. As such, the distance values were not constrained by pre-defined thresholds, artificial administrative boundaries, or potentially error-prone walking time estimates, which would be affected by individual variations in walking speed. To consider the validity of this approach, the Understanding Society analysis in chapter 3 looked at differences in results when using distance scores calculated in this way versus distance scores calculated directly from postcode grid-references and found the results to be comparable.

As outlined in the overall introduction to this thesis, this study is also limited by the Uncertain Geographic Context Problem, another issue likely to be present in any spatial analysis. Whilst the focus on the population over 50 sought to ensure the neighbourhood was the key contextual unit likely to exert influence on AL, it is not possible to confirm this without the inclusion of more subjective measures. In a study looking at perceived and objective distances to healthy food outlets, combining subjective and objective measures identified a group who overestimated distances (perhaps due to identifying personal barriers), with this group at the greatest risk of hypertension (Baldock et al., 2018). As such, future research would benefit from including combinations of subjective and objective measures that better describe how places are being perceived and interacted with.

The presence or proximity of domains does not necessarily expose individuals to anything. A retail outlet could be present but not noticed or be perceived as too expensive, a financial service could be present but not used or trusted, a health service could be present but have long waiting times, a public transport stop could be on your doorstep but offer a poor service with limited routes, and an entertainment venue could be present but inaccessible, and so on. However, the assessment of overall levels of access to each domain at the LSOA level partially addresses some of these issues in that the measure is an indicator of overall areal levels of proximal access, representing a broader sense of how connected areas are to the amenities typically considered fundamental to daily living in 20MN frameworks. The use of MLM sought to address this in part by accounting for baseline levels of individual variability both explicitly (in covariate models) and implicitly (in model 1) accounting for unobserved individual heterogeneity.

A further limitation of this study relates to the construction of AL, which did not include biomarkers of adiposity (such as BMI or wait-to-hip ratio) which are commonly included in other constructions of AL in the literature, particularly in relation to research looking at obesity and the built environment. Given food services were associated with AL this omission may have confounded the results. The measure of AL also did not contain any primary mediators of the stress response (such as adrenaline, cortisol or DHEAS). These biomarkers represent the 'first responders' in the process of allostasis that are released by the HPA-axis and the autonomic nervous system during stress, and are fundamental to the original theory of AL (McEwen, 2000; McEwen & Stellar, 1993b). Primary mediators reflect the immediate physiological adjustments made by the body in response to stress and explain how external stressors ‘get under the skin’ and influence secondary outcomes such as inflammation, cardiovascular health, or metabolic changes (Osei et al., 2022). It is their sustained elevation over time that leads to chronic stress and the cumulative ‘wear and tear’ on the body that defines AL. Their absence may mean that the measure of AL misses upstream processes that lead to the cascade of events leading to physiological dysregulation (Bobba-Alves et al., 2022).

The resulting reliance on secondary outcomes (like blood pressure or glucose levels) may lead to erroneous conclusions when focused on the stress response, due to the fact these biomarkers are likely influenced by factors other than the stress response. As such, future research should seek to include primary mediators where possible. However, given that the absence of these biomarkers is likely to reduce the predictive power of the AL construct, and plausible associations were found to be significant in a number of cases after Bonferroni adjustments for multiple testing, this may indicate the associations were under rather than overplayed. In order for the measure to be comparable over time, only biomarkers available across each of the 4 waves were included, which precluded the inclusion of any primary mediators (such as DHEAS and Insulin-like Growth Factor 1) available in some waves of ELSA.

Whilst it was possible to measure AL over time, the geographic measures were constructed using data from a single time point. These distance measures were linked to LSOA codes and subsequently to each wave of the ELSA data. As such, distances to nearest domains were calculated using a single time point but considered across time. In many instances fewer features representing domains will have been present in the calculations of the distance measures when attached further back in time. For example, overall trends in retail have been towards net closures (PricewaterhouseCoopers, 2024). Primary and secondary schools also saw a decline in numbers from 25,543 in 2004 (corresponding to the baseline wave) declining every year until 2017 down to 24,507 (corresponding to wave 8). The converse of this is also plausible for some domains and in certain areas versus other areas, highlighting the potential for error and bias in these distance measures. However, by grouping features by domain it was hoped that net changes would be minimal, such that where one retail outlet might shut-down another retail outlet may replace it. As the changes in school numbers show, the changes over time are likely very gradual, particularly when additionally grouping features by domain. However, future research would benefit from the inclusion of multiple measures of distances (or densities) at different time points as well as multiple measures of AL.

The grouping of features by domain also introduced the limitation of unequal weightings of features within domains. Whilst no weighting was applied, this effectively sets weights implicitly based on the distribution of features included within domains, as outlined in the technical report to the Index of Multiple Deprivation (*English Indices of Deprivation 2019*, 2019). Whilst this may be suitable where features truly represent the same domain, more specificity may be necessary within some domains. For example, post offices make up 26% of features in the financial services domain, compared to 8% being banks, and the remainder being ATMs. Whilst these features do all offer access to financial services they likely do so in very different ways, with ATMs unlikely to offer any particular social aspect to the service, which both a bank and a post office might. Additionally, one study found that banks in Scotland tended to be located closer to more affluent areas, with post offices more prevalent in areas with the highest deprivation (Macintyre, Macdonald and Ellaway, 2008).

Such variation, and the inclusion of multiple features within a single domain without any theoretical weighting makes the interpretation of the results more challenging, given they may be indicating associations with AL in different ways. If affluent neighbourhoods are associated with lower AL and deprived neighbourhoods are associated with higher AL, and the features to a certain extent indicate both affluence and deprivation, the net result of this may be non-significance or significance that reflects how the domain is weighted (based on how many of each included feature there are within the domain). However, applying a theoretical weighting to specific features would make interpretation of results challenging and be hard to establish. As such, future research seeking to investigate relationships between access to neighbourhood resources, as measured by distance, should seek to limit how many different features are combined into a single domain.

Adding additional complexity to the measures would also be of benefit in future work investigating levels of access to neighbourhood resources. For example, given the presence of public transport stops in almost all LSOAs, this domain would have particularly benefitted from enrichment. This could have included giving consideration to the number of services per hour, the number of different routes offered, and reliability, using datasets like the Public Transport Accessibility Levels (PTALs), in order to better assess the effect of their presence.

5 Thesis Conclusion

5.1 General Discussion

This thesis sought to explain how neighbourhoods, be that how they are perceived or how they are physically composed, gets ‘under the skin’ by exploring pathways identified by Galster (2012) theoretically linking place to the stress pathway, as measured by Allostatic Load (AL). Chapter 2 (*Do Perceived Neighbourhood Qualities Explain the Relationship Between Deprivation and Allostatic Load in Understanding Society?*) considered whether subjective measures of perceived neighbourhood qualities (PNQs) were associated with Allostatic Load (AL) and whether they helped to explain the relationship between neighbourhood deprivation, measured using the Index of Multiple Deprivation[73] (IMD) and AL. Chapter 3 (*Cross-sectional associations between 20-Minute Neighbourhoods and Allostatic Load in Understanding Society*) calculated proximity measures between postcode grid references of Understanding Society participants and the nearest Ordnance Survey (OS) Points of Interest (POI) features representing 10 typical 20-minute neighbourhood (20MN) domains. Chapter 3 also calculated distances to the same 10 domains from every Output Area (OA) population weighted centroid (PWC) and aggregated this at the Lower Super Output Area (LSOA) level. The aggregate measure was also used in Chapter 4. Chapter 3 compared results between the two approaches and assessed cross-sectional associations between both measures of proximal access to 20MN domains and AL in Understanding Society. Chapter 4 (*Longitudinal associations between 20-Minute Neighbourhoods and Allostatic Load in older age groups*) assessed longitudinal associations between the LSOA aggregate measure of proximal access to 20MN domains and AL in the English Longitudinal Study of Aging (ELSA).

[73] Or the indices of multiple deprivation as this study included IMD scores based on Welsh, Scottish, and English indices.

The conclusion to this thesis now summarises the results of each empirical chapter relative to the research questions and hypotheses considered. It then discusses the thesis as a whole, reflecting on implications for policy and research. The overall limitations of the thesis are then described before outlining several future directions for research.

5.2 Summary of the Empirical Chapters

5.2.1 Chapter 2 – Perceived Neighbourhood Qualities and Allostatic Load

The first aim of this thesis was to identify potential subjective and objective causal pathways in the literature in the overall introduction which were assessed in the subsequent chapters. The secondary aim of the thesis was to assess whether subjective measures of perceived neighbourhood qualities explain how neighbourhoods 'get under the skin' drawing on the identified pathways. Chapter 2 first examined associations between IMD and each of the perceived measures of neighbourhood qualities (PNQs). This was guided by the following research questions and hypotheses, with relevant results outlined below each of these pairings below.

1. **Is higher deprivation associated with poorer subjective assessment of perceived neighbourhood qualities (PNQs)?**

   H1) Higher deprivation will be associated with poorer perceived neighbourhood qualities (after controlling for socioeconomic characteristics).

   This hypothesis was supported across each measure with only local service ratings not consistently associated with poorer scores across IMD quintiles. In line with expectations this study found that: higher deprivation was associated with poorer perceived neighbourhood cohesion (social interactive mechanism, collective efficacy); higher perceived crime and disorder (social interactive mechanism, social control/environmental mechanism, physical surroundings); and greater fear of walking alone at night (environmental mechanism, exposure to violence). Higher IMD was associated with poorer overall local service ratings, but this was only significant for quintiles 1 and 2, but not quintiles 3 and 4. This summary score had the lowest internal reliability (Cronbach's alpha = 0.60).

2. Are Poorer perceived neighbourhood qualities (PNQs) associated with AL, when controlling for IMD?

H2) Poorer perceived neighbourhood qualities will be associated with higher AL.

There was mixed evidence for this hypothesis across the PNQs. Consistent with the hypothesis, and previous research highlighting the particular salience of fear of walking alone at night and health in a small sample of people living in a tower block, greater fear of walking alone at night was associated with higher AL (G. Green et al., 2002). Lower ratings of service quality also associated with higher AL. This is consistent with previous research highlighting the importance of social infrastructure in relation to health and wellbeing measures (Davern et al., 2017). This is also consistent with GUTS, which suggests that prolonged stress responses likely arise from generalised perceptions of unsafety rather than from the presence of acute stressors. However, perceived neighbourhood cohesion and perceived crime were not significantly associated with AL, contrasting with prior research in the US that has linked these factors with biological risk (A. J. Schulz et al., 2013). Both measures aligned closely to the transformative idea of the GUTS, that signals of perceived safety (and the converse) are the key to understanding the stress response. Indeed, they appeared well suited to test both a signal of safety and unsafety. However, this null finding may reflect the concurrent measurement of AL and the measures of perceived crime and perceived cohesion with no assessment of the length of time or 'dosage' (Galster, 2012).

3. Does the strength of the relationship between PNQs and AL change depending on level of deprivation?

H3) Poorer PNQs will have stronger effects on AL in areas with higher levels of deprivation. For example, where deprivation is higher, perceived crime will be higher.

Moderation was considered to test whether the strength of relationships between PNQs and AL depended on IMD level. The rationale for this approach was that the broader neighbourhood context may shape how individuals experience and respond to their surroundings, thereby influencing the impact of PNQs on AL. For example, individuals in affluent areas with strong social infrastructure may have alternative sources of support (such as social clubs, green spaces, well-funded public amenities) even if they personally feel disconnected. However, in deprived areas, a lack of community cohesion may amplify stress and worsen health outcomes, if individuals have access to fewer resources or social capital to buffer against a lack of community trust. However, there was no evidence of moderation between objective deprivation and PNQs on AL. In line with the literature, this points to the need for consideration of length of exposure to both the neighbourhood deprivation and the PNQ, such as considering the effects of different trajectories of perceived and objective neighbourhood disadvantages over time on AL (Yakubovich et al., 2020).

4. Are the effects of IMD on AL explained by PNQs?

H4) PNQs will mediate the effects of deprivation on AL.

This hypothesis tested whether IMD shapes people's lived experiences and in turn impacted the stress-response and AL. For example, given IMD score includes a crime dimension reflecting actual crime rates, this may lead to higher perceived crime or fear of walking alone at night that means people consider their neighbourhood to be unsafe and avoid outdoor activities, and experience a prolonged exposure to unsafety contributing more to AL. Here, fear of walking alone at night was supportive of this hypothesis, mediating IMD on AL. However, perceived crime, perceived cohesion, and local service ratings did not mediate the relationship. Although IMD includes crime as a component (as well as access to services, education, employment, health, housing, and the physical environment), which raises the potential for endogeneity bias for (at least) both the fear of crime and fear of safety measures, stronger evidence of mediation would be expected if this were a significant issue. However, as the analysis found little evidence for mediation (other than for PNS), this suggests that endogeneity bias from IMD's crime component (or access to services/health for LSR) is unlikely to have meaningfully influenced the results. Future research could explore this further by assessing IMD's subdomains separately to determine whether specific factors, such as crime, exert a distinct influence on AL.

5.2.2 Chapter 3 – Cross-sectional associations between 20-Minute Neighbourhoods and Allostatic Load in Understanding Society

Associations between proximal access to 20MN domains and AL were first tested cross-sectionally in Understanding Society. This was guided by the following research questions and hypotheses, with relevant results outlined below each of these pairings below.

1. **Is there cross-sectional evidence of an association between distances to 20MN domains and AL and which domains appear to be the most salient[74] in this relationship?**

Hypothesis 1: Improved access to 20MN domains would be associated with a protective effect on AL.

Overall, there was limited evidence of a cross-sectional relationship between proximity to 20MN domains and AL in uncontrolled models[75], either in a positive (harmful) or negative (protective) direction. However, greater distance from the 'Eating and Drinking' and 'Retail Services' domains was associated with higher AL, supporting the expectation that poorer proximal access to key amenities would correspond with worse AL outcomes. There was also evidence against hypothesis 1, as greater distance from 'Greenspace and Recreation' (in the sample under 50) and 'Public Transport' (in the full sample and under 50 sample) was unexpectedly associated with lower AL.

2. **Are these relationships independent of an individual's demographic characteristics?**

Hypothesis 2: Improved access to 20MN domains would be associated with a protective effect on AL over and above demographic characteristics.

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[74] Salient associations were defined as significant associations ($p<0.05$) that survived Bonferroni correction for multiple testing. Corrections were applied on a hypothesis basis with p.values multiplied by 4 in the full sample and by 8 in the sample stratified by age.
[75] Uncontrolled models included the 10 20MN domains only (commercial services, community facilities, cultural, eating and drinking, education, financial services, food services, greenspace and recreation, health services, public transport, retail). These were also run separately for the two distance measurement types.

After adjusting for demographic confounders, the only distance measure supporting the hypothesis was retail. Evidence continued to contradict *Hypothesis 2* (with lower AL associated with increased distance) for the public transport domain across both the full sample and the under-50 sub-sample and for greenspace and recreation for the sample under 50 only.

3. Are these relationships independent of an individual's area-based characteristics?

Hypothesis 3: Improved access to 20MN domains would be associated with a protective effect on AL over and above both demographic and area-based characteristics.

Adding IMD and rural covariates amplified associations between distance to retail and AL. Postcode distance also became significant at model 3 for AL12, and was close to significance when AL15 was included as the outcome. Beta estimates increased by 40% (0.081 to 0.114) between model 2 and model 3 for the OA PWC measure. The increase in the estimate may be attributed to the inclusion of urbanity, which accounts for differences in average distances to retail between urban (1.2 km) and rural (4.6 km) areas. Contrary to expectation but following the pattern of results in models 1 and 2, higher distances to greenspace and recreation remained significantly associated with lower AL for the sample under 50 for the AL12 construct but not AL15, with higher distances to public transport associated with lower AL for AL15 but not AL12, also for the sample under 50.

4. Are these relationships independent of an individual's lifestyle characteristics?

Hypothesis 4: Improved access to 20MN domains would be associated with a protective effect on AL over and above demographic, geographical, and lifestyle characteristics.

In complete models, distance to retail remained significantly associated with increased AL for both the AL15 (OA PWC significant, postcode $p<0.1$[76]) and AL12 (OA PWC and postcode both significant $p<0.05$) constructs in the full sample, supporting Hypothesis 4. However, contrary to the hypothesis, higher distance to the public transport domain was associated with lower AL for the AL15 construct in the full sample (and the under-50 sample $p<0.1$).

5. **How do these associations vary by age group?**

Hypothesis 5: There would be differences in salient associations between the samples stratified by age group.

In the stratified models, significant findings were only present in the sample aged under 50. However, in complete models, only distance to public transport remained significant for this sample, with distance to public transport associated with lower AL in the AL15 construct. This may point to this measure being an indicator of proximity to busy roads, with pollution and noise associated with higher AL (Leach et al., 2024; Recio et al., 2016; Thomson, 2019; Tonne et al., 2016).

[76] All p.values were Bonferroni corrected.

6. Are there differences between the distance measurement approaches?

Hypothesis 6: The distance measures would capture similar relationships to 20MN domains

This hypothesis was not supported in terms of significance, although the beta estimates in complete models pointed in the same direction. Postcode distances to the nearest 20MN domains were not associated with any domains other than retail, perhaps reflecting greater noise in these models due to the higher level of variation in the other measures. For retail, model 3 (including demographic and area-based covariates) was associated with higher AL for the sample under 50 when AL15 was included as an outcome, and higher AL in models 3 and 4 in the full sample when AL12 was included as an outcome. Models 3 and 4 were also close to significance in the full sample for postcode distances.

7. Are there differences between the results based on AL composition?

Hypothesis 7: The composition of AL would not influence the results.

In general, there was agreement between the measures, with the same domains appearing significant and the direction of associations the same, although this was not always the case. For model 1, the only difference in interpretation between results was a loss of significance for the full sample between proximal access to eating and drinking services when AL15 was included as an outcome. From model 2 onwards access to greenspace only appeared significant when AL12 was included as an outcome (the measure that did not include primary mediators). Across the board, when significance remained for both AL constructs, beta estimates were also smaller when including AL15 as an outcome (rather than AL12) for significant associations, suggesting that the inclusion of primary mediators diluted the association with the distance measures.

5.2.3 Chapter 4 - Longitudinal associations between 20-Minute Neighbourhoods and Allostatic Load in older age groups

Associations between proximal access to 20MN domains and AL were then evaluated longitudinally in ELSA. This was guided by the following research questions and hypotheses, with relevant results outlined below each of these pairings below.

1. **Is there longitudinal evidence of an association between distances to 20MN domains and AL and which domains appear to be the most salient in this relationship?**

Hypothesis 1: Improved access to 20MN domains would be associated with a protective effect on AL.

There is longitudinal evidence that access to certain 20MN domains is associated with AL, but the effects vary by domain. Supporting Hypothesis 1, greater distance to food services was linked to higher AL, particularly in rural areas and for those with access to a vehicle, with these sub-samples overlapping to a large degree. However, the protective association was strongest at intermediate distances (200–600m), while the closest (0-<200m) and farthest (600-<800m) distances showed no significant effects relative to the reference group (800m+) .

Contrary to Hypothesis 1, greater distance from financial services was associated with lower AL, and closer proximity was linked to higher AL. Similar unexpected findings emerged for cultural venues and healthcare services, where greater distance sometimes corresponded with lower AL. These findings highlight the importance of considering domains independently as the direction of association was not always in the proximal is better (associated with lower AL) direction of expectation.

2. Are these relationships independent of an individual's demographic characteristics?

Hypothesis 2: Improved access to 20MN domains would be associated with a protective effect on AL over and above demographic characteristics.

After accounting for demographic characteristics, some associations between access to 20MN domains and AL remained. Supporting Hypothesis 2, greater distance to food services continued to be associated with higher AL in the full sample, the rural sample, and among those with access to a vehicle. However, when treated as a categorical measure, only living 200–400m from food services remained significantly associated with lower AL in the full and rural samples.

Contrary to Hypothesis 2, some unexpected associations persisted. Living in an area with low access to eating and drinking services was linked to lower AL among those without access to a vehicle. Additionally, living 600–800m from health services remained associated with higher AL in the rural sample (relative to the 800m+ group). Greater distance from financial services continued to be associated with lower AL in the full sample but was no longer significant in rural areas, suggesting the demographic measures better explained this apparent association in rural areas.

These findings highlight that some associations between access to 20MN domains and AL persisted even after accounting for demographic characteristics, but others weaken or disappear, indicating that demographic factors explain part of the observed relationships in the uncontrolled models. For example, although higher logged distances to financial services were still associated with lower AL in the full sample, this association disappeared in the rural sample.

3. Are these relationships independent of an individual's area-based characteristics?

Hypothesis 3: Improved access to 20MN domains would be associated with a protective effect on AL over and above both demographic and area-based characteristics.

After accounting for both demographic and area-based characteristics, the associations between access to 20MN domains and AL remained largely unchanged, indicating that these factors did not contribute additional explanatory power beyond what was already accounted for. Higher logged distances to food services continued to be associated with higher AL in the full sample, the rural sample, and those with access to a vehicle. Similarly, living in an LSOA with at least one OA lacking access to food services remained linked to higher AL in the rural sample. When treated as a categorical variable, only living 200 to <400 metres from food services remained associated with lower AL in both the full and rural samples.

Associations also persisted in the opposite direction to expectation. Living in a low-low hot-spot cluster of eating and drinking services (indicating low access) remained associated with lower AL in the sample without access to a vehicle. Additionally, residing 600 to <800-metres from a health domain continued to be linked to higher AL in the rural sample (than those living 800-metres or more away), while greater distances from financial services remained associated with lower AL in the full sample.

Overall, the limited changes resultant from the inclusion of the area-based covariates suggests these measures did not meaningfully alter the relationship between the measures of proximal access and AL. However, this could be because individual-level factors were already captured by the random intercept, which may have already accounted for much of the variation that the area-based factors would otherwise explain.

4. Are these relationships independent of an individual's lifestyle characteristics?

Hypothesis 4: Improved access to 20MN domains would be associated with a protective effect on AL over and above demographic, area-based, and lifestyle characteristics.

After accounting for lifestyle covariates, the significant associations observed between distances to food services and AL remained unchanged. Higher logged distances to food services were still significantly associated with higher AL in the full, rural, and vehicle access samples. Additionally, living in an LSOA lacking access to food services in at least one OA PWC remained associated with higher AL, but only in the rural sample. For distance as a categorical variable, living in level 2 areas (200 to <400-metres) remained significantly associated with lower AL in both the full and rural samples. These findings suggest that further investigation into the built environment around food services, such as supermarkets and convenience stores, could offer valuable insights. Exploring common morphometric properties or underlying demographic factors in these areas may also help explain the relationship observed. Since supermarkets tend to locate in less deprived areas, with location decisions likely driven by factors such as sales potential rather than community need, the outcome of these decisions could exacerbate existing inequalities.

Contrary to the hypothesised direction, individuals living in a low-low hot-spot cluster of eating and drinking services continued to show lower AL in the sample without access to a vehicle. Similarly, living between 600-<800-metres of the health domain was still associated with higher AL in the rural sample. Finally, higher logged distances to financial services did not survive Bonferroni correction across all samples, with the full sample coming closest to significance.

5. Does adjusting for medication in the construction of AL influence the findings?

Hypothesis 5: Accounting for medication in AL would not influence the interpretation of results.

In line with the findings elsewhere (McLoughlin et al., 2020), the results were largely supportive of H5 with medication having only a limited influence on the interpretation of results. For example H5 was mostly supported for cultural, eating and drinking, food services, and health services domains. These relationships were consistent across the models when AL was or was not adjusted for medication. However, in some cases when medication was taken into account, associations became significant, and vice versa. Associations that were only present when AL was adjusted for medication included proximity to food services across certain distance categories and higher logged distances to financial services.

6. How do these associations vary by urbanicity and car access?

Hypothesis 6: There would be differences in salient associations between urban and rural areas and the sample with and without access to cars.

There were no significant findings for the urban sample, suggesting the measurement approach, focusing only on the first order proximal feature, was not well suited to the urban environment where greater density may indicate greater choice. There was also a large overlap here between those with a car and the rural sample and those in the urban sample without access to a car. However, interestingly, living in an area that had low counts of eating and drinking venues that was surrounded by similarly underserved LSOAs was associated with lower AL. This relationship was not present in uncontrolled models, but remained significant after the inclusion of demographic, area-based, and lifestyle covariates.

5.3 Overall Summary of the Empirical Chapters

As outlined in the literature review in the introductory chapter to this thesis, neighbourhood effects research has sought to move on from questions focused on 'does place matter?' to questions of 'how?' and 'what?' matters. Chapter 2 followed the approach of Prior et al. (2018) to assess whether subjective perceptions of neighbourhood qualities helped to explain the 'what' in the association between neighbourhood deprivation and AL that has been consistently identified in the neighbourhood effects literature (Johnson et al., 2017). However, Prior et al. (2018) situated AL as an intervening variable on the pathway between the neighbourhood environment, measured by IMD, and health. Whilst this is a legitimate pathway to consider, given the strength of the evidence of AL as a predictor of a wide array of poorer health outcomes and AL more regularly being treated as an outcome in the neighbourhood effects literature (Beckie, 2012), chapter 2 moved the pathway upstream and positioned AL as an outcome. This was preferred since, if seeking to understand the way neighbourhood deprivation impacts individual health over and above the characteristics of the individuals that live there is through AL, then it is necessary to consider what it is about such aggregate deprivation that drives this relationship. As the utility of AL is somewhat premised on its presence as a precursor to chronic disease, such that it can be improved, explaining this relationship directly appears more beneficial.

Whilst it is useful to know that the mechanism through which neighbourhood deprivation operates on health involves the stress pathway, identifying that a measure designed to reflect the negative aspects of place predicts poor health or other negative outcomes for the individuals that live there does not help to explain *what* it is about living in a deprived area that explains this relationship. As such, identifying the stress pathway deals with at least a certain amount of the 'how' neighbourhood effects transpire but it does not further elucidate the 'what' of this relationship. To address this, this chapter looked upstream in the mediatory pathway identified in Prior et al. (2018)[77], to assess whether subjective perceptions of neighbourhood quality helped to explain the relationship between deprivation

[77] From neighbourhood deprivation to poorer mental and physical health through AL.

and AL in an effort to unpick the 'what'. This chapter also addressed a gap in the neighbourhood effects and AL literature as very few studies exploring neighbourhoods and AL have been conducted outside of the US (van Deurzen et al., 2016; Whitley et al., 2022).

Prior et al. note a tendency in the literature to focus either on individual exposures, such as poverty, adverse experiences, or perceptions of neighbourhoods, arguing that "by focusing on individual-level perspectives, researchers are missing the context of health relationships and are not recognising the inherently social construction of life" (Prior et al., 2018a, p. 26). However, at least with regard to perceptions, this appears misplaced as by omitting subjective assessments of the environment in their analysis, the inherently socially constructed nature of subjective experience of place is ignored. As such, chapter 2 drew on the strengths present in subjective assessments of neighbourhoods that rely on the eyes of the beholder to understand how place is actually experienced.

Whilst spatial analysis is not used in chapter 2, the 3 most common problems linked to spatial analysis are still present to a certain extent, due to the treatment of area level IMD as an exposure. However, the inclusion of subjective measures sought to partially mitigate these problems. For example, the MAUP may be mitigated by subjective assessment, as individuals define the extent of their own neighbourhood when assessing perceived cohesion, crime, services, and safety. The Uncertain Geographic Context Problem may be mitigated because people interpret their own key contextual environment relative to the perceived qualities. Ecological fallacy may be mitigated because living in a deprived area isn't treated as being experienced in the same way by all who live there. This final point is particularly important when considering the effect of objective measures of the neighbourhood environment, as the strength of relationships between subjective assessments of place and objective measures have been found to vary considerably over time (Yakubovich et al., 2020). Such a disconnect is also important when thinking about the stress-response which, according to the Generalised Unsafety Theory of Stress (GUTS), involves both conscious and unconscious assessment of the environment (Brosschot et al., 2018). In chapter 2, IMD represented an unconscious signal of unsafety that may lead to the chronic release of the stress-response, whilst the perceived measures indicate potential conscious responses to deprived social conditions that also signal unsafety.

The results of this first chapter showed that objective deprivation, as measured by IMD, was a strong indicator of perceived neighbourhood qualities, with higher deprivation associated with poorer ratings across each PNQ. However, it did not follow that each of the PNQs were associated with AL, with perceived mistrust (PNC) and perceived crime and disorder (PCr) unexpectedly not associated with higher AL. There was no strong evidence of an interaction between living in a deprived area and PNQs on AL. Fear of walking alone at night (PNS) did significantly mediate IMD on AL, but the effect was small, with the direct of effect of IMD explaining most of the total effect. However, given the limited findings in support of the hypotheses that PNQs would explain the relationship between IMD and AL, the following chapters sought to consider objective measures of neighbourhood environments that may help to explain what it is about deprived environments that 'gets under the skin'. As such, the subsequent chapters considered whether objective measures of place helped to explain the relationship between neighbourhood deprivation and AL using the 20MN framework.

5.3.1 Chapters 2 and 3 – 20-Minute Neighbourhoods

The 20MN concept has gained significant traction, particularly since the COVID-19 pandemic, emerging as a key policy focus in urban planning and sustainability discussions. However, most research to date has focused on mapping their implementation rather than assessing their broader impacts. When studies have operationalised the measurement of 20MNs, this has tended to fall at a city scale, or the lower-level regional scale, rather than nationally, and no studies have considered whether any health outcomes are associated with living in areas with improved access to 20MNs to my knowledge. Chapter 3 addressed this by assessing whether there was cross-sectional evidence that living with improved proximal access to 20MN domains was associated with lower AL, within a nationally representative sample[78].

The tertiary aim of this thesis was to assess whether objective measures of access explain how neighbourhoods 'get under the skin'. This involved calculating proximal access to key services, using the 20MN framework to identify amenities key to daily living. The 20MN framework effectively encompassed each of the pathways identified by Galster as linking neighbourhoods to health from both the 'geographical' and 'institutional dimensions' (G. C. Galster, 2012). For example, under the geographical mechanisms, Galster describes 'spatial mismatch' as pathways describing the effects of neighbourhoods that lack accessibility to job opportunities that match the skills of residents, restricting suitable employment prospects. Similarly, 'public services' pathways describe effects form living in neighbourhoods that are governed by local authorities failing to provide essential public services and facilities due to constraints such as restricted funding, ineptitude, or corruption. These reflect issues the 20MN framework seeks to mitigate by highlighting the importance of

[78] The sample was restricted to England to aid comparison with the third chapter of this thesis.

local economies and service accessibility. Spatial mismatch underscores the need for local job opportunities that match the skills of residents, with the 20MN policy goal of reducing reliance on long commutes relevant to this. Similarly, the 'public services' pathway highlights the potential health implications of disparities in access to essential amenities, be that healthcare, education, or transport. Again, a key goal of the 20MN is to ensure equitable, high-quality services are accessible within a short distance.

Under the identified institutional mechanisms, 'stigmatisation' pathways link neighbourhood conditions that shape access to resources, opportunities, and social mobility to health. Neighbourhoods may be stigmatised: due to historical or present biases in perception of place; by environmental or topological misfortunes (such as areas of high flood risk, pollution, limited greenspace, lack of sunlight, or steep terrain); or through the conditions of public and commercial spaces. Each of these factors may themselves influence how institutional and private actors allocate investment and services. For example, the UK's 'levelling-up' fund has disproportionately benefited wealthier areas, reinforcing existing inequalities (Fransham et al., 2023; McIntyre et al., 2022). The 20MN framework was employed to theoretically capture the effects of such stigma and underinvestment, measured as the existent built environment and distribution of proximal access to it.

The 'local institutional resources' pathways seek to capture how the availability and quality of services within a neighbourhood (such as private, non-profit, charity, and public institutions) impact health outcomes. This may occur through the social relations these facilities deliver, be that social and financial support, education, or personal development. Such resources may foster cohesion and build a sense of community and belonging that provides wider signals of safety to the residents that live there (Zahnow, 2024). The 20MN framework was employed to theoretically capture the effects of such resource disparities by highlighting how the distribution of institutional resources, or the lack thereof, impacts health outcomes across space and time, as measured by AL.

The ‘local market actors’ pathway tends to describe environments characterised by the presence or absence of certain businesses or services that may be expected to have a positive or, more frequently, negative health outcome associated with their presence. Here, classic examples might be: the presence of fast food shops and links with obesity (van Erpecum et al., 2022; B. B. Walker et al., 2020); alcohol outlets with behaviours (Martín-Turrero et al., 2024), mental health (Pereira et al., 2013), or violence (Horsefield et al., 2023); and the presence of tobacco outlets with behaviours (Cantrell et al., 2015). Most operationalisations of the 20MN framework necessarily construct environments in a manner that highlights the presence or absence of specific features deemed beneficial or harmful to certain outcomes. However, considering specific resources as necessarily ‘positive’ or ‘negative’ may neglect variability in actual experience.

The initial intention of this thesis was to avoid theoretically assigning positive or negative attributes to the domains being studied, in part as this has been explored elsewhere (M. A. Green et al., 2018), but also due to the inherent variability in how people may relate to specific features or theoretical domains. For example, a pub may be expected to be harmful to health due to associated risks around alcohol misuse but may also reflect a space for social connection and community. As such, the focus on the association of the various measures of proximity to domains with AL itself sought to remove the necessity for pre-classification. However, the 20MN framework inherently assumes that improved access to the included domains will promote positive outcomes. As such, feature selection reflected this, and the overall domains were constructed based on features broadly expected to foster beneficial social relations, akin to ideas in the social infrastructure literature (Davern et al., 2017; Latham & Layton, 2019; Yhee et al., 2021b; Zahnow, 2024).

Including only 'beneficial' domains may appear somewhat contradictory when considering the relationship between neighbourhoods and AL in particular, given AL is widely described[79] as a measure of chronic stress. However, as outlined in the introduction to this thesis and continued descriptions of AL and the stress pathway in the subsequent chapters, the stress pathway reflects biological processes that have positive and negative consequences resultant from environmental and psychosocial challenges. For example, the stress response is necessary to adapt to challenge, but the process itself leads to trade-offs, wear and tear, and, when chronically released, physiological dysregulation and allostatic overload ultimately resulting in disease. In this sense, AL is theorised to capture how relationships to neighbourhood features have actually been experienced, through the resulting biological consequences of conscious and unconscious stress responses. Given the GUTS insight that the stress response is inhibited by signals of safety, and disinhibited by signals of unsafety, the idea that positive expectations, attached to improved proximal access to 20MNs, reflect signals of safety whilst the lack of proximal access is expected to signal unsafety appears justified (Brosschot et al., 2018). This duality allowed for a nuanced interpretation of how neighbourhood features contribute to AL in an effort to account for variability in how people experience, interact with, and are impacted by their environment.

Chapters 2 and 3 of this study contribute to the growing interest in 20MN policies, particularly post-COVID-19 (Pozoukidou & Chatziyiannaki, 2021). They also uniquely

[79] And indeed has been described as such in this thesis.

investigated the cross-sectional and longitudinal health effects, measured by AL, of living near 20MN domains in two nationally representative samples. Understanding Society represented the whole adult age range (aged 16 and above), whilst ELSA represented the non-resident adult population, and their partners, aged 50 and over in England. These chapters addressed a gap in the literature in terms of measuring outcomes relative to the 20MN framework. Descriptive statistics highlighted that individual indicators of socioeconomic deprivation, such as low income or low educational qualifications, generally demonstrated smaller distances to 20MN domains, reflecting the findings in other studies that found more deprived areas had better access to domains (Calafiore et al., 2022; Olsen, Thornton, et al., 2022).

Access to retail stood out as particularly important in chapter 3, even after controlling for confounders and applying the Bonferroni correction, with greater distances to retail services consistently linked to higher AL. However, in chapter 4, retail was not significantly associated with AL. Proximity to food services emerged as being associated with lower AL. Nevertheless, these main findings were in line with the hypothesis that improved access to key amenities would have a positive impact on AL. However, contrary to expectations, closer proximity to the public transport domain was associated with higher AL in chapter 3. This domain was primarily made up of bus stops and possibly served more as an indicator of busy roads, with bus stops more likely to be located next to main roads. This domain and finding in particular highlights the need to consider the quality of the service in future research, rather than proximity alone. Additionally, in chapter 4, living closer to financial services was linked to higher AL, which warrants further exploration of the built environments and demographic characteristics of such areas. Overall, there was limited evidence of cross-sectional and longitudinal associations with many domains, highlighting the importance of incorporating quality measures in future research into 20MNs.

5.4 Thesis limitations

Specific limitations for the empirical chapters were outlined in detail in the chapters themselves. However, there are a number of limitations more broadly related to the overall thesis. These are outlined below with reference to the chapters they relate to and approaches used to address the limitations.

Misaligned and cross-sectional spatial data

A key limitation of this study (across chapters 1, 2, and 3) is the misalignment between the time points at which different datasets were collected. In chapter 2, the IMD data were obtained from multiple time points due to differing collection periods for Wales (2014), England (2015), and Scotland (2016). In chapter 3, although the analysis considered only one time point, the linked OS Maps Points of Interest spatial data (accessed 2021) did not align temporally with the Understanding Society data (2010-2013). Additionally, for chapter 4, while it was possible to measure AL over time, the distance measures were only able to be calculated using data collected at a single period of time (with ELSA data coming from waves 2 (2004-2005), 4 (2008-2009), 6 (2012-2013), and 8 combined with 9 (2016-2019)). These distance measures were linked to LSOA codes, which were then applied across multiple waves of the ELSA data. As a result, features representing domains might have been fewer or changed over time, which could introduce potential bias and reliability issues in the distance measures. However, grouping features by domain sought to ensure net changes in actual resource presence would be minimal. Future research should seek to address this limitation with the inclusion of multiple time points for both spatial measures and AL.

Lack of primary mediator in ELSA

There were no primary mediators of the stress response (such as cortisol, adrenaline, or DHEAS) included in the AL construction for chapter 4. Primary mediators play a crucial role in early physiological adaptations to stress releasing “a cascade of events through which AL develops” (T. E. Seeman et al., 2001). Their absence means the measure may overlook key upstream processes that drive long-term physiological dysregulation, instead relying on secondary outcomes like blood pressure and glucose, which can be influenced by factors beyond stress. However, as chapter 3 highlighted, when primary mediators were included in AL15 and excluded in AL12 (which reflected the measure used in Chapter 4), results were similar, particularly in complete models. Additionally, to maintain consistency across the four waves of ELSA, only biomarkers available in all waves were included. This precluded incorporating certain primary mediators even if they were present in certain waves during the period, such as DHEAS or IGF-1, unless techniques such as multiple imputation were used. However, multiple imputation has its own pitfalls and can sometimes obscure relationships, introduce bias, or distort data (Sterne et al., 2009). Whilst the exclusion of these biomarkers was a limitation, this approach was preferred.

Ecological fallacy

As outlined in the introduction to the thesis, a potential limitation of this study was the risk of ecological fallacy, where inferences about the nature of individuals are deduced from area-level data. This was a particular risk with the inclusion of IMD and, separately, the OA PWC distances to domains aggregated at the LSOA level, as an exposure. However, this concern was mitigated against through the inclusion of subjective measures of neighbourhood quality in chapter 2 which sought to draw out experiences of neighbourhoods, rather than assuming uniformity within larger spatial units. Similarly, in chapters 2 and 3, individual-level relationships with two proximity measures were assessed: one based on precise distances from household postcodes and the other an aggregate value that reflected overall average distances within the LSOA, without assuming equal relationships to the distance. As such, both measures assessed proximity to neighbourhood features while seeking to avoid the ecological fallacy by focusing on individual-level data relative to proximal (and/or aggregate proximal) access.

Modifiable Areal Unit Problem

The MAUP is an inherent challenge in spatial analysis, where the scale or shape of spatial units can influence results. However, this concern was mitigated against in chapter 2 by using subjective measures of neighbourhood quality based on individual-level perceptions of what their neighbourhood was. This issue was also mitigated in chapters 2 and 3 through the use of multiple spatial scales when calculating distances. This included calculating distances at the postcode, OA PWC, and LSOA levels which allowed for the assessment of whether results were sensitive to spatial aggregation. For example, in chapter 3, the study compared distance measures at the individual (postcode) level and at aggregated levels (LSOA) to evaluate scale and zoning effects. The results suggested that both scales captured similar patterns of spatial access, and although the localised postcode-level measure was characterised by greater variability, the main interpretation of significant results, that distance to retail was associated with higher AL, was present in the results for the two measures. Whilst multiple scales were not compared in chapter 4, the aggregate LSOA measure captured variation at the OA PWC level prior to aggregation, with distance values allowed to cross boundaries, limiting the zoning effects.

Uncertain Geographic Context Problem

The UGCoP is a limitation in spatial research that explains the challenge to determine the true geographical areas that exert contextual influences on individuals. For example, the same neighbourhood will likely be interacted with differently by different individuals, making it challenging to pinpoint exactly where spatial features are experienced, or whether this takes place predominantly around the home or the workplace. Proximity to a 20MN domain doesn't necessarily equate to actual exposure or indicate the duration of that exposure, especially given that individuals may experience the same environments differently. This study sought to mitigate against the UGCoP by focusing on a specific cohort, individuals aged 50 and over, who are more likely to rely on their local neighbourhood for daily activities and general life. Multi-level modelling accounted for individual variation across repeated measures, helping to isolate the effect of 20MN access on AL, independent of other contextual factors. While this approach mitigates against the UGCoP to some extent, future studies could further refine this by incorporating subjective measures of use and exposure and considering broader contexts around work and social environments.

5.5 Directions for future research

Directions for future research are outlined below, broken down by chapter 2 and relating to 20-minute neighbourhoods covering chapters 2 and 3.

5.5.1 Directions for future research from chapter 2 - *Do Perceived Neighbourhood Qualities Explain the Relationship Between Deprivation and Allostatic Load in Understanding Society?*

This thesis highlighted a number of interesting avenues for future research. As outlined in the overall introduction to the thesis, there has been very little research into AL outside of the US when it comes to neighbourhood research (Prior et al., 2018a; van Deurzen et al., 2016; Whitley et al., 2022). Chapter 2 of this thesis addressed this by assessing a series of subjective measures of neighbourhood quality relative to AL drawing on one of the few studies to consider this relationship in the UK (Prior et al., 2018a), and studies using similar measures in the US (Carbone, 2020a; Robinette et al., 2016; A. J. Schulz et al., 2013). However, the findings of chapter 2 point to both similarities (cohesion did not mediate area deprivation on AL in the US or UK data (Robinette et al., 2016)), and differences that warrant further investigation, whether through the use of different UK datasets, longitudinal analysis, or implementation of different methodologies. For example, perceived safety did mediate area deprivation on AL in chapter 2, but both did (A. J. Schulz et al., 2013) and did not in the US (Robinette et al., 2016). Additionally, the measures of perceived levels of crime and disorder and perceived levels of cohesion were not found to be associated with AL in the UK data. Here, the dimensions were considered as separate indicators in weighted least squares linear models. However, a US study used structural equation modelling to create a latent construct of perceived neighbourhood quality incorporating safety, trust, and neighbourhood conditions, where this latent measure of improved neighbourhood perceptions was associated with lower AL (Carbone, 2020a).

The null findings and limited evidence of moderation or mediation supported the findings in a US study (Robinette et al., 2016). However, this may reflect the concurrent measurement of indicators and outcomes and not accounting for dosage or level of exposure (although the sample was restricted to non-movers from the previous wave). Future research on these measures should consider the effects of different trajectories of both perceived and objective neighbourhood disadvantages over time on AL, with four distinct trajectories identified in one study using the British Household Panel Study, the precursor to Understanding Society (Yakubovich et al., 2020). A subsequent biomarker wave has also recently been initiated in Understanding Society, offering the potential to assess longitudinal relationships between perceived and objective measures of neighbourhood quality and AL over time in greater detail.

The pathways considered here only reflected a small portion of the potential causal pathways identified in Galster's (2012) wide-ranging literature review, which itself was published nearly 12 years ago at a time when the neighbourhood effects literature was growing and plausible pathways were becoming more of a focus. Given the consistency of findings in the literature linking neighbourhood deprivation to AL, more research needs to be directed towards understanding what aspects of deprivation that present at the neighbourhood and individual level drive this relationship.

5.5.2 20-Minute Neighbourhoods directions for future research

There were 8 main recommendations for future research relating to 20MNs based on chapter 3 (*Cross-sectional associations between 20MNs and AL in Understanding Society*) and chapter 4 (*Longitudinal associations between 20-Minute Neighbourhoods and Allostatic Load in older age groups)*.

1. **Assess outcomes as well as operationalisations of 20-minute neighbourhoods**

   The broader neighbourhood effects, urban planning, and geospatial literature has assessed relationships between spatial aspects of place and health outcomes (Braubach et al., 2017; Davern et al., 2017; Egorov et al., 2017; Fernandez et al., 2024; M. A. Green et al., 2018; Sarkar et al., 2013c, 2013a, 2015). However, within the 20MN framing the literature tends to operationalise and then stop or operationalise, assess access and stop (Calafiore et al., 2022; Chau et al., 2022; Olsen, Thornton, et al., 2022; Thornton et al., 2022). Given the global popularity of the concept (at least in terms of name recognition in the UK), particularly at the city level but also reaching a national scale in Scotland, it provides a useful framework to communicate across disciplines. However, as it currently stands, the literature around the concept tends to assume the intended beneficial outcomes do or will arise. Future research should seek to investigate outcomes to evaluate the impact of improved access to 20MN, be that related to health, local economies, quality of life, or environmental outcomes if 20MNs are to become more than an empty signifier.

2. **Include measures of quality:**

The thesis focused solely on the relationship of proximity to services and AL. However, proximity to a service does not indicate the quality of the service. This was particularly important for the transport domain, where bus stops were present in almost every LSOA but lacked sufficient context as to the service they provided. For example, while the presence of public transport was included as an indicator of access, their actual utility as such depends on service frequency, connectivity, and affordability. Future studies seeking to operationalise 20MNs should seek to incorporate measures of quality into the analysis.

3. **Proximity does not equal accessibility:**

A major assumption of the thesis was that proximity would indicate greater accessibility. However, personal mobility constraints, network routes, subjective perceptions, service availability, and quality are all involved in a more accurate reflection of accessibility. Future research operationalising 20MNs should seek to add greater complexity to the measurement of access itself. For example, this may include topographical measures that account for physical barriers such as steep inclines, obstructed pathways, rivers, busy roads, or railway lines, which can significantly impact ease of movement despite close proximity. Incorporating network analysis rather than Euclidean distance as was used here would also provide a more realistic representation of actual potential travel routes.

4. **Include subjective assessment as well as objective measures:**

The presence or absence of a service, business, or park does not indicate use or exposure. The integration of subjective and objective measures would help to consider the impacts of issues such as the UGCoP and the MAUP with people assessing their own neighbourhood boundaries and interactions with the measure at hand. For example, discrepancies between objective and subjective measures of accessibility may highlight distinctions between actual and perceived access. Whilst objective measures can quantify spatial distance, topological barriers, and potential routes, subjective perceptions reflect how accessible a resource *actually* feels to an individual. Where gaps emerge, this may reveal underlying factors such as mobility constraints, safety concerns, or environmental barriers that objective measures alone may fail to capture. As such, by considering both subjective and objective perspectives, it is possible to understand not just where services are located, but how they are experienced and accessed in reality.

5. **Consider overall complexity:**

This recommendation builds on points 2-4 and is particularly important in response to a common finding in the literature that highlights access to 20MNs tends to appear to better serve disadvantaged areas. For example, Olsen et al. note that "residential locations within the most deprived areas had better access across all 20 MN domains when compared to the least deprived areas and a policy focusing solely on improving access to key facilities and amenities for deprived areas may therefore be ineffective in reducing health inequalities." (Olsen, Thornton, et al., 2022). This was also present in the individual level data, with indicators commonly reflective of deprivation tending to indicate lower average distances to every domain in chapter 3 (with the cultural domain the only exception). This likely reflects the focus on objective measures in operationalisations, such as a focus on features or domains and the distances to them. However, this purely objective focus likely defines city centres and towns where deprivation tends to be higher. For example, in the UK's core cities (Birmingham, Bristol, Leeds, Liverpool, Manchester, Newcastle Upon Tyne Nottingham, and Sheffield) "higher levels of deprivation immediately surrounding city centres are a common trend" (Swan, 2015). Comparisons of composition effects, such as less deprived areas with high access to amenities versus deprived areas with higher access to amenities would be an interesting future research direction. However, focusing on objective measures alone may still overlook variations in service quality, perceived safety, and the actual usability of amenities. They are also unable to capture levels of cohesion which should likely be present in any assessment of a successful 20MN. Incorporating subjective assessments alongside objective proximity metrics, in order to provide a more nuanced understanding of how 20MNs function in practice, is necessary to understand their benefits or otherwise.

6. **Break down domains:**

Whilst it is important for future operationalisations to incorporate complexity into the assessment of access, this should not be done at the expense of maintaining (and potentially increasing) domain separation. As the results showed, proximity to different services was not always associated with a positive relationship with AL. As such, combination into a single index would likely mask relationships (M. A. Green et al., 2018). Whilst the included domains represented distinctive domains, they were all represented by different numbers of features with their own distributions and spatial relationships, with certain domains dominated by certain features. As such, even though the domains appear theoretically congruent, it may be (and is likely) that similar masking may take place through this grouping. For example, the presence of primary educational facilities represent different forms of social relationships and built environments than universities do, post offices do represent financial services but may also offer a more social or multi-purpose function than traditional banks, especially in rural areas, and greenspaces can range from small urban parks to expansive natural reserves, each serving different social, recreational, and environmental roles. This variation means that grouping these features under a single domain may obscure important differences in how they function and are experienced.

7. **Multiple time points of geographical data:**

   Future research should use geographical measures calculated from multiple time-points to allow a more detailed investigation of how changes in the built environment may impact AL or health more generally.

8. **Look at the built, social, and natural environments around food, retail, and financial services domains:**

   Associations between distance to food services and AL were consistent even after controlling for demographic, area-based, and lifestyle characteristics. These findings highlight the need for further examination of the built environment surrounding food services, such as supermarkets and convenience stores, to better understand their impact on AL. Exploring common morphometric properties and underlying demographic factors in these areas could shed light on the observed relationship. Areas around food services, financial services, and retail would be useful places to start.

5.6 Conclusion

This thesis highlights the role of neighbourhood environments in shaping physiological stress responses, as measured by Allostatic Load. By analysing how proximity to key 20-minute neighbourhood domains relates to AL, the research highlights both the theoretical and practical potential health benefits of local accessibility. However, it also shows the limitations of a one-size-fits-all measurement approach, with the null findings in urban environments perhaps reflecting the focus on proximal access (nearest neighbour distance only) was not suitable for urban environments.

The findings suggest that access to food services was consistently associated with lower AL in the longitudinal data, reinforcing the importance of equitable local availability of essential amenities and the value of food services being included in 20MN policies. However, counterintuitive results, such as proximity to public transport being linked to higher AL in the cross-sectional chapter, highlight the need to consider service quality, either through the inclusion of additional metrics or subjective appraisal. These counterintuitive findings also point to the importance of keeping in mind the potential for reverse causation. For example, if AL is an expression of chronic stress, those experiencing less stress might have been able to move to areas with less public transport due to having other resources available allowing choices to be made about commuting, work, and social life (selection effects).

Collectively, the significant, counterintuitive, and null findings point to the importance of keeping domains separate in analysis. Domains may also benefit from further separation, such as the education domain which, whilst reflective of educational services, was perhaps too broad as it reflected facilities likely to represent wildly different built environments with equally different neighbourhood characteristics and social relations. Nevertheless, given that AL serves as an early predictor of chronic disease, these findings have wider public health implications. The literature and the findings did show that neighbourhood design is not merely a question of convenience but can also be a determinant of long-term physiological resilience or ill-health. This is particularly relevant for older populations, who are more reliant on local services, at greater risk of social isolation, and represent a growing proportional population in the UK.

The study emphasizes that, whilst 20MN principles offer a promising framework for healthier places, future policies must account for diverse mobility needs and the lived experience of different demographic groups to ensure that accessibility translates into meaningful health benefits. More research should also seek to explore the effects of improved access to 20MNs rather than stopping at the point the 20MN is operationalised. Overall, this research contributes to a growing body of evidence that shows how neighbourhood environments ‘get under the skin’ not just through physical infrastructure but through the cumulative impact of spatial, social, and environmental stressors that collectively provide signals of safety or unsafety involved in the chronic release or inhibition of the stress response. Measuring and addressing these disparities requires an approach that incorporates proximity metrics whilst also accounting for service quality, individual mobility constraints and barriers, and how people actually use and experience their local environment.

6 References

2011 Census Geography boundaries (Lower Layer Super Output Areas and Data Zones)—UK Data Service CKAN. (2024, November 6). https://statistics.ukdataservice.ac.uk/dataset/2011-census-geography-boundaries-lower-layer-super-output-areas-and-data-zones

#ACFM – Trip 2: Collective Joy. (2019, May 7). [Audio recording]. https://soundcloud.com/novaramedia/acfm-collective-joy

#ACFM – Trip 13: Crowds. (2021, January 17). [Audio recording]. https://soundcloud.com/novaramedia/acfm-trip-13-crowds

#ACFM Microdose: Spatial Equality with Pooja Agrawal. (2021, September 8). [Audio recording]. https://soundcloud.com/novaramedia/acfm-microdose-spatial-equality-with-pooja-agrawal

Addley, E. (2023, October 7). 'This is political expediency': How the Tories turned on 15-minute cities. *The Guardian*. https://www.theguardian.com/cities/2023/oct/07/15-minute-cities-rishi-sunak-tories-conspiracy-theory

Ai, H., Zhang, X., & Zhou, Z. (2023). The impact of greenspace on air pollution: Empirical evidence from China. *Ecological Indicators*, *146*, 109881. https://doi.org/10.1016/j.ecolind.2023.109881

Albanese, N. N. Y., Lin, I., Friedberg, J. P., Lipsitz, S. R., Rundle, A., Quinn, J. W., Neckerman, K. M., Nicholson, A., Allegrante, J. P., Wylie-Rosett, J., & Natarajan, S. (2022). Association of the built environment and neighborhood resources with obesity-related health behaviors in older veterans with hypertension. *Health*

Psychology : Official Journal of the Division of Health Psychology, American Psychological Association. https://doi.org/10.1037/hea0001161

Allan, R., Williamson, P., & Kulu, H. (2019). Gendered mortality differentials over the rural-urban continuum: The analysis of census linked longitudinal data from England and Wales. *Social Science & Medicine*, *221*, 68–78. https://doi.org/10.1016/j.socscimed.2018.10.005

Allen, A. M., Wang, Y., Chae, D. H., Price, M. M., Powell, W., Steed, T. C., Black, A. R., Dhabhar, F. S., Marquez-Magaña, L., & Woods-Giscombe, C. L. (2019). Racial discrimination, the superwoman schema, and allostatic load: Exploring an integrative stress-coping model among African American women. *Annals of the New York Academy of Sciences*, *1457*(1), 104–127. https://doi.org/10.1111/nyas.14188

Alliance. (2021). *Exploring Scotland's 20-minute neighbourhoods: Final report published*. Health and Social Care Alliance Scotland. https://www.alliance-scotland.org.uk/blog/news/exploring-scotlands-20-minute-neighbourhoods-final-report-published/

AlWaer, H., & Cooper, I. (2023). Unpacking the concept of 20-minute neighbourhoods: Disentangling "desired outcomes" from the "means" available for achieving them. *Open House International*, *48*(4), 704–728. https://doi.org/10.1108/OHI-11-2022-0285

Ambrey, C. L., Fleming, C. M., & Manning, M. (2014). Perception or Reality, What Matters Most When it Comes to Crime in Your Neighbourhood? *Social Indicators Research*, *119*(2), 877–896.

Anabtawi, S. (2023). Towards a Better Understanding of Compact Cities. *Journal of Planning Literature*. https://doi.org/10.1177/08854122231158768

Anselin, L. (2020, December 10). *Local Spatial Autocorrelation (1)*. https://geodacenter.github.io/workbook/6a_local_auto/lab6a.html#clusters-and-spatial-outliers

Arcaya, M., Tucker-Seeley, R., Kim, R., Schnake-Mahl, A., So, M., & Subramanian, S. (2016). Research on Neighborhood Effects on Health in the United States: A Systematic Review of Study Characteristics. *Social Science & Medicine (1982)*, *168*, 16–29. https://doi.org/10.1016/j.socscimed.2016.08.047

Awad, N., Saade, R., Bassil, M., Sukkarieh-Haraty, O., & Egede, L. E. (2022). Relationship between social determinants of health and clinical outcomes in adults with type 2 diabetes in Lebanon. *Journal of the National Medical Association*, S0027-9684(22)00049-9. https://doi.org/10.1016/j.jnma.2022.03.002

Bacon, N., caistor-arendar, L., & Gordon, C. (2020). *Connective Social Infrastructure: How London's social spaces and networks help us live well together. A Good Growth by Design Research Inquiry.* https://doi.org/10.13140/RG.2.2.11600.28161

Baldock, K. L., Paquet, C., Howard, N. J., Coffee, N. T., Taylor, A. W., & Daniel, M. (2018). Are Perceived and Objective Distances to Fresh Food and Physical Activity Resources Associated with Cardiometabolic Risk? *International Journal of Environmental Research and Public Health*, *15*(2), Article 2. https://doi.org/10.3390/ijerph15020224

Baranyi, G., Sieber, S., Cullati, S., Pearce, J. R., Dibben, C. J. L., & Courvoisier, D. S. (2020). The Longitudinal Associations of Perceived Neighborhood Disorder and

Lack of Social Cohesion With Depression Among Adults Aged 50 Years or Older: An Individual-Participant-Data Meta-Analysis From 16 High-Income Countries. *American Journal of Epidemiology*, *189*(4), 343–353. https://doi.org/10.1093/aje/kwz209

Barboza Solís, C., Kelly-Irving, M., Fantin, R., Darnaudéry, M., Torrisani, J., Lang, T., & Delpierre, C. (2015). Adverse childhood experiences and physiological wear-and-tear in midlife: Findings from the 1958 British birth cohort. *Proceedings of the National Academy of Sciences of the United States of America*, *112*(7), E738–E746. https://doi.org/10.1073/pnas.1417325112

Barry, L. E., O'Neill, S., Heaney, L. G., & O'Neill, C. (2021). Stress-related health depreciation: Using allostatic load to predict self-rated health. *Social Science & Medicine*, *283*, 114170. https://doi.org/10.1016/j.socscimed.2021.114170

Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). Fitting Linear Mixed-Effects Models Using lme4. *Journal of Statistical Software*, *67*, 1–48. https://doi.org/10.18637/jss.v067.i01

BBC. (2023, October 3). 15 minute cities: How they got caught in conspiracy theories. *BBC News*. https://www.bbc.com/news/uk-politics-66990302

Becker, J. C., Hartwich, L., & Haslam, S. A. (2021). Neoliberalism can reduce well-being by promoting a sense of social disconnection, competition, and loneliness. *British Journal of Social Psychology*, *60*(3), 947–965. https://doi.org/10.1111/bjso.12438

Beckes, L., & Coan, J. A. (2011). Social Baseline Theory: The Role of Social Proximity in Emotion and Economy of Action. *Social and Personality Psychology Compass*, *5*(12), 976–988. https://doi.org/10.1111/j.1751-9004.2011.00400.x

Beckie, T. M. (2012). A Systematic Review of Allostatic Load, Health, and Health Disparities. *Biological Research For Nursing*, *14*(4), 311–346. https://doi.org/10.1177/1099800412455688

Benninger, E., Schmidt-Sane, M., & Spilsbury, J. C. (2021). Conceptualizing Social Determinants of Neighborhood Health through a Youth Lens. *Child Indicators Research*, *14*(6), 2393–2416. https://doi.org/10.1007/s12187-021-09849-6

Berger, M., & Sarnyai, Z. (2015). "More than skin deep": Stress neurobiology and mental health consequences of racial discrimination. *Stress*, *18*(1), 1–10. https://doi.org/10.3109/10253890.2014.989204

Berman, S. L., Kurtines, W. M., Silverman, W. K., & Serafini, L. T. (1996). The impact of exposure to crime and violence on urban youth. *American Journal of Orthopsychiatry*, *66*(3), 329–336. https://doi.org/10.1037/h0080183

Bernardi, E., & Visioli, F. (2024). Fostering wellbeing and healthy lifestyles through conviviality and commensality: Underappreciated benefits of the Mediterranean Diet. *Nutrition Research*, *126*, 46–57. https://doi.org/10.1016/j.nutres.2024.03.007

Bernstein, K. T., Galea, S., Ahern, J., Tracy, M., & Vlahov, D. (2007). The built environment and alcohol consumption in urban neighborhoods. *Drug and Alcohol Dependence*, *91*(2), 244–252. https://doi.org/10.1016/j.drugalcdep.2007.06.006

Bi, Y.-N., & Liu, Y.-A. (2023). GPs in UK: From Health Gatekeepers in Primary Care to Health Agents in Primary Health Care. *Risk Management and Healthcare Policy*, *16*, 1929–1939. https://doi.org/10.2147/RMHP.S416934

Bird, C. E., Seeman, T., Escarce, J. J., Basurto-Dávila, R., Finch, B. K., Dubowitz, T., Heron, M., Hale, L., Merkin, S. S., Weden, M., & Lurie, N. (2010). Neighbourhood socioeconomic status and biological 'wear and tear' in a nationally representative sample of US adults. *Journal of Epidemiology & Community Health*, *64*(10), 860–865. https://doi.org/10.1136/jech.2008.084814

Bjorholm, S., Svenning, J.-C., Skov, F., & Balslev, H. (2008). To what extent does Tobler's 1st law of geography apply to macroecology? A case study using American palms (Arecaceae). *BMC Ecology*, *8*, 11. https://doi.org/10.1186/1472-6785-8-11

Blair, A. (n.d.). *Chapter 14: Mediation and Moderation*. Retrieved 16 January 2025, from https://ademos.people.uic.edu/Chapter14.html#24_method_2:_the_mediation_pacakge_method

Bloom, D. E., Chatterji, S., Kowal, P., Lloyd-Sherlock, P., McKee, M., Rechel, B., Rosenberg, L., & Smith, J. P. (2015). Macroeconomic implications of population ageing and selected policy responses. *Lancet (London, England)*, *385*(9968), 649–657. https://doi.org/10.1016/S0140-6736(14)61464-1

Bobba-Alves, N., Juster, R.-P., & Picard, M. (2022). The energetic cost of allostasis and allostatic load. *Psychoneuroendocrinology*, *146*, 105951. https://doi.org/10.1016/j.psyneuen.2022.105951

Bosch-Farré, C., Malagón-Aguilera, M. C., Ballester-Ferrando, D., Bertran-Noguer, C., Bonmatí-Tomàs, A., Gelabert-Vilella, S., & Juvinyà-Canal, D. (2020). Healthy Ageing in Place: Enablers and Barriers from the Perspective of the Elderly. A Qualitative Study. *International Journal of Environmental Research and Public Health*, *17*(18), 6451. https://doi.org/10.3390/ijerph17186451

Braubach, M., Egorov, A., Mudu, P., Wolf, T., Ward Thompson, C., & Martuzzi, M. (2017). Effects of Urban Green Space on Environmental Health, Equity and Resilience. In N. Kabisch, H. Korn, J. Stadler, & A. Bonn (Eds.), *Nature-Based Solutions to*

Climate Change Adaptation in Urban Areas: Linkages between Science, Policy and Practice (pp. 187–205). Springer International Publishing. https://doi.org/10.1007/978-3-319-56091-5_11

Bray, I., Reece, R., Sinnett, D., Martin, F., & Hayward, R. (2022). Exploring the role of exposure to green and blue spaces in preventing anxiety and depression among young people aged 14–24 years living in urban settings: A systematic review and conceptual framework. *Environmental Research*, *214*, 114081. https://doi.org/10.1016/j.envres.2022.114081

Brenner, A. B., Diez Roux, A. V., Barrientos-Gutierrez, T., & Borrell, L. N. (2015). Associations of Alcohol Availability and Neighborhood Socioeconomic Characteristics With Drinking: Cross-Sectional Results From the Multi-Ethnic Study of Atherosclerosis (MESA). *Substance Use & Misuse*, *50*(12), 1606–1617. https://doi.org/10.3109/10826084.2015.1027927

Brook, O. (2016). Spatial equity and cultural participation: How access influences attendance at museums and galleries in London. *Cultural Trends*, *25*(1), 21–34. https://doi.org/10.1080/09548963.2015.1134098

Brooks, K. P., Gruenwald, T., Karlamanga, A., Hu, P., Koretz, B., & Seeman, T. E. (2014). Social Relationships and Allostatic Load in the MIDUS Study. *Health Psychology : Official Journal of the Division of Health Psychology, American Psychological Association*, *33*(11), 1373–1381. https://doi.org/10.1037/a0034528

Brosschot, J. F., Verkuil, B., & Thayer, J. F. (2017). Exposed to events that never happen: Generalized unsafety, the default stress response, and prolonged autonomic activity. *Neuroscience & Biobehavioral Reviews*, *74*, 287–296. https://doi.org/10.1016/j.neubiorev.2016.07.019

Brosschot, J. F., Verkuil, B., & Thayer, J. F. (2018). Generalized Unsafety Theory of Stress: Unsafe Environments and Conditions, and the Default Stress Response. *International Journal of Environmental Research and Public Health*, *15*(3), Article 3. https://doi.org/10.3390/ijerph15030464

Brown, V., Barr, A., Scheurer, J., Magnus, A., Zapata-Diomedi, B., & Bentley, R. (2019). Better transport accessibility, better health: A health economic impact assessment study for Melbourne, Australia. *International Journal of Behavioral Nutrition and Physical Activity*, *16*(1), 89. https://doi.org/10.1186/s12966-019-0853-y

Bu, S., & Li, Y. (2023). Physical activity is associated with allostatic load: Evidence from the National Health and Nutrition Examination Survey. *Psychoneuroendocrinology*, *154*, 106294. https://doi.org/10.1016/j.psyneuen.2023.106294

Buckner, J. C. (1988). The development of an instrument to measure neighborhood cohesion. *American Journal of Community Psychology*, *16*(6), 771–791. https://doi.org/10.1007/BF00930892

Bush, K. J., Papacosta, A. O., Lennon, L. T., Rankin, J., Whincup, P. H., Wannamethee, S. G., & Ramsay, S. E. (2023). Influence of neighborhood-level socioeconomic deprivation and individual socioeconomic position on risk of developing type 2 diabetes in older men: A longitudinal analysis in the British Regional Heart Study cohort. *BMJ Open Diabetes Research & Care*, *11*(5). https://doi.org/10.1136/bmjdrc-2023-003559

Buzzelli, M. (2020). Modifiable Areal Unit Problem. *International Encyclopedia of Human Geography*, 169–173. https://doi.org/10.1016/B978-0-08-102295-5.10406-8

C40, K. (2020). *How to build back better with a 15-minute city*. https://www.c40knowledgehub.org/s/article/How-to-build-back-better-with-a-15-minute-city?language=en_US

Cailar, A. (1968). *Howard Ebenezer—Garden Cities of To-Morrow; A New City*.

Calafiore, A., Dunning, R., Nurse, A., & Singleton, A. (2022). The 20-minute city: An equity analysis of Liverpool City Region. *Transportation Research Part D: Transport and Environment*, *102*, 103111. https://doi.org/10.1016/j.trd.2021.103111

Camacho Doyle, M., Gerell, M., & Andershed, H. (2022). Perceived Unsafety and Fear of Crime: The Role of Violent and Property Crime, Neighborhood Characteristics, and Prior Perceived Unsafety and Fear of Crime. *Deviant Behavior*, *43*(11), 1347–1365. https://doi.org/10.1080/01639625.2021.1982657

Cantrell, J., Anesetti-Rothermel, A., Pearson, J. L., Xiao, H., Vallone, D., & Kirchner, T. R. (2015). The Impact of the Tobacco Retail Outlet Environment on Adult Cessation and Differences by Neighborhood Poverty. *Addiction (Abingdon, England)*, *110*(1), 152–161. https://doi.org/10.1111/add.12718

Capasso Da Silva, D., King, D. A., & Lemar, S. (2020). Accessibility in Practice: 20-Minute City as a Sustainability Planning Goal. *Sustainability*, *12*(1), Article 1. https://doi.org/10.3390/su12010129

Caraballo, R. S., Rice, K. L., Neff, L. J., & Garrett, B. E. (2019). Social and Physical Environmental Characteristics Associated With Adult Current Cigarette Smoking. *Preventing Chronic Disease*, *16*, E71. https://doi.org/10.5888/pcd16.180373

Carbone, J. T. (2020a). Neighborhood perceptions and allostatic load: Evidence from Midlife in the United States study. *Health & Place*, *61*, 102263. https://doi.org/10.1016/j.healthplace.2019.102263

Carbone, J. T. (2020b). *The mediating effect of allostatic load on the relationship between neighborhood perceptions and depression—PMC*. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7426578/

Carbone, J. T., Clift, J., & Alexander, N. (2022). Measuring allostatic load: Approaches and limitations to algorithm creation. *Journal of Psychosomatic Research*, *163*, 111050. https://doi.org/10.1016/j.jpsychores.2022.111050

Carson et al., J. R. (2023). Neighborhood walkability, neighborhood social health, and self-selection among U.S. adults. *Health & Place*, *82*, 103036. https://doi.org/10.1016/j.healthplace.2023.103036

Castagné, R., Garès, V., Karimi, M., Chadeau-Hyam, M., Vineis, P., Delpierre, C., & Kelly-Irving, M. (2018). Allostatic load and subsequent all-cause mortality: Which biological markers drive the relationship? Findings from a UK birth cohort. *European Journal of Epidemiology*, *33*(5), 441–458. https://doi.org/10.1007/s10654-018-0364-1

Castagné, R., Garès, V., Karimi, M., Chadeau-Hyam, M., Vineis, P., Delpierre, C., Kelly-Irving, M., Alenius, H., Avendano, M., Baltar, V., Bartley, M., Barros, H., Bochud, M., Carmeli, C., Carra, L., Costa, G., Courtin, E., Donkin, A., D'Errico, A., … for the Lifepath Consortium. (2018). Allostatic load and subsequent all-cause mortality: Which biological markers drive the relationship? Findings from a UK birth cohort. *European Journal of Epidemiology*, *33*(5), 441–458. https://doi.org/10.1007/s10654-018-0364-1

Cené, C. W., Beckie, T. M., Sims, M., Suglia, S. F., Aggarwal, B., Moise, N., Jiménez, M. C., Gaye, B., & McCullough, L. D. (2022). Effects of Objective and Perceived Social Isolation on Cardiovascular and Brain Health: A Scientific Statement From the American Heart Association. *Journal of the American Heart Association: Cardiovascular and Cerebrovascular Disease*, *11*(16), e026493. https://doi.org/10.1161/JAHA.122.026493

Census 2021 geographies—Office for National Statistics. (2021). https://www.ons.gov.uk/methodology/geography/ukgeographies/censusgeographies/census2021geographies

Cernat, A. (2024, February 6). *Estimating non-linear change in time using the multilevel model for change—Longitudinal analysis*. https://longitudinalanalysis.com/estimating-non-linear-change-in-time-using-the-multilevel-model-for-change/

Chandola, T., Booker, C. L., Kumari, M., & Benzeval, M. (2019a). Are Flexible Work Arrangements Associated with Lower Levels of Chronic Stress-Related Biomarkers? A Study of 6025 Employees in the UK Household Longitudinal Study. *Sociology*, *53*(4), 779–799. https://doi.org/10.1177/0038038519826014

Chandola, T., Booker, C. L., Kumari, M., & Benzeval, M. (2019b). Are Flexible Work Arrangements Associated with Lower Levels of Chronic Stress-Related Biomarkers? A Study of 6025 Employees in the UK Household Longitudinal Study. *Sociology*, *53*(4), 779–799. https://doi.org/10.1177/0038038519826014

Chandola, T., & Zhang, N. (2018). Re-employment, job quality, health and allostatic load biomarkers: Prospective evidence from the UK Household Longitudinal Study.

International Journal of Epidemiology, *47*(1), 47–57. https://doi.org/10.1093/ije/dyx150

Chau, H.-W., Gilzean, I., Jamei, E., Palmer, L., Preece, T., & Quirke, M. (2022). Comparative Analysis of 20-Minute Neighbourhood Policies and Practices in Melbourne and Scotland. *Urban Planning*, *7*(4), 13–24. https://doi.org/10.17645/up.v7i4.5668

Chauntry, A. J., Bishop, N. C., Hamer, M., Kingsnorth, A. P., Chen, Y.-L., & Paine, N. J. (2022). Sedentary behaviour is associated with heightened cardiovascular, inflammatory and cortisol reactivity to acute psychological stress. *Psychoneuroendocrinology*, *141*, 105756. https://doi.org/10.1016/j.psyneuen.2022.105756

Chen, X., Ye, X., Widener, M. J., Delmelle, E., Kwan, M.-P., Shannon, J., Racine, E. F., Adams, A., Liang, L., & Jia, P. (2022). A systematic review of the modifiable areal unit problem (MAUP) in community food environmental research. *Urban Informatics*, *1*(1), 22. https://doi.org/10.1007/s44212-022-00021-1

Chinmoy Sarkar, Chris Webster, & John Gallacher. (2015). *UK Biobank Urban Morphometric Platform (UKBUMP) – a nationwide resource for evidencebased healthy city planning and public health interventions*. Annals of GIS. https://www.tandfonline.com/doi/full/10.1080/19475683.2015.1027791

Chiu, D. T., Parker, J. E., Wiley, C. R., Epel, E. S., Laraia, B. A., Leung, C. W., & Tomiyama, A. J. (2024). Food insecurity, poor diet, and metabolic measures: The roles of stress and cortisol. *Appetite*, *197*, 107294. https://doi.org/10.1016/j.appet.2024.107294

Chodzko-Zajko, W. J., Proctor, D. N., Fiatarone Singh, M. A., Minson, C. T., Nigg, C. R., Salem, G. J., & Skinner, J. S. (2009). Exercise and Physical Activity for Older Adults. *Medicine & Science in Sports & Exercise*, *41*(7), 1510. https://doi.org/10.1249/MSS.0b013e3181a0c95c

CIHT. (2015). *Streets And Transport In the Urban Environment | CIHT*. https://www.ciht.org.uk/knowledge-resource-centre/resources/streets-and-transport-in-the-urban-environment/

Clark, M. S., Bond, M. J., & Hecker, J. R. (2007). Environmental stress, psychological stress and allostatic load. Psychology. *health &*, *12*(1), 18–30. https://doi.org/10.1080/13548500500429338

Clarke, P., & Gallagher, N. A. (2013). Optimizing Mobility in Later Life: The Role of the Urban Built Environment for Older Adults Aging in Place. *Journal of Urban Health*, *90*(6), 997–1009. https://doi.org/10.1007/s11524-013-9800-4

ClimateXChange, C. (2021). 20 minute neighbourhoods in a Scottish context [Website]. *ClimateXChange*. https://www.climatexchange.org.uk/projects/20-minute-neighbourhoods-in-a-scottish-context/

Conceição, M. A., Monteiro, M. M., Kasraian, D., van den Berg, P., Haustein, S., Alves, I., Azevedo, C. L., & Miranda, B. (2023). The effect of transport infrastructure, congestion and reliability on mental wellbeing: A systematic review of empirical studies. *Transport Reviews*, *43*(2), 264–302. https://doi.org/10.1080/01441647.2022.2100943

Coulton, C. (2012). Defining Neighborhoods for Research and Policy. *Cityscape*, *14*(2), 231–236.

Coulton, C. J., Korbin, J., Chan, T., & Su, M. (2001). Mapping Residents' Perceptions of Neighborhood Boundaries: A Methodological Note. *American Journal of Community Psychology*, *29*(2), 371–383. https://doi.org/10.1023/A:1010303419034

Crimmins, E. M., Johnston, M., Hayward, M., & Seeman, T. (2003). Age differences in allostatic load: An index of physiological dysregulation. *Experimental Gerontology*, *38*(7), 731–734. https://doi.org/10.1016/S0531-5565(03)00099-8

Cuevas, A. G., McSorley, A.-M., Lyngdoh, A., Kaba-Diakité, F., Harris, A., Rhodes-Bratton, B., & Rouhani, S. (2024). Education, Income, Wealth, and Discrimination in Black-White Allostatic Load Disparities. *American Journal of Preventive Medicine*, *67*(1), 97–104. https://doi.org/10.1016/j.amepre.2024.02.021

Curry, A., Latkin, C., & Davey-Rothwell, M. (2008). Pathways to depression: The impact of neighborhood violent crime on inner-city residents in Baltimore, Maryland, USA. *Social Science & Medicine*, *67*(1), 23–30. https://doi.org/10.1016/j.socscimed.2008.03.007

Daly, M., Boyce, C., & Wood, A. (2015). A Social Rank Explanation of How Money Influences Health. *Health Psychology*, *34*(3), 222–230. https://doi.org/10.1037/hea0000098

Davern, M., Gunn, L., Whitzman, C., Higgs, C., Giles-Corti, B., Simons, K., Villanueva, K., Mavoa, S., Roberts, R., & Badland, H. (2017). Using spatial measures to test a conceptual model of social infrastructure that supports health and wellbeing. *Cities & Health*. https://www.tandfonline.com/doi/abs/10.1080/23748834.2018.1443620

Davidsen, K., Carstensen, S., Kriegbaum, M., Bruunsgaard, H., & Lund, R. (2022). Do partnership dissolutions and living alone affect systemic chronic inflammation? A cohort study of Danish adults. *J Epidemiol Community Health*, *76*(5), 490–496. https://doi.org/10.1136/jech-2021-217422

Davis, M. L., Neelon, B., Nietert, P. J., Hunt, K. J., Burgette, L. F., Lawson, A. B., & Egede, L. E. (2019). Addressing geographic confounding through spatial propensity scores: A study of racial disparities in diabetes. *Statistical Methods in Medical Research*, *28*(3), 734–748. https://doi.org/10.1177/0962280217735700

Department of Health and Social Care. (2024, September 12). *Build Back Better: Our Plan for Health and Social Care*. GOV.UK. https://www.gov.uk/government/publications/build-back-better-our-plan-for-health-and-social-care/build-back-better-our-plan-for-health-and-social-care

Derose, K. P., Han, B., Park, S., Williamson, S., & Cohen, D. A. (2019). The mediating role of perceived crime in gender and built environment associations with park use and park-based physical activity among park users in high poverty neighborhoods. *Preventive Medicine*, *129*, 105846. https://doi.org/10.1016/j.ypmed.2019.105846

Diez Roux, A. V. (2001a). Investigating Neighborhood and Area Effects on Health. *American Journal of Public Health*, *91*(11), 1783–1789.

Diez Roux, A. V. (2001b). Investigating neighborhood and area effects on health. *American Journal of Public Health*, *91*(11), 1783–1789. https://doi.org/10.2105/ajph.91.11.1783

Diez Roux, A. V., & Mair, C. (2010a). Neighborhoods and health. *Annals of the New York Academy of Sciences*, *1186*, 125–145. https://doi.org/10.1111/j.1749-6632.2009.05333.x

Diez Roux, A. V., & Mair, C. (2010b). Neighborhoods and health. *Annals of the New York Academy of Sciences*, *1186*, 125–145. https://doi.org/10.1111/j.1749-6632.2009.05333.x

Dimitratos, S. M., Hercules, M., Stephensen, C. B., Cervantes, E., & Laugero, K. D. (2021). Association between physiological stress load and diet quality patterns differs between male and female adults. *Physiology & Behavior*, *240*, 113538. https://doi.org/10.1016/j.physbeh.2021.113538

Ding, X., Barban, N., & Mills, M. C. (2019). Educational attainment and allostatic load in later life: Evidence using genetic markers. *Preventive Medicine*, *129*, 105866. https://doi.org/10.1016/j.ypmed.2019.105866

Dixon, J., & Everest, G. (2021). *The government's levelling up agenda | The Health Foundation*. The Health Foundation. https://www.health.org.uk/reports-and-analysis/briefings/the-government-s-levelling-up-agenda

Dobner, S., Musterd, S., & Droogleever Fortuijn, J. (2016). 'Ageing in place': Experiences of older adults in Amsterdam and Portland. *GeoJournal*, *81*(2), 197–209. https://doi.org/10.1007/s10708-014-9613-3

Druta, O., Ronald, R., & Heath, S. (2021). Urban singles and shared housing. *Social & Cultural Geography*, *22*(9), 1195–1203. https://doi.org/10.1080/14649365.2021.1987507

Dubey, S., Bailey, A., & Lee, J. (Brian). (2025). Women's perceived safety in public places and public transport: A narrative review of contributing factors and measurement methods. *Cities*, *156*, 105534. https://doi.org/10.1016/j.cities.2024.105534

Dunbar, R. I. M. (2017). Breaking Bread: The Functions of Social Eating. *Adaptive Human Behavior and Physiology*, *3*(3), 198–211. https://doi.org/10.1007/s40750-017-0061-4

Dunning, R. J., Dolega, L., Nasuto, A., Nurse, A., & Calafiore, A. (2023). Age and the 20-min city: Accounting for variation in mobility. *Applied Geography*, *156*, 103005. https://doi.org/10.1016/j.apgeog.2023.103005

Duru, O. K., Harawa, N. T., Kermah, D., & Norris, K. C. (2012). Allostatic Load Burden and Racial Disparities in Mortality. *Journal of the National Medical Association*, *104*(1–2), 89–95.

Egorov, A. I., Griffin, S. M., Converse, R. R., Styles, J. N., Sams, E. A., Wilson, A., Jackson, L. E., & Wade, T. J. (2017). Vegetated Land Cover Near Residence is Associated with Reduced Allostatic Load and Improved Biomarkers of Neuroendocrine, Metabolic and Immune Functions. *Environmental Research*, *158*, 508. https://doi.org/10.1016/j.envres.2017.07.009

Egorov, A. I., Griffin, S. M., Styles, J. N., Kobylanski, J., Klein, J., Wickersham, L., Ritter, R., Sams, E., Hudgens, E. E., & Wade, T. J. (2024). Time outdoors and residential greenness are associated with reduced systemic inflammation and allostatic load. *Environmental Pollution*, *344*, 123408. https://doi.org/10.1016/j.envpol.2024.123408

Ellaway, A., Lamb, K. E., Ferguson, N. S., & Ogilvie, D. (2016). Associations between access to recreational physical activity facilities and body mass index in Scottish adults. *BMC Public Health*, *16*(1), 756. https://doi.org/10.1186/s12889-016-3444-8

Elldér, E. (2024). The 15-minute city dilemma? Balancing local accessibility and gentrification in Gothenburg, Sweden. *Transportation Research Part D: Transport and Environment*, *135*, 104360. https://doi.org/10.1016/j.trd.2024.104360

ELSA. (n.d.). *User guides*. ELSA. Retrieved 12 February 2025, from https://www.elsa-project.ac.uk/user-guides

English indices of deprivation 2019: Technical report. (2019, September 26). GOV.UK. https://www.gov.uk/government/publications/english-indices-of-deprivation-2019-technical-report

EVAW. (2021, August 25). *New data shows extent to which women feel unsafe at night*. End Violence Against Women. https://www.endviolenceagainstwomen.org.uk/new-data-women-feel-unsafe-at-night/

Everyday Places: Creating strong locations to support daily life in Britain. (2021, April 29). Demos. https://demos.co.uk/research/everyday-places-creating-strong-locations-to-support-daily-life-in-britain/

Fang, L., Zhang, D., Liu, T., Yao, S., Fan, Z., Xie, Y., Wang, X., & Li, X. (2021). A multi-level investigation of environmental justice on cultural ecosystem services at a national scale based on social media data: A case of accessibility to Five-A ecological attractions in China. *Journal of Cleaner Production*, *286*, 124923. https://doi.org/10.1016/j.jclepro.2020.124923

Fernandez, C. C., Maddock, J., Patalay, P., Fett, A.-K., Pitman, A., Vaughan, L., & Krenz, K. (2024). Proximity to high streets, social isolation and social support in British adolescents: A longitudinal analysis of sociospatial influences on social connectedness using geospatial data. *Health & Place*, *88*, 103260. https://doi.org/10.1016/j.healthplace.2024.103260

Ferraro, K. F. (1996). Women's Fear of Victimization: Shadow of Sexual Assault?*. *Social Forces*, *75*(2), 667–690. https://doi.org/10.1093/sf/75.2.667

Ferrer-Ortiz, C., Marquet, O., Mojica, L., & Vich, G. (2022). Barcelona under the 15-Minute City Lens: Mapping the Accessibility and Proximity Potential Based on Pedestrian Travel Times. *Smart Cities*, *5*(1), Article 1. https://doi.org/10.3390/smartcities5010010

Flores, A. R., Langton, L., Meyer, I. H., & Romero, A. P. (2020). Victimization rates and traits of sexual and gender minorities in the United States: Results from the National Crime Victimization Survey, 2017. *Science Advances*, *6*(40), eaba6910. https://doi.org/10.1126/sciadv.aba6910

Fone, D. L., Farewell, D. M., & Dunstan, F. D. (2006). An ecometric analysis of neighbourhood cohesion. *Population Health Metrics*, *4*(1), 17. https://doi.org/10.1186/1478-7954-4-17

Ford, M. M., & Highfield, L. D. (2016). Exploring the Spatial Association between Social Deprivation and Cardiovascular Disease Mortality at the Neighborhood Level. *PLOS ONE*, *11*(1), e0146085. https://doi.org/10.1371/journal.pone.0146085

Forde, D. R. (1993). Perceived crime, fear of crime, and walking alone at night. *Psychological Reports*, *73*(2), 403–407. https://doi.org/10.2466/pr0.1993.73.2.403

Forrester, S. N., Leoutsakos, J.-M., Gallo, J. J., Thorpe Jr, R., & Seeman, T. E. (2019). *Association between allostatic load and health behaviours: A latent class* *approach | Journal of Epidemiology & Community Health*. https://jech.bmj.com/content/73/4/340

Frank, L. D., Andresen, M. A., & Schmid, T. L. (2004). Obesity relationships with community design, physical activity, and time spent in cars. *American Journal of Preventive Medicine*, *27*(2), 87–96. https://doi.org/10.1016/j.amepre.2004.04.011

Frank, L. D., Saelens, B. E., Powell, K. E., & Chapman, J. E. (2007). Stepping towards causation: Do built environments or neighborhood and travel preferences explain physical activity, driving, and obesity? *Social Science & Medicine*, *65*(9), 1898–1914. https://doi.org/10.1016/j.socscimed.2007.05.053

Fransham, M., Herbertson, M., Pop, M., Bandeira Morais, M., & Lee, N. (2023). Level best? The levelling up agenda and UK regional inequality. *Regional Studies*, *57*(11), 2339–2352. https://doi.org/10.1080/00343404.2022.2159356

French, D. (2023). From financial wealth shocks to ill-health: Allostatic load and overload. *Health Economics*, *32*(4), 939–952. https://doi.org/10.1002/hec.4648

Friedline, T., Masa, R. D., & Chowa, G. A. N. (2015). Transforming wealth: Using the inverse hyperbolic sine (IHS) and splines to predict youth's math achievement. *Social Science Research*, *49*, 264–287. https://doi.org/10.1016/j.ssresearch.2014.08.018

Friel, C., Walsh, D., Whyte, B., Dibben, C., Feng, Z., Baker, G., Kelly, P., Demou, E., Dundas, R., & Weller, J. (2024). Health benefits of pedestrian and cyclist commuting: Evidence from the Scottish Longitudinal Study. *BMJ Public Health*, *2*(1). https://doi.org/10.1136/bmjph-2024-001295

Fritsch, N.-S., Riederer, B., & Seewann, L. (2023). Living Alone in the City: Differentials in Subjective Well-Being Among Single Households 1995–2018. *Applied Research in Quality of Life*, *18*(4), 2065–2087. https://doi.org/10.1007/s11482-023-10177-w

Gallagher, S., & Kate M, B. (2021). Caregiving and allostatic load predict future illness and disability: A population-based study. *Brain, Behavior, & Immunity - Health*, *16*, 100295. https://doi.org/10.1016/j.bbih.2021.100295

Gallucci, G., Tartarone, A., Lerose, R., Lalinga, A. V., & Capobianco, A. M. (2020). Cardiovascular risk of smoking and benefits of smoking cessation. *Journal of Thoracic Disease*, *12*(7), 3866–3876. https://doi.org/10.21037/jtd.2020.02.47

Galster, G. (2010). *The Mechanism(s) of Neighbourhood Effects*.

Galster, G. C. (2012). The Mechanism(s) of Neighbourhood Effects: Theory, Evidence, and Policy Implications. In M. van Ham, D. Manley, N. Bailey, L. Simpson, & D. Maclennan (Eds.), *Neighbourhood Effects Research: New Perspectives* (pp. 23–56). Springer Netherlands. https://doi.org/10.1007/978-94-007-2309-2_2

Ganster, D. C., & Rosen, C. C. (2013). Work Stress and Employee Health: A Multidisciplinary Review. *Journal of Management*, *39*(5), 1085–1122. https://doi.org/10.1177/0149206313475815

Gary, T. L., Safford, M. M., Gerzoff, R. B., Ettner, S. L., Karter, A. J., Beckles, G. L., & Brown, A. F. (2008). Perception of Neighborhood Problems, Health Behaviors, and Diabetes Outcomes Among Adults With Diabetes in Managed Care: The Translating Research Into Action for Diabetes (TRIAD) Study. *Diabetes Care*, *31*(2), 273–278. https://doi.org/10.2337/dc07-1111

Gilmore, D. R., Carreño, T. M., Zare, H., Moore, J. X., Rogers, C. R., Brooks, E., Petersen, E., Kennedy, C., & Thorpe, R. J. (2022). Investigating Racial Differences in

Allostatic Load by Educational Attainment among Non-Hispanic Black and White Men. *International Journal of Environmental Research and Public Health*, *19*(9), Article 9. https://doi.org/10.3390/ijerph19095486

Godhwani, S., Jivraj, S., Marshall, A., & Bécares, L. (2019a). Comparing subjective and objective neighbourhood deprivation and their association with health over time among older adults in England. *Health & Place*, *55*, 51–58. https://doi.org/10.1016/j.healthplace.2018.10.006

Godhwani, S., Jivraj, S., Marshall, A., & Bécares, L. (2019b). Comparing subjective and objective neighbourhood deprivation and their association with health over time among older adults in England. *Health & Place*, *55*, 51–58. https://doi.org/10.1016/j.healthplace.2018.10.006

Goel, R., Oyebode, O., Foley, L., Tatah, L., Millett, C., & Woodcock, J. (2023). Gender differences in active travel in major cities across the world. *Transportation*, *50*(2), 733–749. https://doi.org/10.1007/s11116-021-10259-4

Gongadze, S., & Maassen, A. (2023). *Paris' Vision for a '15-Minute City' Sparks a Global Movement*. https://www.wri.org/insights/paris-15-minute-city

Goodman, A., & Aldred, R. (2021). The Impact of Introducing a Low Traffic Neighbourhood on Street Crime, in Waltham Forest, London. *Findings*. https://doi.org/10.32866/001c.19414

Goodwin-Hawkins, B., Oedl-Wieser, T., Ovaska, U., & Morse, A. (2021). Rural service hubs and socially innovative rural-urban linkages: A conceptual framework for nexogenous development. *Local Economy*, *36*(7–8), 551–568. https://doi.org/10.1177/02690942221082040

GOV.UK. (2010). *English indices of deprivation 2010—GOV.UK*. https://www.gov.uk/government/statistics/english-indices-of-deprivation-2010

GOV.UK. (2019). *Access to Transport and Life Opportunities*. GOV.UK. https://www.gov.uk/government/publications/access-to-transport-and-life-opportunities

GOV.UK. (2021, October 27). *Levelling Up Fund: First round successful bidders*. GOV.UK. https://www.gov.uk/government/publications/levelling-up-fund-first-round-successful-bidders

GOV.UK. (2025, January 14). *Key Findings, Statistical Digest of Rural England*. GOV.UK. https://www.gov.uk/government/statistics/key-findings-statistical-digest-of-rural-england/key-findings-statistical-digest-of-rural-england

Green, G., Gilbertson, J. M., & Grimsley, M. F. J. (2002). Fear of crime and health in residential tower blocks: A case study in Liverpool, UK. *European Journal of Public Health*, *12*(1), 10–15. https://doi.org/10.1093/eurpub/12.1.10

Green, M. A., Daras, K., Davies, A., Barr, B., & Singleton, A. (2018). Developing an openly accessible multi-dimensional small area index of 'Access to Healthy Assets and Hazards' for Great Britain, 2016. *Health & Place*, *54*, 11–19. https://doi.org/10.1016/j.healthplace.2018.08.019

Gress, T. W., Denvir, J., & Shapiro, J. I. (2018). Effect of removing outliers on statistical inference: Implications to interpretation of experimental data in medical research. *Marshall Journal of Medicine*, *4*(2), 9. https://doi.org/10.18590/mjm.2018.vol4.iss2.9

Grimmer, K., Kay, D., Foot, J., & Pastakia, K. (2015). Consumer views about aging-in-place. *Clinical Interventions in Aging*, *10*, 1803–1811. https://doi.org/10.2147/CIA.S90672

Guidi, J., Lucente, M., Sonino, N., & Fava, G. A. (2020). Allostatic Load and Its Impact on Health: A Systematic Review. *Psychotherapy and Psychosomatics*, *90*(1), 11–27. https://doi.org/10.1159/000510696

Guidi, J., Lucente, M., Sonino, N., & Fava, G. A. (2021). Allostatic Load and Its Impact on Health: A Systematic Review. *Psychotherapy and Psychosomatics*, *90*(1), 11–27. https://doi.org/10.1159/000510696

Gustafsson, P. E., San Sebastian, M., Janlert, U., Theorell, T., Westerlund, H., & Hammarström, A. (2014). Life-Course Accumulation of Neighborhood Disadvantage and Allostatic Load: Empirical Integration of Three Social Determinants of Health Frameworks. *American Journal of Public Health*, *104*(5), 904–910. https://doi.org/10.2105/AJPH.2013.301707

Hagedoorn, P., & Helbich, M. (2021). Longitudinal exposure assessments of neighbourhood effects in health research: What can be learned from people's residential histories? *Health & Place*, *68*, 1-7,. https://doi.org/10.1016/j.healthplace.2021.102543

Hajat, A., Diez-Roux, A. V., Adar, S. D., Auchincloss, A. H., Lovasi, G. S., O'Neill, M. S., Sheppard, L., & Kaufman, J. D. (2013). Air pollution and individual and neighborhood socioeconomic status: Evidence from the Multi-Ethnic Study of Atherosclerosis (MESA). *Environmental Health Perspectives*, *121*(11–12), 1325–1333. https://doi.org/10.1289/ehp.1206337

Ham, M., Manley, D., Bailey, N., Simpson, L., & Maclennan, D. (2012). *Neighbourhood Effects Research: New Perspectives*. Springer.".

Hansen, Å. M., Nabe-Nielsen, K., Bruunsgaard, H., Jensen, M. A., Molbo, D., Lund, R., & Garde, A. H. (2022). Educational attainment in young adulthood and self-rated health in midlife – Does allostatic load mediate the association? *Psychoneuroendocrinology*, *139*, 105708. https://doi.org/10.1016/j.psyneuen.2022.105708

Harrell, J. P., Hall, S., & Taliaferro, J. (2003). Physiological Responses to Racism and Discrimination: An Assessment of the Evidence. *American Journal of Public Health*, *93*(2), 243–248. https://doi.org/10.2105/AJPH.93.2.243

Havard Health. (2024, April 3). *Understanding the stress response*. Harvard Health. https://www.health.harvard.edu/staying-healthy/understanding-the-stress-response

Healthwatch. (2023, July 13). *Third of people in England lack confidence they can access critical NHS services | Healthwatch*. https://www.healthwatch.co.uk/news/2023-09-12/third-people-england-lack-confidence-they-can-access-critical-nhs-services

Healthy High Streets: Good place making in an urban setting. (2018, January 17). GOV.UK. https://www.gov.uk/government/publications/healthy-high-streets-good-place-making-in-an-urban-setting

Hedman, L., & van Hamm, M. (2011). *Understanding Neighbourhood Effects: Selection Bias and Residential Mobility | SpringerLink*. https://link.springer.com/chapter/10.1007/978-94-007-2309-2_4

Hendry, A. (2017). Living well in later life in Scotland. *Working with Older People*, *21*(1), 22–30. https://doi.org/10.1108/WWOP-12-2016-0037

Hindi, A. M. K., Schafheutle, E. I., & Jacobs, S. (2018). Patient and public perspectives of community pharmacies in the United Kingdom: A systematic review. *Health Expectations : An International Journal of Public Participation in Health Care and Health Policy*, *21*(2), 409–428. https://doi.org/10.1111/hex.12639

Hinnant, L., Hairgrove, S., Kane, H., Williams, J., & Cance, J. D. (2022). *Social Determinants of Health: A Review of Publicly Available Indices*. RTI Press. https://doi.org/10.3768/rtipress.2022.op.0081.2212

Hipp, J. R., & Williams, S. A. (2020). Advances in Spatial Criminology: The Spatial Scale of Crime. *Annual Review of Criminology*, *3*(Volume 3, 2020), 75–95. https://doi.org/10.1146/annurev-criminol-011419-041423

Hoffimann, E., Barros, H., & Ribeiro, A. I. (2017). Socioeconomic Inequalities in Green Space Quality and Accessibility—Evidence from a Southern European City. *International Journal of Environmental Research and Public Health*, *14*(8), Article 8. https://doi.org/10.3390/ijerph14080916

Holt-Lunstad, J., Birmingham, W., & Jones, B. Q. (2008). Is there something unique about marriage? The relative impact of marital status, relationship quality, and network social support on ambulatory blood pressure and mental health. *Annals of Behavioral Medicine: A Publication of the Society of Behavioral Medicine*, *35*(2), 239–244. https://doi.org/10.1007/s12160-008-9018-y

Horsefield, O. J., Lightowlers, C., & Green, M. A. (2023). The spatial effect of alcohol availability on violence: A geographically weighted regression analysis. *Applied Geography*, *150*, 102824. https://doi.org/10.1016/j.apgeog.2022.102824

Housing | State of Ageing in 2020 | Centre for Ageing Better. (2020). https://ageing-better.org.uk/housing-state-ageing-2020

Howard, J. T., & Sparks, P. J. (2015). The role of education in explaining racial/ethnic allostatic load differentials in the United States. *Biodemography and Social Biology*, *61*(1), 18–39. https://doi.org/10.1080/19485565.2014.937000

Howard, J. T., & Sparks, P. J. (2016). Does allostatic load calculation method matter? Evaluation of different methods and individual biomarkers functioning by race/ethnicity and educational level. *American Journal of Human Biology*, *28*(5), 627–635. https://doi.org/10.1002/ajhb.22843

Hu, S., Zhao, R., Cui, Y., Zhang, D., & Ge, Y. (2023). Identifying the uneven distribution of health and education services in China using open geospatial data. *Geography and Sustainability*, *4*(2), 91–99. https://doi.org/10.1016/j.geosus.2023.01.002

Hua, H., Xie, H., & Tanin, E. (2018). Is Euclidean Distance Really that Bad with Road Networks? *Proceedings of the 11th ACM SIGSPATIAL International Workshop on Computational Transportation Science*, 11–20. https://doi.org/10.1145/3283207.3283215

Ige-Elegbede, J., Pilkington, P., Orme, J., Williams, B., Prestwood, E., Black, D., & Carmichael, L. (2022). Designing healthier neighbourhoods: A systematic review of the impact of the neighbourhood design on health and wellbeing. *Cities & Health*, *6*(5), 1004–1019. https://doi.org/10.1080/23748834.2020.1799173

Institute for Social and Economic Research. (2022). *Understanding Society: Biomarker User Guide and Glossary, Version 2, September 2022*. https://doc.ukdataservice.ac.uk/doc/7251/mrdoc/pdf/7251_biomarker_user_guide.pdf

Iscenko, Z., Bardrick, T., Oryshchenko, V., & Woodward, L. (2020, September 29). *[ARCHIVED CONTENT] Cash and Covid: Identifying gaps in provision during Covid-19 | FCA Insight*. Insight. https://webarchive.nationalarchives.gov.uk/ukgwa/20240123093427/https://www.fca.org.uk/insight/cash-and-covid-identifying-gaps-provision-during-covid-19

James, G. (Gareth M., Witten, D., Hastie, T., & Tibshirani, R. (2021). *An Introduction to Statistical Learning: With Applications in R* (Second Edition.). Springer US. https://doi.org/10.1007/978-1-0716-1418-1

Janatabadi, F., Newing, A., & Ermagun, A. (2024). Social and spatial inequalities of contemporary food deserts: A compound of store and online access to food in the United Kingdom. *Applied Geography*, *163*, 103184. https://doi.org/10.1016/j.apgeog.2023.103184

Jarrett, J., Woodcock, J., Griffiths, U. K., Chalabi, Z., Edwards, P., Roberts, I., & Haines, A. (2012). Effect of increasing active travel in urban England and Wales on costs to the National Health Service. *The Lancet*, *379*(9832), 2198–2205. https://doi.org/10.1016/S0140-6736(12)60766-1

Jeffares, S. R. (2008). *Why public policy ideas catch on: Empty signifiers and flourishing neighbourhoods* [D_ph, University of Birmingham]. https://etheses.bham.ac.uk/id/eprint/193/

Jimenez, M. P., DeVille, N. V., Elliott, E. G., Schiff, J. E., Wilt, G. E., Hart, J. E., & James, P. (2021). Associations between Nature Exposure and Health: A Review of the Evidence. *International Journal of Environmental Research and Public Health*, *18*(9), 4790. https://doi.org/10.3390/ijerph18094790

Jivraj, S., Murray, E., Norman, P., & Nicholas, O. (2020). The impact of life course exposures to neighbourhood deprivation on health and well-being: A review of the long-term neighbourhood effects literature. *European Journal of Public Health*, *30*(ue 5), 922-928,. https://doi.org/10.1093/eurpub/ckz153

Jivraj, S., Murray, E. T., Norman, P., & Nicholas, O. (2019). The impact of life course exposures to neighbourhood deprivation on health and well-being: A review of the long-term neighbourhood effects literature. *The European Journal of Public Health*, *30*(5), 922–928. https://doi.org/10.1093/eurpub/ckz153

Jivraj, S., Norman, P., Nicholas, O., & Murray, E. T. (2019). Are there sensitive neighbourhood effect periods during the life course on midlife health and wellbeing? *Health & Place*, *57*, 147–156. https://doi.org/10.1016/j.healthplace.2019.03.009

Johansson, K., Laflamme, L., & Eliasson, M. (2012). Adolescents' Perceived Safety and Security in Public Space—A Swedish Focus Group Study with a Gender Perspective. *YOUNG*, *20*(1), 69–88. https://doi.org/10.1177/110330881102000104

Johansson, S., & Haandrikman, K. (2023). Gendered fear of crime in the urban context: A comparative multilevel study of women's and men's fear of crime. *Journal of Urban Affairs*, *45*(7), 1238–1264. https://doi.org/10.1080/07352166.2021.1923372

Johnson, S. C., Cavallaro, F. L., & Leon, D. A. (2017). A systematic review of allostatic load in relation to socioeconomic position: Poor fidelity and major inconsistencies in biomarkers employed. *Social Science & Medicine*, *192*, 66–73. https://doi.org/10.1016/j.socscimed.2017.09.025

Juster, R.-P., de Torre, M. B., Kerr, P., Kheloui, S., Rossi, M., & Bourdon, O. (2019). Sex Differences and Gender Diversity in Stress Responses and Allostatic Load Among Workers and LGBT People. *Current Psychiatry Reports*, *21*(11), 110. https://doi.org/10.1007/s11920-019-1104-2

Juster, R.-P., McEwen, B. S., & Lupien, S. J. (2010). Allostatic load biomarkers of chronic stress and impact on health and cognition. *Neuroscience & Biobehavioral Reviews*, *35*(1), 2–16. https://doi.org/10.1016/j.neubiorev.2009.10.002

Juster, R.-P., & Misiak, B. (2023). Advancing the allostatic load model: From theory to therapy. *Psychoneuroendocrinology*, *154*, 106289. https://doi.org/10.1016/j.psyneuen.2023.106289

Kamel, A. A., Ford, P. B., & Kaczynski, A. T. (2014). Disparities in park availability, features, and characteristics by social determinants of health within a U.S.-Mexico border urban area. *Preventive Medicine*, *69 Suppl 1*, S111-113. https://doi.org/10.1016/j.ypmed.2014.10.001

Kamruzzaman, L. (2022). Typologies of 20-Minute Neighbourhoods, Active Transport Use, and Spatial Spillovers. *Findings*. https://doi.org/10.32866/001c.33158

Karlamangla, A. S., Singer, B. H., McEwen, B. S., Rowe, J. W., & Seeman, T. E. (2002). Allostatic load as a predictor of functional decline. MacArthur studies of successful aging. *Journal of Clinical Epidemiology*, *55*(7), 696–710. https://doi.org/10.1016/s0895-4356(02)00399-2

Kelli, H. M., Kim, J. H., Samman Tahhan, A., Liu, C., Ko, Y., Hammadah, M., Sullivan, S., Sandesara, P., Alkhoder, A. A., Choudhary, F. K., Gafeer, M. M., Patel, K., Qadir, S., Lewis, T. T., Vaccarino, V., Sperling, L. S., & Quyyumi, A. A. (2019). Living in Food Deserts and Adverse Cardiovascular Outcomes in Patients With Cardiovascular

Disease. *Journal of the American Heart Association: Cardiovascular and Cerebrovascular Disease*, *8*(4), e010694. https://doi.org/10.1161/JAHA.118.010694

Kerr, P., Kheloui, S., Rossi, M., Désilets, M., & Juster, R.-P. (2020). Allostatic load and women's brain health: A systematic review. *Frontiers in Neuroendocrinology*, *59*, 100858. https://doi.org/10.1016/j.yfrne.2020.100858

Kershaw, K. N., Magnani, J. W., Diez Roux, A. V., Camacho-Rivera, M., Jackson, E. A., Johnson, A. E., Magwood, G. S., Morgenstern, L. B., Salinas, J. J., Sims, M., Mujahid, M. S., & on behalf of the Council on Quality of Care and Outcomes Research; Council on Epidemiology and Prevention; Council on Clinical Cardiology; Council on Hypertension; Council on Cardiovascular and Stroke Nursing; Council on Peripheral Vascular Disease; and Council on the Kidney in Cardiovascular Disease. (2024). Neighborhoods and Cardiovascular Health: A Scientific Statement From the American Heart Association. *Circulation: Cardiovascular Quality and Outcomes*, *17*(1), e000124. https://doi.org/10.1161/HCQ.0000000000000124

Khan, M. M., Roberson, S., Reid, K., Jordan, M., & Odoi, A. (2021). Geographic disparities and temporal changes of diabetes prevalence and diabetes self-management education program participation in Florida. *PLOS ONE*, *16*(7), e0254579. https://doi.org/10.1371/journal.pone.0254579

Kim, E. S., Chen, Y., Kawachi, I., & VanderWeele, T. J. (2020). Perceived Neighborhood Social Cohesion and Subsequent Health and Well-Being in Older Adults: An Outcome-Wide Longitudinal Approach. *Health & Place*, *66*, 102420. https://doi.org/10.1016/j.healthplace.2020.102420

Kim, L. G., Carson, C., Lawlor, D. A., & Ebrahim, S. (2010). Geographical variation in cardiovascular incidence: Results from the British Women's Heart and Health Study. *BMC Public Health*, *10*(1), 696. https://doi.org/10.1186/1471-2458-10-696

Knies, G. (2018a). *Understanding Society: The UK Household Longitudinal Study, Waves 1-8 User Guide*. nstitute for Social and Economic Research, University of Essex.".

Knies, G. (2018b). *Understanding Society: The UK Household Longitudinal Study, Waves 1-8 User Guide*. nstitute for Social and Economic Research, University of Essex.".

Knies, G., Burgess, S., & Propper, C. (2008). Keeping up with the Schmidt's – An Empirical Test of Relative Deprivation Theory in the Neighbourhood Context. *Journal of Contextual Economics – Schmollers Jahrbuch*, *{"id":79,"journal_id":24,"name":"128","created_at":"2023-01-05 22:18:15","updated_at":"2023-01-05 22:18:15","price_individual_gbp":null,"price_individual_eur":null,"price_individual_usd":null,"price_institutional_gbp":null,"price_institutional_eur":null,"price_institutional_usd":null,"price_individual_hkd":null,"price_individual_rmb":null,"price_institutional_hkd":null,"price_institutional_rmb":null}*(1), 75–108. https://doi.org/10.3790/schm.128.1.75

Koob, G. F., & Le Moal, M. (2001). Drug Addiction, Dysregulation of Reward, and Allostasis. *Neuropsychopharmacology*, *24*(2), 97–129. https://doi.org/10.1016/S0893-133X(00)00195-0

Kuznetsova, A., Brockhoff, P. B., & Christensen, R. H. B. (2017). lmerTest Package: Tests in Linear Mixed Effects Models. *Journal of Statistical Software*, *82*, 1–26. https://doi.org/10.18637/jss.v082.i13

Kwan, M.-P. (2009). From place-based to people-based exposure measures. *Social Science & Medicine*, *69*(9), 1311–1313. https://doi.org/10.1016/j.socscimed.2009.07.013

Kwan, M.-P. (2012). The Uncertain Geographic Context Problem. *Annals of the Association of American Geographers*, *102*(5), 958–968. https://doi.org/10.1080/00045608.2012.687349

Laclau, E. (2001). 8.5 'Why do empty signifiers matter in politics?' In *Deconstruction: A Reader* (pp. 405–413). Edinburgh University Press. https://doi.org/10.1515/9781474470919-047

Lak, A., Rashidghalam, P., Amiri, S. N., Myint, P. K., & Baradaran, H. R. (2021). An ecological approach to the development of an active aging measurement in urban areas (AAMU). *BMC Public Health*, *21*(1), 4. https://doi.org/10.1186/s12889-020-10036-5

Lamb, K. E., Daniel, M., Chaix, B., Kestens, Y., Coffee, N. T., & Thornton, L. E. (2023). Socioeconomic differences in associations between living in a 20-min neighbourhood and diet, physical activity and self-rated health: Cross-sectional findings from ProjectPLAN. *Health & Place*, *84*, 103119. https://doi.org/10.1016/j.healthplace.2023.103119

Lamb, K. E., Thornton, L. E., King, T. L., Ball, K., White, S. R., Bentley, R., Coffee, N. T., & Daniel, M. (2020). Methods for accounting for neighbourhood self-selection in physical activity and dietary behaviour research: A systematic review. *International Journal of Behavioral Nutrition and Physical Activity*, *17*(1), 45. https://doi.org/10.1186/s12966-020-00947-2

Lanfear, C. C., Matsueda, R. L., & Beach, L. R. (2020). Broken Windows, Informal Social Control, and Crime: Assessing Causality in Empirical Studies. *Annual Review of Criminology*, *3*, 97–120. https://doi.org/10.1146/annurev-criminol-011419-041541

Latham, A., & Layton, J. (2019). Social infrastructure and the public life of cities: Studying urban sociality and public spaces. *Geography Compass*, *13*(7), e12444. https://doi.org/10.1111/gec3.12444

Latham, A., & Layton, J. (2022). Social infrastructure: Why it matters and how urban geographers might study it. *Urban Geography*. https://www.tandfonline.com/doi/abs/10.1080/02723638.2021.2003609

Laverty, A. A., Mindell, J. S., Webb, E. A., & Millett, C. (2013). Active Travel to Work and Cardiovascular Risk Factors in the United Kingdom. *American Journal of Preventive Medicine*, *45*(3), 282–288. https://doi.org/10.1016/j.amepre.2013.04.012

Leach, F. C. P., Yang, J., Shankar, V., Cole, S., Parnell, K., Entezami, M., & Bartington, S. E. (2024). The impact of a low traffic neighbourhood intervention on urban noise measured with low-cost sensors in Oxford, UK. *Transportation Research Part D: Transport and Environment*, *134*, 104357. https://doi.org/10.1016/j.trd.2024.104357

Lee, D. C., Jiang, Q., Tabaei, B. P., Elbel, B., Koziatek, C. A., Konty, K. J., & Wu, W. Y. (2018). Using Indirect Measures to Identify Geographic Hot Spots of Poor Glycemic Control: Cross-sectional Comparisons With an A1C Registry. *Diabetes Care*, *41*(7), 1438–1447. https://doi.org/10.2337/dc18-0181

Lee, K. H. (2020). Mental Health and Recreation Opportunities. *International Journal of Environmental Research and Public Health*, *17*(24), 9338. https://doi.org/10.3390/ijerph17249338

Lewis, C., & Buffel, T. (2020). Aging in place and the places of aging: A longitudinal study. *Journal of Aging Studies*, *54*, 100870. https://doi.org/10.1016/j.jaging.2020.100870

Lewis, N. A., & Hill, P. L. (2023). Sense of purpose in life and allostatic load in two longitudinal cohorts. *Journal of Psychosomatic Research*, *170*, 111346. https://doi.org/10.1016/j.jpsychores.2023.111346

Li, F., Harmer, P., Cardinal, B. J., Bosworth, M., & Johnson-Shelton, D. (2009). Obesity and the Built Environment: Does the Density of Neighborhood Fast-Food Outlets Matter? *American Journal of Health Promotion : AJHP*, *23*(3), 203–209.

Li, X. (2021, June 1). *Tutorial of rgeoda*. https://geodacenter.github.io/rgeoda/articles/rgeoda_tutorial.html

Li, Y., Yoshida, K., Kaufman, J. S., & Mathur, M. B. (2023). A Brief Primer on Conducting Regression-Based Causal Mediation Analysis—PMC. *Psychol Trauma*, *26*(6), 930–938. https://doi.org/10.1037/tra0001421

Lima, F. T., & Costa, F. (2023). The Quest for Proximity: A Systematic Review of Computational Approaches towards 15-Minute Cities. *Architecture*, *3*(3), Article 3. https://doi.org/10.3390/architecture3030021

Living Streets. (2023, March). *Campaigning in Scotland*. Living Streets. https://www.livingstreets.org.uk/about-us/living-streets-scotland/campaigning-in-scotland/

Logan, T. M., Hobbs, M. H., Conrow, L. C., Reid, N. L., Young, R. A., & Anderson, M. J. (2022). The x-minute city: Measuring the 10, 15, 20-minute city and an evaluation of its use for sustainable urban design. *Cities*, *131*, 103924. https://doi.org/10.1016/j.cities.2022.103924

Longpré-Poirier, C., Dougoud, J., Jacmin-Park, S., Moussaoui, F., Vilme, J., Desjardins, G., Cartier, L., Cipriani, E., Kerr, P., Page, C. L., & Juster, R.-P. (2022). Sex and Gender and Allostatic Mechanisms of Cardiovascular Risk and Disease. *Canadian Journal of Cardiology*, *38*(12), 1812–1827. https://doi.org/10.1016/j.cjca.2022.09.011

Lorenc, T., Petticrew, M., Whitehead, M., Neary, D., Clayton, S., Wright, K., Thomson, H., Cummins, S., Sowden, A., & Renton, A. (2014). Review of theories and pathways: Findings. In *Crime, fear of crime and mental health: Synthesis of theory and systematic reviews of interventions and qualitative evidence*. NIHR Journals Library. https://www.ncbi.nlm.nih.gov/books/NBK262852/

Lower Layer Super Output Areas (December 2011) Boundaries Super Generalised Clipped (BSC) EW V3. (n.d.). Retrieved 10 August 2022, from https://geoportal.statistics.gov.uk/datasets/ons::lower-layer-super-output-areas-december-2011-boundaries-super-generalised-clipped-bsc-ew-v3/about

Lu & Diab. (2023). Understanding the determinants of x-minute city policies: A review of the North American and Australian cities' planning documents. *Journal of Urban Mobility*, *3*, 100040. https://doi.org/10.1016/j.urbmob.2022.100040

Lucas, K. (2019). A new evolution for transport-related social exclusion research? *Journal of Transport Geography*, *81*, 102529. https://doi.org/10.1016/j.jtrangeo.2019.102529

Lucas, K., Philips, I., Mulley, C., & Ma, L. (2018). Is transport poverty socially or environmentally driven? Comparing the travel behaviours of two low-income populations living in central and peripheral locations in the same city. *Transportation Research Part A: Policy and Practice*, *116*, 622–634. https://doi.org/10.1016/j.tra.2018.07.007

Maas, J., van Dillen, S. M. E., Verheij, R. A., & Groenewegen, P. P. (2009). Social contacts as a possible mechanism behind the relation between green space and health. *Health & Place*, *15*(2), 586–595. https://doi.org/10.1016/j.healthplace.2008.09.006

Macdonald, L., Olsen, J. R., Shortt, N. K., & Ellaway, A. (2018). Do 'environmental bads' such as alcohol, fast food, tobacco, and gambling outlets cluster and co-locate in more deprived areas in Glasgow City, Scotland? *Health & Place*, *51*, 224–231. https://doi.org/10.1016/j.healthplace.2018.04.008

Macintyre, S., Macdonald, L., & Ellaway, A. (2008). Do poorer people have poorer access to local resources and facilities? The distribution of local resources by area deprivation in Glasgow, Scotland. *Social Science & Medicine*, *67*(6), 900–914. https://doi.org/10.1016/j.socscimed.2008.05.029

Macit, M. S., & Acar-Tek, N. (2020). *Evaluation of Nutritional Status and Allostatic Load in Adult Patients With Type 2 Diabetes—ScienceDirect*. *44*(2). https://doi.org/10.1016/j.jcjd.2019.05.011

Maier, S. F. (2014). Behavioral control blunts reactions to contemporaneous and future adverse events: Medial prefrontal cortex plasticity and a corticostriatal network. *Neurobiology of Stress*, *1*, 12. https://doi.org/10.1016/j.ynstr.2014.09.003

Maizlish, N., Linesch, N. J., & Woodcock, J. (2017). Health and greenhouse gas mitigation benefits of ambitious expansion of cycling, walking, and transit in California. *Journal of Transport & Health*, *6*, 490–500. https://doi.org/10.1016/j.jth.2017.04.011

Manley, D. (2019). Scale, Aggregation, and the Modifiable Areal Unit Problem. In M. M. Fischer & P. Nijkamp (Eds.), *Handbook of Regional Science* (pp. 1–15). Springer. https://doi.org/10.1007/978-3-642-36203-3_69-1

Maresova, P., Krejcar, O., Maskuriy, R., Bakar, N. A. A., Selamat, A., Truhlarova, Z., Horak, J., Joukl, M., & Vítkova, L. (2023). Challenges and opportunity in mobility among older adults – key determinant identification. *BMC Geriatrics*, *23*(1), 447. https://doi.org/10.1186/s12877-023-04106-7

Marmot, M. (2010). *Fair society, healthy lives: The Marmot Review : strategic review of health inequalities in England post-2010*. GOV.UK. https://www.gov.uk/research-for-development-outputs/fair-society-healthy-lives-the-marmot-review-strategic-review-of-health-inequalities-in-england-post-2010

Marmot, M., Allen, J., Boyce, T., Goldblatt, P., & Morrison, J. (2020). *Marmot Review 10 Years On*. https://www.instituteofhealthequity.org/resources-reports/marmot-review-10-years-on

Martín-Turrero, I., Valiente, R., Pastor, A., Bilal, U., & Sureda, X. (2024). Does geographic availability of alcohol influence drinking in adolescents? A systematic review of literature associations. *Health & Place*, *90*, 103362. https://doi.org/10.1016/j.healthplace.2024.103362

Mattei, J., Demissie, S., Falcon, L. M., Ordovas, J. M., & Tucker, K. (2010). Allostatic load is associated with chronic conditions in the Boston Puerto Rican Health Study.

Social Science & Medicine, *70*(12), 1988–1996. https://doi.org/10.1016/j.socscimed.2010.02.024

Matthews, S. A., & Yang, T.-C. (2010). Exploring the Role of the Built and Social Neighborhood Environment in Moderating Stress and Health. *Annals of Behavioral Medicine : A Publication of the Society of Behavioral Medicine*, *39*(2), 170–183. https://doi.org/10.1007/s12160-010-9175-7

Mawhorter, S., Crimmins, E. M., & Ailshire, J. A. (2023). Housing and cardiometabolic risk among older renters and homeowners. *Housing Studies*. https://www.tandfonline.com/doi/abs/10.1080/02673037.2021.1941792

McCrory, C., McLoughlin, S., Layte, R., NiCheallaigh, C., O'Halloran, A. M., Barros, H., Berkman, L. F., Bochud, M., M. Crimmins, E., T. Farrell, M., Fraga, S., Grundy, E., Kelly-Irving, M., Petrovic, D., Seeman, T., Stringhini, S., Vollenveider, P., & Kenny, R. A. (2023). Towards a consensus definition of allostatic load: A multi-cohort, multi-system, multi-biomarker individual participant data (IPD) meta-analysis. *Psychoneuroendocrinology*, *153*, 106117. https://doi.org/10.1016/j.psyneuen.2023.106117

McEwen, B. S. (1998a). Protective and Damaging Effects of Stress Mediators. *New England Journal of Medicine*, *338*(3), 171–179. https://doi.org/10.1056/NEJM199801153380307

McEwen, B. S. (1998b). Stress, Adaptation, and Disease: Allostasis and Allostatic Load. *Annals of the New York Academy of Sciences*, *840*(1), 33–44. https://doi.org/10.1111/j.1749-6632.1998.tb09546.x

McEwen, B. S. (2000). Allostasis and Allostatic Load: Implications for Neuropsychopharmacology. *Neuropsychopharmacology*, *22*(2), 108–124. https://doi.org/10.1016/S0893-133X(99)00129-3

McEwen, B. S. (2005). Stressed or stressed out: What is the difference? *Journal of Psychiatry and Neuroscience*, *30*(5), 315–318.

McEwen, B. S. (2017). *Neurobiological and Systemic Effects of Chronic Stress. Chronic Stress*. https://doi.org/10.1177/2470547017692328

McEwen, B. S., & Stellar, E. (1993a). Stress and the individual. Mechanisms leading to disease. *Archives of Internal Medicine*, *153*(18), 2093–2101.

McEwen, B. S., & Stellar, E. (1993b). Stress and the individual. Mechanisms leading to disease. *Archives of internal medicine*, *153*(18), 2093–2101.

McIntyre, N., Duncan, P., & Halliday, J. (2022, February 2). Levelling-up: Some wealthy areas of England to see 10 times more funding than poorest. *The Guardian*. https://www.theguardian.com/inequality/2022/feb/02/levelling-up-funding-inequality-exposed-by-guardian-research

McLoughlin, S., Kenny, R. A., & McCrory, C. (2020). Does the choice of Allostatic Load scoring algorithm matter for predicting age-related health outcomes? *Psychoneuroendocrinology*, *120*, 104789. https://doi.org/10.1016/j.psyneuen.2020.104789

Means, R. (2007). Safe as Houses? Ageing in Place and Vulnerable Older People in the UK. *Social Policy & Administration*, *41*(1), 65–85. https://doi.org/10.1111/j.1467-9515.2007.00539.x

Memiah, P., Biadgilign, S., Kuhlman, J., Cook, C., Mburia, P., Kingori, C., Sarpong, D., Buluku, G., & Hawkins, M. (2022). Allostatic Load, Single, and Dual Chronic

Conditions: Evidence from the National Health and Nutrition Examination Survey. *Metabolic Syndrome and Related Disorders*, *20*(2), 104–113. https://doi.org/10.1089/met.2021.0008

Mendes de Leon, C. F., Cagney, K. A., Bienias, J. L., Barnes, L. L., Skarupski, K. A., Scherr, P. A., & Evans, D. A. (2009). Neighborhood Social Cohesion and Disorder in Relation to Walking in Community-Dwelling Older Adults: A Multi-Level Analysis. *Journal of Aging and Health*, *21*(1), 155–171. https://doi.org/10.1177/0898264308328650

Merkin, S. S., Basurto-Dávila, R., Karlamangla, A., Bird, C. E., Lurie, N., Escarce, J., & Seeman, T. (2009). Neighborhoods and Cumulative Biological Risk Profiles by Race/Ethnicity in a National Sample of U.S. Adults: NHANES III. *Annals of Epidemiology*, *19*(3), 194–201. https://doi.org/10.1016/j.annepidem.2008.12.006

Meyer, D., & Denise, E. J. (2014). Sexual Orientation and Fear at Night: Gender Differences Among Sexual Minorities and Heterosexuals. *Journal of Homosexuality*, *61*(4), 453–470. https://doi.org/10.1080/00918369.2013.834212

Meyer, O. L., Castro-Schilo, L., & Aguilar-Gaxiola, S. (2014). Determinants of Mental Health and Self-Rated Health: A Model of Socioeconomic Status, Neighborhood Safety, and Physical Activity. *American Journal of Public Health*, *104*(9), 1734–1741. https://doi.org/10.2105/AJPH.2014.302003

Michimi, A., & Wimberly, M. C. (2010). Associations of supermarket accessibility with obesity and fruit and vegetable consumption in the conterminous United States. *International Journal of Health Geographics*, *9*(1), 49. https://doi.org/10.1186/1476-072X-9-49

Middleton, G., Patterson, K. A., Muir-Cochrane, E., Velardo, S., McCorry, F., & Coveney, J. (2022). The Health and Well-being Impacts of Community Shared Meal Programs for Older Populations: A Scoping Review. *Innovation in Aging*, *6*(7), igac068. https://doi.org/10.1093/geroni/igac068

Mihaylova, N. (2021). *How transport offers a route to better health | The Health Foundation*. https://www.health.org.uk/reports-and-analysis/briefings/how-transport-offers-a-route-to-better-health

Moreno, C., Allam, Z., Chabaud, D., Gall, C., & Pratlong, F. (2021). Introducing the "15-Minute City": Sustainability, Resilience and Place Identity in Future Post-Pandemic Cities. *Smart Cities*, *4*(1), 93–111. https://doi.org/10.3390/smartcities4010006

Mouratidis, K. (2018). Built environment and social well-being: How does urban form affect social life and personal relationships? *Cities*, *74*, 7–20. https://doi.org/10.1016/j.cities.2017.10.020

Mouratidis, K., & Yiannakou, A. (2022). What makes cities livable? Determinants of neighborhood satisfaction and neighborhood happiness in different contexts. *Land Use Policy*, *112*, 105855. https://doi.org/10.1016/j.landusepol.2021.105855

Murayama, H., Fujiwara, Y., & Kawachi, I. (2012). Social Capital and Health: A Review of Prospective Multilevel Studies. *Journal of Epidemiology*, *22*(3), 179–187. https://doi.org/10.2188/jea.JE20110128

Murray, E. T., Ben-Shlomo, Y., Tilling, K., Southall, H., Aucott, P., Kuh, D., & Hardy, R. (2013). Area Deprivation Across the Life Course and Physical Capability in

Midlife: Findings From the 1946 British Birth Cohort. *American Journal of Epidemiology*, *178*(3), 441–450. https://doi.org/10.1093/aje/kwt003

Myers, C. A. (2020). Food Insecurity and Psychological Distress: A Review of the Recent Literature. *Current Nutrition Reports*, *9*(2), 107–118. https://doi.org/10.1007/s13668-020-00309-1

National Travel Survey 2021: Travel by region and rural and urban classification of residence. (2022, August 31). GOV.UK. https://www.gov.uk/government/statistics/national-travel-survey-2021/national-travel-survey-2021-travel-by-region-and-rural-and-urban-classification-of-residence

Navarrete-Hernandez, P., & Afarin, K. (2023). The impact of nature-based solutions on perceptions of safety in public space. *Journal of Environmental Psychology*, *91*, 102132. https://doi.org/10.1016/j.jenvp.2023.102132

Nazmi, A., Diez Roux, A., Ranjit, N., Seeman, T. E., & Jenny, N. S. (2010). Cross-sectional and longitudinal associations of neighborhood characteristics with inflammatory markers: Findings from the multi-ethnic study of atherosclerosis. *Health & Place*, *16*(6), 1104–1112. https://doi.org/10.1016/j.healthplace.2010.07.001

Nesse, R., Bhatnagar, S., & Ellis, B. (2016). Evolutionary Origins and Functions of the Stress Response System. In *Stress: Concepts, Cognition, Emotion, and Behavior: Handbook of Stress* (pp. 95–101). https://doi.org/10.1016/B978-0-12-800951-2.00011-X

Nesse, R. M. (2005). Natural selection and the regulation of defenses: A signal detection analysis of the smoke detector principle. *Evolution and Human Behavior*, *26*(1), 88–105. https://doi.org/10.1016/j.evolhumbehav.2004.08.002

Nguyen, P.-Y., Astell-Burt, T., Rahimi-Ardabili, H., & Feng, X. (2021). Green Space Quality and Health: A Systematic Review. *International Journal of Environmental Research and Public Health*, *18*(21), 11028. https://doi.org/10.3390/ijerph182111028

Nowossadeck, S., Romeu Gordo, L., & Lozano Alcántara, A. (2023). Mobility restriction and barrier-reduced housing among people aged 65 or older in Germany: Do those who need it live in barrier-reduced residences? *Frontiers in Public Health*, *11*. https://doi.org/10.3389/fpubh.2023.1098005

Obasi, E. M., Shirtcliff, E. A., Cavanagh, L., Ratliff, K. L., Pittman, D. M., & Brooks, J. J. (2017). Hypothalamic-Pituitary-Adrenal Reactivity to Acute Stress: An Investigation into the Roles of Perceived Stress and Family Resources. *Prevention Science : The Official Journal of the Society for Prevention Research*, *18*(8), 923–931. https://doi.org/10.1007/s11121-017-0759-3

Okwuosa, I. S., Lewsey, S. C., Adesiyun, T., Blumenthal, R. S., & Yancy, C. W. (2016). Worldwide disparities in cardiovascular disease: Challenges and solutions. *International Journal of Cardiology*, *202*, 433–440. https://doi.org/10.1016/j.ijcard.2015.08.172

Oliver, L. N., Schuurman, N., & Hall, A. W. (2007). Comparing circular and network buffers to examine the influence of land use on walking for leisure and errands. *International Journal of Health Geographics*, *6*(1), 41. https://doi.org/10.1186/1476-072X-6-41

Olsen, J. R., Caryl, F., Nicholls, N., Smith, M., McCrorie, P., & Mitchell, R. (2023). Inequalities in neighbourhood features within children’s 20-minute neighbourhoods and variation in time spent locally, measured using GPS.

Wellbeing, Space and Society, *5*, 100174. https://doi.org/10.1016/j.wss.2023.100174

Olsen, J. R., Nicholls, N., Panter, J., Burnett, H., Tornow, M., & Mitchell, R. (2022). Trends and inequalities in distance to and use of nearest natural space in the context of the 20-min neighbourhood: A 4-wave national repeat cross-sectional study, 2013 to 2019. *Environmental Research*, *213*, 113610. https://doi.org/10.1016/j.envres.2022.113610

Olsen, J. R., Thornton, L., Tregonning, G., & Mitchell, R. (2022). Nationwide equity assessment of the 20-min neighbourhood in the scottish context: A socio-spatial proximity analysis of residential locations. *Social Science & Medicine*, *315*, 115502. https://doi.org/10.1016/j.socscimed.2022.115502

ONS. (2017, October 9). *Rural Urban Classification (2011) of LSOAs in EW*. https://geoportal.statistics.gov.uk/datasets/ons::rural-urban-classification-2011-of-lsoas-in-ew/about

ONS. (2020a). *Overview of the UK population—Office for National Statistics*. https://www.ons.gov.uk/peoplepopulationandcommunity/populationandmigration/populationestimates/articles/overviewoftheukpopulation/2020

ONS. (2020b, July 20). *Living longer: Trends in subnational ageing across the UK - Office for National Statistics*. https://www.ons.gov.uk/peoplepopulationandcommunity/birthsdeathsandmarriages/ageing/articles/livinglongertrendsinsubnationalageingacrosstheuk/2020-07-20

ONS. (2022, March 13). *Perceptions of personal safety and experiences of harassment, Great Britain—Office for National Statistics*.

https://www.ons.gov.uk/peoplepopulationandcommunity/crimeandjustice/bulletins/perceptionsofpersonalsafetyandexperiencesofharassmentgreatbritain/16februaryto13march2022

ONS. (2025). *Statistical geographies—Office for National Statistics*. https://www.ons.gov.uk/methodology/geography/ukgeographies/statisticalgeographies

Oostenbach, L. H., Burnett, A. J., Lamb, K. E., & Thornton, L. E. (2024). Exploring food shopping behaviours in 20-minute neighbourhoods: A cross-sectional analysis of ProjectPLAN. *Cities & Health*, *8*(4), 588–600. https://doi.org/10.1080/23748834.2023.2297333

Openshaw, S. (1979). A million or so correlated coefficients: Three experiment on the modifiable areal unit problem. *Statistical Applications in the Spatial Sciences*. https://cir.nii.ac.jp/crid/1571135650655620224

Osei, F., Block, A., & Wippert, P.-M. (2022). Association of primary allostatic load mediators and metabolic syndrome (MetS): A systematic review. *Frontiers in Endocrinology*, *13*, 946740. https://doi.org/10.3389/fendo.2022.946740

Osmënaj, T., Lam, T. M., Wagtendonk, A. J., & den Braver, N. R. (2024). Walking to work: The role of walkability around the workplace in a Dutch adult commuting population. *SSM - Population Health*, *25*, 101578. https://doi.org/10.1016/j.ssmph.2023.101578

Ottaviani, C., Thayer, J. F., Verkuil, B., Lonigro, A., Medea, B., Couyoumdjian, A., & Brosschot, J. F. (2016). Physiological concomitants of perseverative cognition: A systematic review and meta-analysis. *Psychological Bulletin*, *142*(3), 231–259. https://doi.org/10.1037/bul0000036

Our Ageing Population | The State of Ageing 2023-24 | Centre for Ageing Better. (2023). https://ageing-better.org.uk/our-ageing-population-state-ageing-2023-4

Our Place. (2021). *20 Minute Neighbourhoods | Our Place*. https://www.ourplace.scot/about-place/themes/20-minute-neighbourhoods-home/20-minute-neighbourhoods

Padeiro, M., José, J. de S., Amado, C., Sousa, L., Oliveira, C. R., Esteves, A., & McGarrigle, J. (2021). Neighborhood Attributes and Well-Being Among Older Adults in Urban Areas: A Mixed-Methods Systematic Review. *Research on Aging*, *44*(5–6), 351. https://doi.org/10.1177/0164027521999980

Pani-Harreman, K. E., Bours, G. J. J. W., Zander, I., Kempen, G. I. J. M., & Duren, J. M. A. van. (2021). Definitions, key themes and aspects of 'ageing in place': A scoping review. *Ageing & Society*, *41*(9), 2026–2059. https://doi.org/10.1017/S0144686X20000094

Panter, J., Mytton, O., Sharp, S., Brage, S., Cummins, S., Laverty, A. A., Wijndaele, K., & Ogilvie, D. (2018). Using alternatives to the car and risk of all-cause, cardiovascular and cancer mortality. *Heart*, *104*(21), 1749–1755. https://doi.org/10.1136/heartjnl-2017-312699

Parenteau, M.-P., & Sawada, M. C. (2011). The modifiable areal unit problem (MAUP) in the relationship between exposure to NO2 and respiratory health. *International Journal of Health Geographics*, *10*(1), 58. https://doi.org/10.1186/1476-072X-10-58

Parker, H. W., Abreu, A. M., Sullivan, M. C., & Vadiveloo, M. K. (2022). Allostatic Load and Mortality: A Systematic Review and Meta-Analysis. *American Journal of*

Preventive Medicine, *63*(1), 131–140. https://doi.org/10.1016/j.amepre.2022.02.003

parliament.uk. (2017, March 25). *House of Lords—Tackling financial exclusion: A country that works for everyone? - Select Committee on Financial Exclusion*. https://publications.parliament.uk/pa/ld201617/ldselect/ldfinexcl/132/13209.htm

parliament.uk. (2022). *Current levels of public transport demand*. https://committees.parliament.uk/writtenevidence/107021/html/

Pasanen, T. P., White, M. P., Elliott, L. R., van den Bosch, M., Bratman, G. N., Ojala, A., Korpela, K., & Fleming, L. E. (2023). Urban green space and mental health among people living alone: The mediating roles of relational and collective restoration in an 18-country sample. *Environmental Research*, *232*, 116324. https://doi.org/10.1016/j.envres.2023.116324

Patias, N., Rowe, F., & Arribas-Bel, D. (2023). Local urban attributes defining ethnically segregated areas across English cities: A multilevel approach. *Cities*, *132*, 103967. https://doi.org/10.1016/j.cities.2022.103967

Patterson, R., de Oliveira, C., Schneider, I. J. C., Mindell, J. S., Panter, J., & Laverty, A. A. (2024). Public transport use and mortality among older adults in England: A cohort study. *Preventive Medicine*, *186*, 108064. https://doi.org/10.1016/j.ypmed.2024.108064

Patterson, R., Panter, J., Vamos, E. P., Cummins, S., Millett, C., & Laverty, A. A. (2020). Associations between commute mode and cardiovascular disease, cancer, and all-cause mortality, and cancer incidence, using linked Census data over 25 years in England and Wales: A cohort study. *The Lancet Planetary Health*, *4*(5), e186–e194. https://doi.org/10.1016/S2542-5196(20)30079-6

Pearce, J., Witten, K., Hiscock, R., & Blakely, T. (2007). Are socially disadvantaged neighbourhoods deprived of health-related community resources? *International Journal of Epidemiology*, *36*(2), 348–355. https://doi.org/10.1093/ije/dyl267

Pearson, A. L., Clevenger, K. A., Horton, T. H., Gardiner, J. C., Asana, V., Dougherty, B. V., & Pfeiffer, K. A. (2021). Feelings of safety during daytime walking: Associations with mental health, physical activity and cardiometabolic health in high vacancy, low-income neighborhoods in Detroit, Michigan. *International Journal of Health Geographics*, *20*(1), 19. https://doi.org/10.1186/s12942-021-00271-3

Pearson, A. L., Tribby, C., Brown, C. D., Yang, J.-A., Pfeiffer, K., & Jankowska, M. M. (2024). Systematic review of best practices for GPS data usage, processing, and linkage in health, exposure science and environmental context research. *BMJ Open*, *14*(2), e077036. https://doi.org/10.1136/bmjopen-2023-077036

Pebesma, E. (2018). Simple Features for R: Standardized Support for Spatial Vector Data. *The R Journal*, *10*(1), 439–446.

Pelikh, A., Borkowska, M., & Patel, R. (2020). *Understanding geographical mobility: Data note*. https://www.understandingsociety.ac.uk/research/publications/publication-547460/

Pereira, G., Wood, L., Foster, S., & Haggar, F. (2013). Access to Alcohol Outlets, Alcohol Consumption and Mental Health. *PLoS ONE*, *8*(1), e53461. https://doi.org/10.1371/journal.pone.0053461

Pérez, E., Braën, C., Boyer, G., Mercille, G., Rehany, É., Deslauriers, V., Bilodeau, A., & Potvin, L. (2020). Neighbourhood community life and health: A systematic review of reviews. *Health & Place*, *61*, 102238. https://doi.org/10.1016/j.healthplace.2019.102238

Perissinotto, C. M., & Covinsky, K. E. (2014). Living Alone, Socially Isolated or Lonely—What are We Measuring? *Journal of General Internal Medicine*, *29*(11), 1429–1431. https://doi.org/10.1007/s11606-014-2977-8

Petrović, A., van Ham, M., & Manley, D. (2022). Where Do Neighborhood Effects End? Moving to Multiscale Spatial Contextual Effects. *Annals of the American Association of Geographers*, *112*(2), 581–601. https://doi.org/10.1080/24694452.2021.1923455

Piazza, J. R., Stawski, R. S., & Sheffler, J. L. (2019). Age, Daily Stress Processes, and Allostatic Load: A Longitudinal Study. *Journal of Aging and Health*, *31*(9), 1671–1691. https://doi.org/10.1177/0898264318788493

Planning. (2024, March 22). *20-minute neighbourhoods*. Planning; Planning. https://www.planning.vic.gov.au/guides-and-resources/strategies-and-initiatives/20-minute-neighbourhoods

PointX, & OS. (2025). *This product includes data licensed from PointX © Database Right/Copyright 2025 and OS © Crown Copyright 2025. All rights reserved. Licence number 100034829*. [Dataset]. https://www.ordnancesurvey.co.uk/products/points-of-interest

Pozoukidou, G., & Chatziyiannaki, Z. (2021). 15-Minute City: Decomposing the New Urban Planning Eutopia. *Sustainability*, *13*(2), Article 2. https://doi.org/10.3390/su13020928

Preacher, K. J., & Hayes, A. F. (2008). Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. *Behavior Research Methods*, *40*(3), 879–891. https://doi.org/10.3758/BRM.40.3.879

PricewaterhouseCoopers. (2024). *Store Openings and Closures H1 2024*. PwC. https://www.pwc.co.uk/industries/retail-consumer/insights/store-openings-and-closures.html

Prior, L. (2021). Allostatic Load and Exposure Histories of Disadvantage. *International Journal of Environmental Research and Public Health*, *18*(14), Article 14. https://doi.org/10.3390/ijerph18147222

Prior, L., Manley, D., & Jones, K. (2018a). Stressed out? An investigation of whether allostatic load mediates associations between neighbourhood deprivation and health. *Health & Place*, *52*, 25–33. https://doi.org/10.1016/j.healthplace.2018.05.003

Prior, L., Manley, D., & Jones, K. (2018b). Stressed out? An investigation of whether allostatic load mediates associations between neighbourhood deprivation and health. *Health & Place*, *52*, 25–33. https://doi.org/10.1016/j.healthplace.2018.05.003

Public space. (n.d.). Engender. Retrieved 10 December 2024, from https://www.engender.org.uk/research-public-space/

Puciato, D., & Rozpara, M. (2021). Physical activity and socio-economic status of single and married urban adults: A cross-sectional study. *PeerJ*, *9*, e12466. https://doi.org/10.7717/peerj.12466

Qin, W., Xiang, X., & Taylor, H. (2020). Driving Cessation and Social Isolation in Older Adults. *Journal of Aging and Health*, *32*(9), 962–971. https://doi.org/10.1177/0898264319870400

Qiu, X., Shi, L., Kubzansky, L. D., Wei, Y., Castro, E., Li, H., Weisskopf, M. G., & Schwartz, J. D. (2023). Association of Long-term Exposure to Air Pollution With Late-Life Depression in Older Adults in the US. *JAMA Network Open*, *6*(2), e2253668. https://doi.org/10.1001/jamanetworkopen.2022.53668

Read, S., & Grundy, E. (2014). Allostatic Load and Health in the Older Population of England: A Crossed-Lagged Analysis. *Psychosomatic Medicine*, *76*(7), 490. https://doi.org/10.1097/PSY.0000000000000083

Recio, A., Linares, C., Banegas, J. R., & Díaz, J. (2016). Road traffic noise effects on cardiovascular, respiratory, and metabolic health: An integrative model of biological mechanisms. *Environmental Research*, *146*, 359–370. https://doi.org/10.1016/j.envres.2015.12.036

Reinhard, E., Courtin, E., van Lenthe, F. J., & Avendano, M. (2018). Public transport policy, social engagement and mental health in older age: A quasi-experimental evaluation of free bus passes in England. *Journal of Epidemiology and Community Health*, *72*(5), 361–368. https://doi.org/10.1136/jech-2017-210038

Revised annual mid-year population estimates, UK - Office for National Statistics. (2024, October 31). https://www.ons.gov.uk/peoplepopulationandcommunity/populationandmigration/populationestimates/bulletins/annualmidyearpopulationestimates/2013-12-17

Ribeiro, A. I., Amaro, J., Lisi, C., & Fraga, S. (2018). Neighborhood Socioeconomic Deprivation and Allostatic Load: A Scoping Review. *International Journal of Environmental Research and Public Health*, *15*(6), 1092. https://doi.org/10.3390/ijerph15061092

Ribeiro, A. I., Fraga, S., & Kelly-Irving, M. (2019). Neighbourhood socioeconomic deprivation and allostatic load: A multi-cohort study. *Sci Rep*, *9*, 8790. https://doi.org/10.1038/s41598-019-45432-4

Ribeiro, A. I., Fraga, S., Kelly-Irving, M., Delpierre, C., Kivimaki, M., Joost, S., Guessos, I., Gandini, M., Vineis, P., & Barros, H. (2019). *Neighbourhood socioeconomic deprivation and allostatic load: A multi-cohort study | Scientific Reports*. https://www.nature.com/articles/s41598-019-45432-4

Ribeiro, A. I., Gullón, P., & Murray, E. T. (2022). Neighbourhood Influences on Population Health: Time to Unpack the Black Box. *Public Health Reviews*, *43*, 1605053. https://doi.org/10.3389/phrs.2022.1605053

Ribeiro, A. I., Tavares, C., Guttentag, A., & Barros, H. (2019). Association between neighbourhood green space and biological markers in school-aged children. Findings from the Generation XXI birth cohort. *Environment International*, *132*, 105070. https://doi.org/10.1016/j.envint.2019.105070

Richards, L., Maharani, A., & Präg, P. (2023). *Subjective social status and allostatic load among older people in England: A longitudinal analysis—ScienceDirect*. *320*(115749). https://www.sciencedirect.com/science/article/pii/S0277953623001053#sec3

Richardson, E. A., Hill, S. E., Mitchell, R., Pearce, J., & Shortt, N. K. (2015). Is local alcohol outlet density related to alcohol-related morbidity and mortality in

Scottish cities? *Health & Place*, *33*, 172–180. https://doi.org/10.1016/j.healthplace.2015.02.014

Richardson, L. J., Goodwin, A. N., & Hummer, R. A. (2021). Social status differences in allostatic load among young adults in the United States. *SSM - Population Health*, *15*, 100771. https://doi.org/10.1016/j.ssmph.2021.100771

Robertson, T., Benzeval, M., Whitley, E., & Popham, F. (2015). The role of material, psychosocial and behavioral factors in mediating the association between socioeconomic position and allostatic load (measured by cardiovascular, metabolic and inflammatory markers). *Brain, Behavior, and Immunity*, *45*, 41–49. https://doi.org/10.1016/j.bbi.2014.10.005

Robertson, T., Popham, F., & Benzeval, M. (2014). Socioeconomic position across the lifecourse & allostatic load: Data from the West of Scotland Twenty-07 cohort study. *BMC Public Health*, *14*(1), 184. https://doi.org/10.1186/1471-2458-14-184

Robertson, T., & Watts, E. (2016). The importance of age, sex and place in understanding socioeconomic inequalities in allostatic load: Evidence from the Scottish Health Survey (2008–2011). *BMC Public Health*, *16*(1), 126. https://doi.org/10.1186/s12889-016-2796-4

Robinette, J. W., Charles, S. T., Almeida, D. M., & Gruenewald, T. L. (2016). Neighborhood features and physiological risk: An examination of allostatic load. *Health & Place*, *41*, 110–118. https://doi.org/10.1016/j.healthplace.2016.08.003

Robinson, D., Hayes, A., Couch [aut, S., cre, Software, P., PBC, Patil, I., Chiu, D., Gomez, M., Demeshev, B., Menne, D., Nutter, B., Johnston, L., Bolker, B., Briatte, F., Arnold, J., Gabry, J., Selzer, L., Simpson, G., … Reinhart, A. (2024). *broom:*

Convert Statistical Objects into Tidy Tibbles (Version 1.0.7) [Computer software]. https://cran.r-project.org/web/packages/broom/index.html

Robinson, D., & Wilkinson, D. (1995). Sense of community in a remote mining town: Validating a Neighborhood Cohesion scale. *American Journal of Community Psychology*, *23*(1), 137–148. https://doi.org/10.1007/BF02506926

Robinson, W. S. (1950). Ecological Correlations and the Behavior of Individuals. *American Sociological Review*, *15*(3), 351–357. https://doi.org/10.2307/2087176

Roest, A. M., Martens, E. J., de Jonge, P., & Denollet, J. (2010). Anxiety and Risk of Incident Coronary Heart Disease: A Meta-Analysis. *Journal of the American College of Cardiology*, *56*(1), 38–46. https://doi.org/10.1016/j.jacc.2010.03.034

Ross, C. E., & Mirowsky, J. (2001). Neighborhood Disadvantage, Disorder, and Health. *Journal of Health and Social Behavior*, *42*(3), 258–276. https://doi.org/10.2307/3090214

Rote, S. (2017). Marital Disruption and Allostatic Load in Late Life. *Journal of Aging and Health*, *29*(4), 688–707. https://doi.org/10.1177/0898264316641084

Roux, A. V. D., & Mair, C. (2010). Neighborhoods and health. *Annals of the New York Academy of Sciences*, *1186*(1), 125–145. https://doi.org/10.1111/j.1749-6632.2009.05333.x

Roy, N., Dubé, R., Després, C., Freitas, A., & Légaré, F. (2018). Choosing between staying at home or moving: A systematic review of factors influencing housing decisions among frail older adults. *PLOS ONE*, *13*(1), e0189266. https://doi.org/10.1371/journal.pone.0189266

RSPH. (2018). *Britain's unhealthiest high streets revealed: Northern towns and cities top the rankings for unhealthiest high streets*. https://www.rsph.org.uk/about-us/news/britain-s-unhealthiest-high-streets-revealed-northern-towns-and-cities-top-the-rankings-for-unhealthiest-high-streets.html

RTPI. (2021, March). *Implementing 20 Minute Neighbourhoods in Planning Policy and Practice*. https://www.rtpi.org.uk/research-rtpi/2021/march/20-minute-neighbourhoods/

Ryu, S., & Fan, L. (2023). The Relationship Between Financial Worries and Psychological Distress Among U.S. Adults. *Journal of Family and Economic Issues*, *44*(1), 16–33. https://doi.org/10.1007/s10834-022-09820-9

Saelens, B. E., & Handy, S. L. (2008). Built Environment Correlates of Walking: A Review. *Medicine and Science in Sports and Exercise*, *40*(7 Suppl), S550–S566. https://doi.org/10.1249/MSS.0b013e31817c67a4

Sait, N., & Jivraj, S. (2022). Assessing changes in neighbourhood satisfaction among older age adults in England using the English Longitudinal Study of Ageing. *Wellbeing, Space and Society*, *3*, 100107. https://doi.org/10.1016/j.wss.2022.100107

Salvatore, M. A., & Grundy, E. (2021). Area deprivation, perceived neighbourhood cohesion and mental health at older ages: A cross lagged analysis of UK longitudinal data. *Health & Place*, *67*, 102470. https://doi.org/10.1016/j.healthplace.2020.102470

Sampson, R. J., & Raudenbush, S. W. (2004). Seeing Disorder: Neighborhood Stigma and the Social Construction of “Broken Windows”. *Social Psychology Quarterly*, *67*(4), 319–342. https://doi.org/10.1177/019027250406700401

Sarkar, C. (2018). Residential greenness and prevalence of major depressive disorders: A cross-sectional, observational, associational study of 94?879 adult UK Biobank participants. *The Lancet Planetary Health*, *2*(ue 4), 162–173.

Sarkar, C., Gallacher, J., & Webster, C. (2013a). Built environment configuration and change in body mass index: The Caerphilly Prospective Study (CaPS). *Health & Place*, *19*, 33–44. https://doi.org/10.1016/j.healthplace.2012.10.001

Sarkar, C., Gallacher, J., & Webster, C. (2013b). Urban built environment configuration and psychological distress in older men: Results from the Caerphilly study. *BMC Public Health*, *13*, 695. https://doi.org/10.1186/1471-2458-13-695

Sarkar, C., Gallacher, J., & Webster, C. (2013c). Urban built environment configuration and psychological distress in older men: Results from the Caerphilly study. *BMC Public Health*, *13*, 695. https://doi.org/10.1186/1471-2458-13-695

Sarkar, C., Webster, C., & Gallacher, J. (2015). UK Biobank Urban Morphometric Platform (UKBUMP) – a nationwide resource for evidence-based healthy city planning and public health interventions. *Annals of GIS*, *21*(2), 135–148. https://doi.org/10.1080/19475683.2015.1027791

Saxbe, D. E., Beckes, L., Stoycos, S. A., & Coan, J. A. (2020a). Social Allostasis and Social Allostatic Load: A New Model for Research in Social Dynamics. *Stress, and Health*. *Perspectives on Psychological Science*, *15*(2), 469–482. https://doi.org/10.1177/1745691619876528

Saxbe, D. E., Beckes, L., Stoycos, S. A., & Coan, J. A. (2020b). Social Allostasis and Social Allostatic Load: A New Model for Research in Social Dynamics, Stress, and Health. *Perspectives on Psychological Science*, *15*(2), 469–482. https://doi.org/10.1177/1745691619876528

Schulz, A. J., Mentz, G., Lachance, L., Zenk, S. N., Johnson, J., Stokes, C., & Mandell, R. (2013). Do observed or perceived characteristics of the neighborhood environment mediate associations between neighborhood poverty and cumulative biological risk? *Health & Place*, *24*, 10.1016/j.healthplace.2013.09.005. https://doi.org/10.1016/j.healthplace.2013.09.005

Schulz, A., & Northridge, M. E. (2004). Social determinants of health: Implications for environmental health promotion. *Health Education & Behavior: The Official Publication of the Society for Public Health Education*, *31*(4), 455–471. https://doi.org/10.1177/1090198104265598

Scott, K. A., Melhorn, S. J., & Sakai, R. R. (2012). Effects of Chronic Social Stress on Obesity. *Current Obesity Reports*, *1*(1), 16–25. https://doi.org/10.1007/s13679-011-0006-3

Seeman, T. E., McEwen, B. S., Rowe, J. W., & Singer, B. H. (2001). Allostatic load as a marker of cumulative biological risk: MacArthur studies of successful aging. *Proceedings of the National Academy of Sciences*, *98*(8), 4770–4775. https://doi.org/10.1073/pnas.081072698

Seeman, T. E., Singer, B. H., Rowe, J. W., Horwitz, R. I., & McEwen, B. S. (1997). Price of adaptation—Allostatic load and its health consequences. MacArthur studies of successful aging. *Archives of Internal Medicine*, *157*(19), 2259–2268.

Seeman, T., Epel, E., Gruenewald, T., Karlamangla, A., & McEwen, B. S. (2010). Socio-economic differentials in peripheral biology: Cumulative allostatic load. *Annals of the New York Academy of Sciences*, *1186*, 223–239. https://doi.org/10.1111/j.1749-6632.2009.05341.x

Shahid, R., Bertazzon, S., Knudtson, M. L., & Ghali, W. A. (2009). Comparison of distance measures in spatial analytical modeling for health service planning. *BMC Health Services Research*, *9*(1), 200. https://doi.org/10.1186/1472-6963-9-200

Shaw, J. (2023, January 27). Where has the levelling-up fund money been distributed? *New Statesman*. https://www.newstatesman.com/spotlight/2023/01/levelling-up-fund-money-how-distributed

Silva, D. C. D., King, D. A., & Lemar, S. (2019). Accessibility in Practice: 20-Minute City as a Sustainability Planning Goal. *Sustainability*, *12*(1), 1–20.

Sjoberg, D. D., Whiting, K., Curry, M., Lavery, J. A., & Larmarange, J. (2021). Reproducible Summary Tables with the gtsummary Package. *The R Journal*, *13*(1), 570–580.

Skelly, A. C., Dettori, J. R., & Brodt, E. D. (2012). Assessing bias: The importance of considering confounding. *Evidence-Based Spine-Care Journal*, *3*(1), 9–12. https://doi.org/10.1055/s-0031-1298595

Social Determinants of Health—Healthy People 2030 | *health.gov*. (2024, July 29). https://health.gov/healthypeople/priority-areas/social-determinants-health

Stephen, G., Muldoon Orla, T., & Bennett Kate, M. (2021). Multiple group membership, social network size, allostatic load and well-being: A mediation analysis. *Journal of Psychosomatic Research*, *151*, 110636. https://doi.org/10.1016/j.jpsychores.2021.110636

Sterne, J. A. C., White, I. R., Carlin, J. B., Spratt, M., Royston, P., Kenward, M. G., Wood, A. M., & Carpenter, J. R. (2009). Multiple imputation for missing data in epidemiological and clinical research: Potential and pitfalls. *BMJ*, *338*, b2393. https://doi.org/10.1136/bmj.b2393

Stillwell, J., Daras, K., & Bell, M. (2018). Spatial Aggregation Methods for Investigating the MAUP Effects in Migration Analysis. *Applied Spatial Analysis and Policy*, *11*(4), 693–711. https://doi.org/10.1007/s12061-018-9274-6

Stone, R. A., Brown, A., Douglas, F., Green, M. A., Hunter, E., Lonnie, M., Johnstone, A. M., & Hardman, C. A. (2024). The impact of the cost of living crisis and food insecurity on food purchasing behaviours and food preparation practices in people living with obesity. *Appetite*, *196*, 107255. https://doi.org/10.1016/j.appet.2024.107255

Stonehaven. (2024). *Moving Hearts and Minds—Delivering Infrastructure for the Age of Populism*. https://www.stonehavenglobal.com/moving_hearts_and_minds_delivering_infrastructure_for_the_age_of_populism

Study documentation. (2024, accessed). ELSA. https://www.elsa-project.ac.uk/study-documentation

Sugiyama, T., Chandrabose, M., Homer, A. R., Sugiyama, M., Dunstan, D. W., & Owen, N. (2020). Car use and cardiovascular disease risk: Systematic review and implications for transport research. *Journal of Transport & Health*, *19*, 100930. https://doi.org/10.1016/j.jth.2020.100930

SUSTRANS. (2018, February 1). *Exploring gender and active travel*. Sustrans. https://www.sustrans.org.uk/our-blog/research/exploring-gender-and-active-travel/

SUSTRANS. (2020). *What is a 20-minute neighbourhood?* https://www.sustrans.org.uk/our-blog/get-active/what-is-a-20-minute-neighbourhood/

Suvarna, B., Suvarna, A., Phillips, R., Juster, R.-P., McDermott, B., & Sarnyai, Z. (2020). Health risk behaviours and allostatic load: A systematic review. *Neuroscience & Biobehavioral Reviews*, *108*, 694–711. https://doi.org/10.1016/j.neubiorev.2019.12.020

Swan, G. (2015, October 19). *Cities and deprivation*. https://lichfields.uk/blog/2015/october/19/cities-and-deprivation

Szanton, S. L., Gill, J. M., & Allen, J. K. (2005). Allostatic load: A mechanism of socioeconomic health disparities? *Biological Research for Nursing*, *7*(1), 7–15. https://doi.org/10.1177/1099800405278216

Taborsky, B., Kuijper, B., Fawcett, T. W., English, S., Leimar, O., McNamara, J. M., & Ruuskanen, S. (2022). An evolutionary perspective on stress responses, damage and repair. *Hormones and Behavior*, *142*, 105180. https://doi.org/10.1016/j.yhbeh.2022.105180

Tampubolon, G., & Maharani, A. (2018). Trajectories of allostatic load among older Americans and Britons: Longitudinal cohort studies. *BMC Geriatrics*, *18*(1), 255. https://doi.org/10.1186/s12877-018-0947-4

Tanner, E. C., Vann, R. J., & Kizilova, E. (2020). Consumer-Level Perceived Access to Health Services and Its Effects on Vulnerability and Health Outcomes. *Journal of Public Policy & Marketing*, *39*(2), 240–255. https://doi.org/10.1177/0743915620903299

Tatit, P., Adhinugraha, K., & Taniar, D. (2024). Navigating the Maps: Euclidean vs. Road Network Distances in Spatial Queries. *Algorithms*, *17*(1), Article 1. https://doi.org/10.3390/a17010029

Taylor, S. E., Repetti, R. L., & Seeman, T. (1997). Health Psychology: What is an Unhealthy Environment and How Does It Get under the Skin? *Annual Review of Psychology*, *48*, 411–447. Scopus. https://doi.org/10.1146/annurev.psych.48.1.411

TCPA, G. (2021, March 1). The 20-Minute Neighbourhood Guide. *Town and Country Planning Association*. https://www.tcpa.org.uk/resources/the-20-minute-neighbourhood/

The Health Foundation. (2024, March 5). *Rethinking access to general practice: It's not all about supply | The Health Foundation*. https://www.health.org.uk/reports-and-analysis/briefings/rethinking-access-to-general-practice-it-s-not-all-about-supply

Thomson, E. M. (2019). Air Pollution, Stress, and Allostatic Load: Linking Systemic and Central Nervous System Impacts. *Journal of Alzheimer's Disease*, *69*(3), 597. https://doi.org/10.3233/JAD-190015

Thornton, L. E., Schroers, R.-D., Lamb, K. E., Daniel, M., Ball, K., Chaix, B., Kestens, Y., Best, K., Oostenbach, L., & Coffee, N. T. (2022). Operationalising the 20-minute neighbourhood. *International Journal of Behavioral Nutrition and Physical Activity*, *19*(1), 15. https://doi.org/10.1186/s12966-021-01243-3

Tigran et al, H. (2020). Urban Form and Human Behavior in Context of Livable Cities and their Public Realms. *Scholarly Journal of Psychology and Behavioral Sciences*, *3*(4). https://doi.org/10.32474/SJPBS.2020.03.000167

Tingley, D., Yamamoto, T., Hirose, K., Keele, L., & Imai, K. (2014). mediation: R Package for Causal Mediation Analysis. *Journal of Statistical Software*, *59*, 1–38. https://doi.org/10.18637/jss.v059.i05

Tonne, C., Halonen, J. I., Beevers, S. D., Dajnak, D., Gulliver, J., Kelly, F. J., Wilkinson, P., & Anderson, H. R. (2016). Long-term traffic air and noise pollution in relation to mortality and hospital readmission among myocardial infarction survivors. *International Journal of Hygiene and Environmental Health*, *219*(1), 72–78. https://doi.org/10.1016/j.ijheh.2015.09.003

Troxel, W. M., Haas, A., Ghosh-Dastidar, B., Holliday, S. B., Richardson, A. S., Schwartz, H., Gary-Webb, T. L., Hale, L., Buysse, D. J., Buman, M. P., & Dubowitz, T. (2020). Broken Windows, Broken Zzs: Poor Housing and Neighborhood Conditions Are Associated with Objective Measures of Sleep Health. *Journal of Urban Health : Bulletin of the New York Academy of Medicine*, *97*(2), 230–238. https://doi.org/10.1007/s11524-019-00418-5

Tsatsoulis, A., & Fountoulakis, S. (2006). The protective role of exercise on stress system dysregulation and comorbidities. *Annals of the New York Academy of Sciences*, *1083*, 196–213. https://doi.org/10.1196/annals.1367.020

Tuson, M., Yap, M., Kok, M. R., Murray, K., Turlach, B., & Whyatt, D. (2019). Incorporating geography into a new generalized theoretical and statistical framework addressing the modifiable areal unit problem. *International Journal of Health Geographics*, *18*(1), 6. https://doi.org/10.1186/s12942-019-0170-3

Twelves, A. (2024, December 2). To save the UK from morons, progressives need to build. [Substack newsletter]. *Twelves' Blog*. https://beartwelves.substack.com/p/to-save-the-uk-from-morons-progressives

UKHLS. (2016). Main survey variable: Imd2014qw_dv IMD (Wal) quintile (1 is most deprived 20%). *Understanding Society*.

https://www.understandingsociety.ac.uk/documentation/mainstage/variables/imd2014qw_dv/

Valeri, L., & VanderWeele, T. J. (2013). Mediation Analysis Allowing for Exposure–Mediator Interactions and Causal Interpretation: Theoretical Assumptions and Implementation With SAS and SPSS Macros. *Psychological Methods*, *18*(2). https://doi.org/10.1037/a0031034

Valiente, R., Escobar, F., Urtasun, M., Franco, M., Shortt, N. K., & Sureda, X. (2021). Tobacco Retail Environment and Smoking: A Systematic Review of Geographic Exposure Measures and Implications for Future Studies. *Nicotine & Tobacco Research*, *23*(8), 1263–1273. https://doi.org/10.1093/ntr/ntaa223

van den Berg, M. M. H. E., Maas, J., Muller, R., Braun, A., Kaandorp, W., van Lien, R., van Poppel, M. N. M., van Mechelen, W., & van den Berg, A. E. (2015). Autonomic Nervous System Responses to Viewing Green and Built Settings: Differentiating Between Sympathetic and Parasympathetic Activity. *International Journal of Environmental Research and Public Health*, *12*(12), 15860–15874. https://doi.org/10.3390/ijerph121215026

van Deurzen, I., Rod, N. H., Christensen, U., Hansen, Å. M., Lund, R., & Dich, N. (2016). Neighborhood perceptions and allostatic load: Evidence from Denmark. *Health & Place*, *40*, 1–8. https://doi.org/10.1016/j.healthplace.2016.04.010

van Deurzen, I., & Vanhoutte, B. (2019). A Longitudinal Study of Allostatic Load in Later Life: The Role of Sex, Birth Cohorts, and Risk Accumulation. *Research on Aging*, *41*(5), 419–442. https://doi.org/10.1177/0164027518813839

van Erpecum, C.-P. L., van Zon, S. K. R., Bültmann, U., & Smidt, N. (2022). The association between fast-food outlet proximity and density and Body Mass

Index: Findings from 147,027 Lifelines Cohort Study participants. *Preventive Medicine*, *155*, 106915. https://doi.org/10.1016/j.ypmed.2021.106915

Vasunilashorn, S., Steinman, B. A., Liebig, P. S., & Pynoos, J. (2012). Aging in Place: Evolution of a Research Topic Whose Time Has Come. *Journal of Aging Research*, *2012*(1), 120952. https://doi.org/10.1155/2012/120952

Velasquez, A. J., Douglas, J. A., Guo, F., & Robinette, J. W. (2021). What predicts how safe people feel in their neighborhoods and does it depend on functional status? *SSM - Population Health*, *16*, 100927. https://doi.org/10.1016/j.ssmph.2021.100927

Villalonga-Olives, E., & Kawachi, I. (2017). The dark side of social capital: A systematic review of the negative health effects of social capital. *Social Science & Medicine (1982)*, *194*, 105–127. https://doi.org/10.1016/j.socscimed.2017.10.020

Villanova, D. (2023). The Appropriateness of Outlier Exclusion Approaches Depends on the Expected Contamination: Commentary on André (2022). *Advances in Methods and Practices in Psychological Science*, *6*(3), 25152459231186577. https://doi.org/10.1177/25152459231186577

Waldvogel, D., van Gelderen, P., Muellbacher, W., Ziemann, U., Immisch, I., & Hallett, M. (2000). The relative metabolic demand of inhibition and excitation. *Nature*, *406*(6799), 995–998. https://doi.org/10.1038/35023171

Walker, A. (2020, July 17). Trans people twice as likely to be victims of crime in England and Wales. *The Guardian*. https://www.theguardian.com/society/2020/jul/17/trans-people-twice-as-likely-to-be-victims-of-in-england-and-wales

Walker, B. B., Shashank, A., Gasevic, D., Schuurman, N., Poirier, P., Teo, K., Rangarajan, S., Yusuf, S., & Lear, S. A. (2020). The Local Food Environment and Obesity: Evidence from Three Cities. *Obesity (Silver Spring, Md.)*, *28*(1), 40–45. https://doi.org/10.1002/oby.22614

Walker, E. (2024). Social, economic and cultural capital & health: Exploring independent associations between cultural engagement and health: A biosocial analysis of self-reported mental and physical health and biomarkers in Understanding Society. [Doctoral, UCL (University College London)]. In *Doctoral thesis, UCL (University College London).* (pp. 1–458). https://discovery.ucl.ac.uk/id/eprint/10186816/

Wang, C. (2022). Do planning concepts matter? A Lacanian interpretation of the urban village in a British context. *Planning Theory*, *21*(2), 155–180. https://doi.org/10.1177/14730952211038936

Wang, S., Li, L. Z., Zhang, J., & Rehkopf, D. H. (2021). Leisure time activities and biomarkers of chronic stress: The mediating roles of alcohol consumption and smoking. *Scandinavian Journal of Public Health*, *49*(8), 940–950. https://doi.org/10.1177/1403494820987461

WBG. (2020, February 26). *2020 WBG Briefing: Public transport and gender*. https://www.wbg.org.uk/publication/2019-wbg-briefing-public-transport-and-gender/

We Own It. (2024, July 2). *The destruction of the last 14 years, in numbers*. We Own It. https://weownit.org.uk/blog/destruction-last-14-years-numbers

Webber, R., May, V., & Lewis, C. (2023). Ageing in Place Over Time: The Making and Unmaking of Home. *Sociological Research Online*, *28*(3), 759–774. https://doi.org/10.1177/13607804221089351

Weden, M. M., Carpiano, R. M., & Robert, S. A. (2008). Subjective and objective neighborhood characteristics and adult health. *Social Science & Medicine*, *66*(6), 1256–1270. https://doi.org/10.1016/j.socscimed.2007.11.041

Wedyan, M., & Saeidi-Rizi, F. (2025). Assessing the impact of walkability indicators on health outcomes using machine learning algorithms: A case study of Michigan. *Travel Behaviour and Society*, *39*, 100983. https://doi.org/10.1016/j.tbs.2025.100983

Weiss, L., Ompad, D., Galea, S., & Vlahov, D. (2007). Defining Neighborhood Boundaries for Urban Health Research. *American Journal of Preventive Medicine*, *32*(6, Supplement), S154–S159. https://doi.org/10.1016/j.amepre.2007.02.034

Wen, M., Hawkley, L. C., & Cacioppo, J. T. (2006). Objective and perceived neighborhood environment, individual SES and psychosocial factors, and self-rated health: An analysis of older adults in Cook County, Illinois. *Social Science & Medicine*, *63*(10), 2575–2590. https://doi.org/10.1016/j.socscimed.2006.06.025

Weng, M., Ding, N., Li, J., Jin, X., Xiao, H., He, Z., & Su, S. (2019). The 15-minute walkable neighborhoods: Measurement, social inequalities and implications for building healthy communities in urban China. *Journal of Transport & Health*, *13*, 259–273. https://doi.org/10.1016/j.jth.2019.05.005

Whitley, E., Olsen, J., & Benzeval, M. (2022). Impact of subjective and objective neighbourhood characteristics and individual socioeconomic position on allostatic load: A cross-sectional analysis of an all-age UK household panel study. *Health & Place*, *78*, 102930. https://doi.org/10.1016/j.healthplace.2022.102930

WHO. (2007, October 5). *Global age-friendly cities: A guide*. https://www.who.int/publications/i/item/9789241547307

Wiewel, W., & Kafoury, D. (2012). *The Portland Plan*.

Wiley, J. F., Gruenewald, T. L., Karlamangla, A. S., & Seeman, T. E. (2016). Modeling Multisystem Physiological Dysregulation. *Psychosomatic Medicine*, *78*(3), 290–301. https://doi.org/10.1097/PSY.0000000000000288

Williamson, Tim. (2021, October 12). *Air Pollution and Inequalities in London: 2019 | London City Hall* [London Assembly]. Air Pollution and Inequalities in London: 2019 | London City Hall. https://www.london.gov.uk/programmes-and-strategies/environment-and-climate-change/environment-publications/air-pollution-and-inequalities-london-2019

Willsher, K. (2020, February 7). *Paris mayor unveils '15-minute city' plan in re-election campaign*. The Guardian. http://www.theguardian.com/world/2020/feb/07/paris-mayor-unveils-15-minute-city-plan-in-re-election-campaign

Wise, J. (2022). Life expectancy: Parts of England and Wales see "shocking" fall. *BMJ*, o1056. https://doi.org/10.1136/bmj.o1056

Wolfson, J. A., Garcia, T., & Leung, C. W. (2021). Food Insecurity Is Associated with Depression, Anxiety, and Stress: Evidence from the Early Days of the COVID-19 Pandemic in the United States. *Health Equity*, *5*(1), 64–71. https://doi.org/10.1089/heq.2020.0059

Wu, Y.-T., Prina, A. M., Jones, A., Barnes, L. E., Matthews, F. E., Brayne, C., & Mrc cfas. (2016). Land use mix and five-year mortality in later life: Results from the

Cognitive Function and Ageing Study. *Health & Place*, *38*, 54–60. https://doi.org/10.1016/j.healthplace.2015.12.002

Wylie, I. (2015, February 11). How supermarkets choose where to open … and where to close. *The Guardian*. https://www.theguardian.com/cities/2015/feb/11/how-supermarkets-choose-where-open-close-tesco

Xiao, C. S., Sinclair, N., Saunders, L., & Panter, J. (2023). Evaluating the impact of low traffic neighbourhoods in areas with low car ownership: A natural experimental evaluation. *Journal of Transport & Health*, *33*, 101658. https://doi.org/10.1016/j.jth.2023.101658

Xu, H., Yang, T., Guo, B., Silang, Y., Dai, Y., Baima, K., Gao, Y., Tang, S., Wei, J., Jiang, Y., Feng, S., Li, S., Xiao, X., & Zhao, X. (2022). Increased allostatic load associated with ambient air pollution acting as a stressor: Cross-sectional evidence from the China multi-ethnic cohort study. *Science of The Total Environment*, *831*, 155658. https://doi.org/10.1016/j.scitotenv.2022.155658

Yakubovich, A. R., Heron, J., & Humphreys, D. K. (2020). How do perceived and objective measures of neighbourhood disadvantage vary over time? Results from a prospective-longitudinal study in the UK with implications for longitudinal research on neighbourhood effects on health. *PLoS ONE*, *15*(4), e0231779. https://doi.org/10.1371/journal.pone.0231779

Yang, T.-C., & South, S. J. (2020). Neighborhood Poverty and Physical Health at Midlife: The Role of Life-Course Exposure. *Journal of Urban Health : Bulletin of the New York Academy of Medicine*, *97*(4), 486–501. https://doi.org/10.1007/s11524-020-00444-8

Yhee, H., Kim, S., & Kang, S. (2021a). Gis-based evaluation method for accessibility of social infrastructure facilities. *Applied Sciences (Switzerland)*, *11*(12). https://doi.org/10.3390/app11125581

Yhee, H., Kim, S., & Kang, S. (2021b). GIS-Based Evaluation Method for Accessibility of Social Infrastructure Facilities. *Applied Sciences*, *11*(12), Article 12. https://doi.org/10.3390/app11125581

Yoshino, K., & Matsuoka, K. (2009). Effect of mood during daily life on autonomic nervous activity balance during subsequent sleep. *Autonomic Neuroscience*, *150*(1), 147–149. https://doi.org/10.1016/j.autneu.2009.03.013

Zahnow, R. (2024). Social infrastructure, social cohesion and subjective wellbeing. *Wellbeing, Space and Society*, *7*, 100210. https://doi.org/10.1016/j.wss.2024.100210

Zajacova, A., & Lawrence, E. M. (2018). The Relationship Between Education and Health: Reducing Disparities Through a Contextual Approach. *Annual Review of Public Health*, *39*(Volume 39, 2018), 273–289. https://doi.org/10.1146/annurev-publhealth-031816-044628

Zhang, L., Muscat, J. E., Chinchilli, V. M., Kris-Etherton, P. M., Al-Shaar, L., & Richie, J. P. (2023). *Berry Consumption in Relation to Allostatic Load in US Adults: The National Health and Nutrition Examination Survey, 2003–2010*. *16*(3). https://doi.org/10.3390/nu16030403

Zhou, Q., Zhao, L., Zhang, L., Xiao, Q., Wu, T., Visscher, T., Zhao, J., Xin, J., Yu, X., Xue, H., Li, H., Pan, J., & Jia, P. (2021). Neighborhood supermarket access and childhood obesity: A systematic review. *Obesity Reviews*, *22*(Suppl 1), e12937. https://doi.org/10.1111/obr.12937

7 Data Citation

University of Essex, Institute for Social and Economic Research. (2023). *Understanding Society: Waves 1-13, 2009-2022 and Harmonised BHPS: Waves 1-18, 1991-2009: Secure Access*. [data collection]. *16th Edition.* UK Data Service. SN: 6676, DOI: http://doi.org/10.5255/UKDA-SN-6676-16

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8 Appendices

8.1 Appendix A – Comparison of significant domains in Chapter 3 by Allostatic Load Outcome

Domain	AL	Value label	Model	Analytic Sample (FS) (N=10,052),	Beta if sig p<0.05	FS bonf
Eating and drinking	AL12	Logged mean distance in kilometres to eating and drinking veneues	M1	***(FS) model-1, B:0.202, S.E.:0.072, p<0.005, p.bonf<0.02***	*0.202*	0.02
Eating and drinking	AL15	Logged mean distance in kilometres to eating and drinking veneues	M1	(FS) model-1, B:0.131, S.E.:0.059, p<0.026, p.bonf<0.104		0.104
Greenspace & recreation	AL12	Logged mean distance in kilometres to greenspace	M1	(FS) model-1, B:-0.166, S.E.:0.077, p<0.031, p.bonf<0.124		0.124
Greenspace & recreation	AL12	Logged mean distance in kilometres to greenspace	M2	(FS) model-2, B:-0.17, S.E.:0.072, p<0.018, p.bonf<0.072		0.072
Greenspace & recreation	AL12	Logged mean distance in kilometres to greenspace	M3	(FS) model-3, B:-0.159, S.E.:0.072, p<0.026, p.bonf<0.104		0.104
Greenspace & recreation	AL15	Logged mean distance in kilometres to greenspace	M1	(FS) model-1, B:-0.127, S.E.:0.063, p<0.045, p.bonf<0.18		0.18
Public transport	AL12	Logged mean distance in kilometres to public transport	M1	***(FS) model-1, B:-0.257, S.E.:0.08, p<0.001, p.bonf<0.004***	*-0.257*	0.004
Public transport	AL12	Logged mean distance in kilometres to public transport	M2	***(FS) model-2, B:-0.228, S.E.:0.075, p<0.002, p.bonf<0.008***	*-0.228*	0.008
Public transport	AL15	Logged mean distance in kilometres to public transport	M1	***(FS) model-1, B:-0.188, S.E.:0.065, p<0.004, p.bonf<0.016***	*-0.188*	0.016

Public transport	AL15	Logged mean distance in kilometres to public transport	M2	*(FS) model-2, B:-0.189, S.E.:0.062, p<0.002, p.bonf<0.008*	*-0.189*	0.008
Public transport	AL15	Logged mean distance in kilometres to public transport	M3	**(FS) model-3, B:-0.152, S.E.:0.063, p<0.015, p.bonf<0.06**	**-0.152**	0.06
Public transport	AL15	Logged mean distance in kilometres to public transport	M4	**(FS) model-4, B:-0.142, S.E.:0.062, p<0.023, p.bonf<0.092**	**-0.142**	0.092
Retail services	AL15	log of metres to Retail Services from postcode	M3	*(FS) model-3, B:0.153, S.E.:0.062, p<0.014, p.bonf<0.056*	*0.153*	0.056
Retail services	AL15	log of metres to Retail Services from postcode	M4	**(FS) model-4, B:0.15, S.E.:0.062, p<0.015, p.bonf<0.06**	**0.15**	0.06
Retail services	AL12	Log of mean distances (metres) to retail services	M1	*(FS) model-1, B:0.126, S.E.:0.045, p<0.005, p.bonf<0.02*	*0.126*	0.02
Retail services	AL12	Log of mean distances (metres) to retail services	M2	*(FS) model-2, B:0.116, S.E.:0.042, p<0.006, p.bonf<0.024*	*0.116*	0.024
Retail services	AL12	Log of mean distances (metres) to retail services	M3	*(FS) model-3, B:0.151, S.E.:0.045, p<0.001, p.bonf<0.004*	*0.151*	0.004
Retail services	AL12	Log of mean distances (metres) to retail services	M4	*(FS) model-4, B:0.147, S.E.:0.045, p<0.001, p.bonf<0.004*	*0.147*	0.004
Retail services	AL12	log of metres to Retail Services from postcode	M3	*(FS) model-3, B:0.198, S.E.:0.076, p<0.01, p.bonf<0.04*	*0.198*	0.04
Retail services	AL12	log of metres to Retail Services from postcode	M4	*(FS) model-4, B:0.193, S.E.:0.076, p<0.011, p.bonf<0.044*	*0.193*	0.044
Retail services	AL15	Log of mean distances (metres) to retail services	M1	*(FS) model-1, B:0.098, S.E.:0.037, p<0.007, p.bonf<0.028*	*0.098*	0.028
Retail services	AL15	Log of mean distances (metres) to retail services	M3	*(FS) model-3, B:0.114, S.E.:0.037, p<0.002, p.bonf<0.008*	*0.114*	0.008
Retail services	AL15	Log of mean distances (metres) to retail services	M4	*(FS) model-4, B:0.111, S.E.:0.037, p<0.003, p.bonf<0.012*	*0.111*	0.012

Eating and drinking	AL12	Logged mean distance in kilometres to eating and drinking veneues	M1	***(<50) model-1, B:0.318, S.E.:0.106, p<0.003, p.bonf<0.024***	***0.318***	0.024
Eating and drinking	AL15	Logged mean distance in kilometres to eating and drinking veneues	M1	***(<50) model-1, B:0.214, S.E.:0.08, p<0.007, p.bonf<0.043***	***0.214***	0.043
Greenspace & recreation	AL12	Logged mean distance in kilometres to greenspace	M1	***(<50) model-1, B:-0.336, S.E.:0.113, p<0.003, p.bonf<0.024***	***-0.336***	0.024
Greenspace & recreation	AL12	Logged mean distance in kilometres to greenspace	M2	***(<50) model-2, B:-0.31, S.E.:0.101, p<0.002, p.bonf<0.016***	***-0.31***	0.016
Greenspace & recreation	AL12	Logged mean distance in kilometres to greenspace	M3	***(<50) model-3, B:-0.295, S.E.:0.101, p<0.004, p.bonf<0.032***	***-0.295***	0.032
Greenspace & recreation	AL15	Logged mean distance in kilometres to greenspace	M1	***(<50) model-1, B:-0.231, S.E.:0.085, p<0.006, p.bonf<0.039***	***-0.231***	0.039
Public transport	AL12	Logged mean distance in kilometres to public transport	M1	***(<50) model-1, B:-0.351, S.E.:0.119, p<0.003, p.bonf<0.024***	***-0.351***	0.024
Public transport	AL12	Logged mean distance in kilometres to public transport	M2	***(<50) model-2, B:-0.31, S.E.:0.107, p<0.004, p.bonf<0.032***	***-0.31***	0.032
Public transport	AL15	Logged mean distance in kilometres to public transport	M1	***(<50) model-1, B:-0.283, S.E.:0.089, p<0.002, p.bonf<0.009***	***-0.283***	0.009
Public transport	AL15	Logged mean distance in kilometres to public transport	M2	***(<50) model-2, B:-0.286, S.E.:0.087, p<0.001, p.bonf<0.006***	***-0.286***	0.006
Public transport	AL15	Logged mean distance in kilometres to public transport	M3	***(<50) model-3, B:-0.254, S.E.:0.088, p<0.004, p.bonf<0.024***	***-0.254***	0.024
Public transport	AL15	Logged mean distance in kilometres to public transport	M4	***(<50) model-4, B:-0.24, S.E.:0.087, p<0.006, p.bonf<0.036***	***-0.24***	0.036

Retail services	AL15	log of metres to Retail Services from postcode	M3	***(<50) model-3, B:0.24, S.E.:0.091, p<0.008, p.bonf<0.049***	***0.24***	0.049
Retail services	AL15	log of metres to Retail Services from postcode	M4	(<50) model-4, B:0.214, S.E.:0.09, p<0.017, p.bonf<0.103		0.103
Retail services	AL12	Log of mean distances (metres) to retail services	M1	(<50) model-1, B:0.079, S.E.:0.068, p<0.244, p.bonf<1.952		1.952
Retail services	AL12	Log of mean distances (metres) to retail services	M2	(<50) model-2, B:0.102, S.E.:0.061, p<0.093, p.bonf<0.744		0.744
Retail services	AL12	Log of mean distances (metres) to retail services	M3	(<50) model-3, B:0.119, S.E.:0.065, p<0.068, p.bonf<0.544		0.544
Retail services	AL12	Log of mean distances (metres) to retail services	M4	(<50) model-4, B:0.099, S.E.:0.065, p<0.125, p.bonf<1		1
Retail services	AL12	log of metres to Retail Services from postcode	M3	(<50) model-3, B:0.213, S.E.:0.113, p<0.06, p.bonf<0.48		0.48
Retail services	AL12	log of metres to Retail Services from postcode	M4	(<50) model-4, B:0.181, S.E.:0.112, p<0.107, p.bonf<0.856		0.856
Retail services	AL15	Log of mean distances (metres) to retail services	M1	(<50) model-1, B:0.086, S.E.:0.051, p<0.09, p.bonf<0.542		0.542
Retail services	AL15	Log of mean distances (metres) to retail services	M3	(<50) model-3, B:0.119, S.E.:0.053, p<0.023, p.bonf<0.141		0.141
Retail services	AL15	Log of mean distances (metres) to retail services	M4	(<50) model-4, B:0.105, S.E.:0.052, p<0.045, p.bonf<0.268		0.268
Eating and drinking	AL12	Logged mean distance in kilometres to eating and drinking veneues	M1	(50+) model-1, B:0.093, S.E.:0.095, p<0.326, p.bonf<2.608		2.608
Eating and drinking	AL15	Logged mean distance in kilometres to eating and drinking veneues	M1	(50+) model-1, B:0.066, S.E.:0.081, p<0.418, p.bonf<3.344		3.344
Greenspace & recreation	AL12	Logged mean distance in kilometres to greenspace	M1	(50+) model-1, B:-0.009, S.E.:0.103, p<0.931, p.bonf<7.448		7.448

Greenspace & recreation	AL12	Logged mean distance in kilometres to greenspace	M2	(50+) model-2, B:-0.024, S.E.:0.101, p<0.81, p.bonf<6.48		6.48
Greenspace & recreation	AL12	Logged mean distance in kilometres to greenspace	M3	(50+) model-3, B:-0.031, S.E.:0.101, p<0.76, p.bonf<6.08		6.08
Greenspace & recreation	AL15	Logged mean distance in kilometres to greenspace	M1	(50+) model-1, B:-0.084, S.E.:0.088, p<0.338, p.bonf<2.704		2.704
Public transport	AL12	Logged mean distance in kilometres to public transport	M1	(50+) model-1, B:-0.158, S.E.:0.106, p<0.135, p.bonf<1.08		1.08
Public transport	AL12	Logged mean distance in kilometres to public transport	M2	(50+) model-2, B:-0.098, S.E.:0.104, p<0.346, p.bonf<2.768		2.768
Public transport	AL15	Logged mean distance in kilometres to public transport	M1	(50+) model-1, B:-0.095, S.E.:0.09, p<0.291, p.bonf<2.328		2.328
Public transport	AL15	Logged mean distance in kilometres to public transport	M2	(50+) model-2, B:-0.064, S.E.:0.089, p<0.469, p.bonf<3.752		3.752
Public transport	AL15	Logged mean distance in kilometres to public transport	M3	(50+) model-3, B:-0.032, S.E.:0.09, p<0.725, p.bonf<5.8		5.8
Public transport	AL15	Logged mean distance in kilometres to public transport	M4	(50+) model-4, B:-0.019, S.E.:0.089, p<0.832, p.bonf<6.656		6.656
Retail services	AL15	log of metres to Retail Services from postcode	M3	(50+) model-3, B:0.072, S.E.:0.086, p<0.401, p.bonf<3.208		3.208
Retail services	AL15	log of metres to Retail Services from postcode	M4	(50+) model-4, B:0.086, S.E.:0.085, p<0.312, p.bonf<2.496		2.496
Retail services	AL12	Log of mean distances (metres) to retail services	M1	(50+) model-1, B:0.142, S.E.:0.058, p<0.015, p.bonf<0.12		0.12
Retail services	AL12	Log of mean distances (metres) to retail services	M2	**(50+) model-2, B:0.148, S.E.:0.057, p<0.009, p.bonf<0.072**	**0.148**	0.072

Retail services	AL12	Log of mean distances (metres) to retail services	M3	***(50+) model-3, B:0.195, S.E.:0.062, p<0.002, p.bonf<0.016***	***0.195***	0.016
Retail services	AL12	Log of mean distances (metres) to retail services	M4	***(50+) model-4, B:0.205, S.E.:0.062, p<0.001, p.bonf<0.008***	***0.205***	0.008
Retail services	AL12	log of metres to Retail Services from postcode	M3	(50+) model-3, B:0.196, S.E.:0.101, p<0.053, p.bonf<0.424		0.424
Retail services	AL12	log of metres to Retail Services from postcode	M4	(50+) model-4, B:0.209, S.E.:0.101, p<0.039, p.bonf<0.312		0.312
Retail services	AL15	Log of mean distances (metres) to retail services	M1	(50+) model-1, B:0.073, S.E.:0.049, p<0.138, p.bonf<1.104		1.104
Retail services	AL15	Log of mean distances (metres) to retail services	M3	(50+) model-3, B:0.107, S.E.:0.053, p<0.042, p.bonf<0.336		0.336
Retail services	AL15	Log of mean distances (metres) to retail services	M4	(50+) model-4, B:0.115, S.E.:0.052, p<0.028, p.bonf<0.224		0.224

8.2 Appendix B – Complete logged distance model for adjusted AL ELSA

Grouping Variable Sample	Beta	p-value	Bonferroni Corrected p-value	SE
community facilities				
Logged mean distance in kilometres to community facilities				
Full Sample (n=14,100)	-0.03	0.535	2.14	0.048
Has Car (n=12,467)	-0.058	0.252	2.016	0.05
No Car (n=1,624)	0.12	0.403	3.224	0.144
Rural Sample (n=3727)	-0.038	0.628	5.024	0.078
Urban Sample (n=10,373)	-0.052	0.398	3.184	0.061
Culture				
Logged mean distance in kilometres to Cultural Venues				
Full Sample (n=14,100)	-0.019	0.716	2.864	0.052
Has Car (n=12,467)	-0.017	0.762	6.096	0.055
No Car (n=1,624)	-0.057	0.698	5.584	0.146
Rural Sample (n=3727)	-0.023	0.819	6.552	0.101
Urban Sample (n=10,373)	-0.027	0.663	5.304	0.063
demographic covariate				
Centred Age				
Full Sample (n=14,100)	0.027	0	0	0.003
Has Car (n=12,467)	0.028	0	0	0.003
No Car (n=1,624)	0.017	0.009	0.072	0.007
Rural Sample (n=3727)	0.033	0	0	0.005
Urban Sample (n=10,373)	0.025	0	0	0.003
Ethnicity				
Full Sample (n=14,100)	-0.124	0.474	1.896	0.173
Has Car (n=12,467)	-0.079	0.67	5.36	0.185
No Car (n=1,624)	-0.381	0.395	3.16	0.448
Rural Sample (n=3727)	0.112	0.839	6.712	0.552
Urban Sample (n=10,373)	-0.137	0.455	3.64	0.183
Gender - Female				
Full Sample (n=14,100)	0.019	0.665	2.66	0.045
Has Car (n=12,467)	0.03	0.524	4.192	0.047
No Car (n=1,624)	0.034	0.796	6.368	0.131
Rural Sample (n=3727)	0.054	0.533	4.264	0.087
Urban Sample (n=10,373)	0.01	0.849	6.792	0.052
Highest qualification greater than O-level or equivalent				
Full Sample (n=14,100)	-0.145	0.001	0.004	0.045
Has Car (n=12,467)	-0.121	0.009	0.072	0.046
No Car (n=1,624)	-0.402	0.013	0.104	0.161
Rural Sample (n=3727)	-0.098	0.236	1.888	0.083
Urban Sample (n=10,373)	-0.158	0.003	0.024	0.053
Log of total net wealth in benefit units				
Full Sample (n=14,100)	-0.003	0.81	3.24	0.014
Has Car (n=12,467)	-0.014	0.416	3.328	0.017
No Car (n=1,624)	0.01	0.702	5.616	0.027
Rural Sample (n=3727)	-0.063	0.065	0.52	0.034

Urban Sample (n=10,373)	0.008	0.635	5.08	0.016
Paid employment last 7 days - Yes				
Full Sample (n=14,100)	-0.229	0	0	0.047
Has Car (n=12,467)	-0.216	0	0	0.048
No Car (n=1,624)	-0.622	0.001	0.008	0.192
Rural Sample (n=3727)	-0.305	0	0	0.087
Urban Sample (n=10,373)	-0.207	0	0	0.056
Single, widowed or divorced				
Full Sample (n=14,100)	0.027	0.585	2.34	0.05
Has Car (n=12,467)	0.007	0.894	7.152	0.055
No Car (n=1,624)	0.039	0.759	6.072	0.127
Rural Sample (n=3727)	-0.1	0.327	2.616	0.102
Urban Sample (n=10,373)	0.058	0.315	2.52	0.058
Wave, centred at wave 2				
Full Sample (n=14,100)	0.031	0.062	0.248	0.017
Has Car (n=12,467)	0.022	0.223	1.784	0.018
No Car (n=1,624)	0.106	0.037	0.296	0.051
Rural Sample (n=3727)	0.037	0.246	1.968	0.032
Urban Sample (n=10,373)	0.028	0.15	1.2	0.019
Eating and drinking				
Logged mean distance in kilometres to eating and drinking veneues				
Full Sample (n=14,100)	0.03	0.547	2.188	0.05
Has Car (n=12,467)	0.022	0.671	5.368	0.053
No Car (n=1,624)	0.014	0.919	7.352	0.138
Rural Sample (n=3727)	0.07	0.413	3.304	0.085
Urban Sample (n=10,373)	0.019	0.754	6.032	0.062
Education				
Logged mean distance in kilometres to education facilities				
Full Sample (n=14,100)	-0.029	0.588	2.352	0.054
Has Car (n=12,467)	-0.046	0.415	3.32	0.057
No Car (n=1,624)	0.02	0.899	7.192	0.156
Rural Sample (n=3727)	-0.112	0.262	2.096	0.1
Urban Sample (n=10,373)	0.007	0.919	7.352	0.065
financial services				
Logged mean distance in kilometres to financial services				
Full Sample (n=14,100)	-0.163	0.013	0.052	0.066
Has Car (n=12,467)	-0.142	0.038	0.304	0.068
No Car (n=1,624)	-0.319	0.129	1.032	0.21
Rural Sample (n=3727)	-0.192	0.046	0.368	0.096
Urban Sample (n=10,373)	-0.118	0.195	1.56	0.091
Food services				
Logged mean distance in kilometres to food services				
Full Sample (n=14,100)	0.172	0.012	0.048	0.068
Has Car (n=12,467)	0.198	0.006	0.048	0.071
No Car (n=1,624)	0.041	0.843	6.744	0.209
Rural Sample (n=3727)	0.313	0.002	0.016	0.103
Urban Sample (n=10,373)	0.118	0.208	1.664	0.094
Greenspace & recreation				
Logged mean distance in kilometres to greenspace				

Full Sample (n=14,100)	0.003	0.96	3.84	0.054
Has Car (n=12,467)	0.009	0.878	7.024	0.057
No Car (n=1,624)	0.043	0.784	6.272	0.155
Rural Sample (n=3727)	-0.104	0.316	2.528	0.103
Urban Sample (n=10,373)	0.051	0.428	3.424	0.065
Health				
Logged mean distance in kilometres to health services				
Full Sample (n=14,100)	0.018	0.693	2.772	0.045
Has Car (n=12,467)	-0.006	0.903	7.224	0.048
No Car (n=1,624)	0.24	0.08	0.64	0.137
Rural Sample (n=3727)	-0.046	0.546	4.368	0.076
Urban Sample (n=10,373)	0.05	0.386	3.088	0.058
lifestyle covariate				
Alcohol use - Monthly/Once or twice a year				
Full Sample (n=14,100)	-0.061	0.164	0.656	0.044
Has Car (n=12,467)	-0.069	0.142	1.136	0.047
No Car (n=1,624)	-0.031	0.806	6.448	0.127
Rural Sample (n=3727)	-0.047	0.579	4.632	0.084
Urban Sample (n=10,373)	-0.069	0.186	1.488	0.052
Alcohol use - Not at all in the last 12 months				
Full Sample (n=14,100)	0.019	0.772	3.088	0.067
Has Car (n=12,467)	-0.004	0.96	7.68	0.075
No Car (n=1,624)	0.021	0.891	7.128	0.156
Rural Sample (n=3727)	0.067	0.633	5.064	0.14
Urban Sample (n=10,373)	0.013	0.869	6.952	0.077
Current smoker				
Full Sample (n=14,100)	0.073	0.211	0.844	0.058
Has Car (n=12,467)	0.085	0.173	1.384	0.063
No Car (n=1,624)	-0.003	0.983	7.864	0.148
Rural Sample (n=3727)	-0.111	0.357	2.856	0.121
Urban Sample (n=10,373)	0.118	0.074	0.592	0.066
Has access to a car or vehicle				
Full Sample (n=14,100)	0.067	0.289	1.156	0.064
Rural Sample (n=3727)	0.17	0.286	2.288	0.159
Urban Sample (n=10,373)	0.039	0.574	4.592	0.07
Public Transport Use - Often				
Full Sample (n=14,100)	0.04	0.459	1.836	0.053
Has Car (n=12,467)	0.021	0.717	5.736	0.059
No Car (n=1,624)	0.093	0.544	4.352	0.153
Rural Sample (n=3727)	0.136	0.285	2.28	0.127
Urban Sample (n=10,373)	0.027	0.651	5.208	0.06
Public Transport Use - Sometimes				
Full Sample (n=14,100)	-0.091	0.025	0.1	0.041
Has Car (n=12,467)	-0.106	0.011	0.088	0.042
No Car (n=1,624)	0.014	0.936	7.488	0.169
Rural Sample (n=3727)	-0.039	0.6	4.8	0.075
Urban Sample (n=10,373)	-0.102	0.035	0.28	0.048
Tenure - Mortgage Owner				
Full Sample (n=14,100)	-0.026	0.602	2.408	0.051
Has Car (n=12,467)	-0.039	0.454	3.632	0.052

No Car (n=1,624)	0.172	0.438	3.504	0.221
Rural Sample (n=3727)	-0.051	0.606	4.848	0.098
Urban Sample (n=10,373)	-0.015	0.795	6.36	0.059
Tenure - Other				
Full Sample (n=14,100)	0.254	0.153	0.612	0.178
Has Car (n=12,467)	0.118	0.543	4.344	0.194
No Car (n=1,624)	0.864	0.071	0.568	0.479
Rural Sample (n=3727)	-0.082	0.775	6.2	0.287
Urban Sample (n=10,373)	0.409	0.073	0.584	0.228
Tenure - Renting				
Full Sample (n=14,100)	0.088	0.367	1.468	0.098
Has Car (n=12,467)	0.081	0.48	3.84	0.115
No Car (n=1,624)	0.006	0.974	7.792	0.189
Rural Sample (n=3727)	-0.042	0.838	6.704	0.206
Urban Sample (n=10,373)	0.123	0.275	2.2	0.112
Walk - Has much Difficulty walking quarter of a mile				
Full Sample (n=14,100)	0.202	0	0	0.048
Has Car (n=12,467)	0.165	0.002	0.016	0.053
No Car (n=1,624)	0.393	0.002	0.016	0.127
Rural Sample (n=3727)	0.306	0.001	0.008	0.096
Urban Sample (n=10,373)	0.174	0.002	0.016	0.056
Walk - Unable to walk a quarter of a mile				
Full Sample (n=14,100)	0.208	0.005	0.02	0.075
Has Car (n=12,467)	0.199	0.018	0.144	0.084
No Car (n=1,624)	0.199	0.267	2.136	0.18
Rural Sample (n=3727)	0.265	0.079	0.632	0.151
Urban Sample (n=10,373)	0.184	0.033	0.264	0.086
public transport T1				
Logged mean distance in kilometres to public transport				
Full Sample (n=14,100)	-0.08	0.154	0.616	0.056
Has Car (n=12,467)	-0.066	0.262	2.096	0.059
No Car (n=1,624)	-0.036	0.831	6.648	0.168
Rural Sample (n=3727)	0.009	0.926	7.408	0.1
Urban Sample (n=10,373)	-0.107	0.132	1.056	0.071
retail				
Logged mean distance in kilometres to retail				
Full Sample (n=14,100)	-0.029	0.374	1.496	0.033
Has Car (n=12,467)	-0.038	0.275	2.2	0.035
No Car (n=1,624)	0.03	0.741	5.928	0.091
Rural Sample (n=3727)	-0.011	0.839	6.712	0.057
Urban Sample (n=10,373)	-0.034	0.412	3.296	0.041

8.3 Appendix C - Full results for domains models 1-4 in chapter 4 (ELSA) including adjusted and unadjusted AL (medication)

	AL unadjusted for medication				AL adjusted for medication			
Domains, variables, and value labels	**1**	**2**	**3**	**4**	**1**	**2**	**3**	**4**
community facilities								
0 to <200 metres mean distance to community facilities								
Full Sample (n=14,100)	0.035	0.01	0.008	0.001	0.121	0.056	0.042	0.04
Has Car (n=12,467)	0.09	0.069	0.061	0.052	0.195	0.134	0.112	0.108
No Car (n=1,624)	-0.416	-0.405	-0.387	-0.386	-0.53	-0.574	-0.555	-0.518
Rural Sample (n=3727)	0.048	-0.007	-0.023	-0.033	0.104	0.066	0.034	0.048
Urban Sample (n=10,373)	0.05	0.022	0.025	0.012	0.126	0.053	0.043	0.029
200 to <400 metres mean distance to community facilities								
Full Sample (n=14,100)	0.023	0.029	0.028	0.019	0.058	0.044	0.036	0.032
Has Car (n=12,467)	0.067	0.076	0.072	0.062	0.097	0.091	0.08	0.074
No Car (n=1,624)	-0.364	-0.326	-0.32	-0.31	-0.467	-0.46	-0.451	-0.414
Rural Sample (n=3727)	0.1	0.104	0.097	0.091	0.191	0.196	0.181	0.185
Urban Sample (n=10,373)	0.02	0.017	0.018	0.006	0.04	0.016	0.009	-0.001
400 to <600 metres mean distance to community facilities								
Full Sample (n=14,100)	-0.039	-0.041	-0.042	-0.049	-0.01	-0.024	-0.029	-0.034
Has Car (n=12,467)	0.002	0.004	0.001	-0.005	0.019	0.012	0.006	0.002
No Car (n=1,624)	-0.437	-0.435	-0.437	-0.47	-0.431	-0.48	-0.477	-0.494
Rural Sample (n=3727)	-0.045	-0.026	-0.022	-0.026	0.02	0.062	0.064	0.059
Urban Sample (n=10,373)	-0.025	-0.04	-0.039	-0.053	-0.009	-0.037	-0.041	-0.055
600 to <800 metres mean distance to community facilities								
Full Sample (n=14,100)	-0.008	-0.006	-0.005	-0.006	0.005	-0.012	-0.014	-0.017
Has Car (n=12,467)	0.018	0.023	0.022	0.022	0.022	0.008	0.004	0.001
No Car (n=1,624)	-0.286	-0.296	-0.303	-0.297	-0.353	-0.368	-0.364	-0.337
Rural Sample (n=3727)	-0.053	-0.006	0.001	0.002	-0.005	0.057	0.061	0.063
Urban Sample (n=10,373)	0.01	-0.011	-0.011	-0.014	0.007	-0.036	-0.038	-0.046
At least 1 OA lacks access to Community Facilities within 800-metres of PWC								

Full Sample (n=14,100)	-0.063	-0.066	-0.065	-0.059	-0.106	-0.092	-0.086	-0.087
Has Car (n=12,467)	-0.089	-0.096	-0.094	-0.088	-0.135	-0.13	-0.124	-0.124
No Car (n=1,624)	0.116	0.068	0.064	0.074	0.23	0.205	0.207	0.195
Rural Sample (n=3727)	-0.242	-0.216	-0.212	-0.205	-0.253	-0.232	-0.227	-0.236
Urban Sample (n=10,373)	-0.035	-0.045	-0.045	-0.037	-0.077	-0.067	-0.06	-0.056
High-High LISA hotspot cluster of Community Facilities								
Full Sample (n=14,100)	-0.031	-0.046	-0.046	-0.041	-0.125	-0.136	-0.142	-0.14
Has Car (n=12,467)	-0.021	-0.042	-0.043	-0.038	-0.123	-0.142	-0.147	-0.146
No Car (n=1,624)	-0.097	-0.075	-0.063	-0.047	-0.042	-0.055	-0.055	-0.026
Rural Sample (n=3727)	-0.06	-0.082	-0.08	-0.076	-0.181	-0.184	-0.184	-0.187
Urban Sample (n=10,373)	-0.029	-0.024	-0.025	-0.005	-0.087	-0.11	-0.116	-0.098
High-Low LISA hotspot cluster of Community Facilities								
Full Sample (n=14,100)	0.107	0.135	0.135	0.131	0.105	0.11	0.112	0.103
Has Car (n=12,467)	0.099	0.113	0.112	0.112	0.132	0.123	0.124	0.117
No Car (n=1,624)	0.196	0.296	0.295	0.274	0.035	0.073	0.073	0.053
Rural Sample (n=3727)	0.627	0.717	0.709	0.746	0.525	0.647	0.64	0.635
Urban Sample (n=10,373)	0.071	0.095	0.095	0.092	0.072	0.074	0.074	0.066
Logged mean distance in kilometres to community facilities								
Full Sample (n=14,100)	-0.017	-0.014	-0.013	-0.01	-0.048	-0.035	-0.029	-0.03
Has Car (n=12,467)	-0.033	-0.033	-0.031	-0.028	-0.072	-0.065	-0.059	-0.058
No Car (n=1,624)	0.033	0.051	0.044	0.035	0.118	0.144	0.144	0.12
Rural Sample (n=3727)	-0.009	-0.006	0	0.008	-0.043	-0.049	-0.038	-0.038
Urban Sample (n=10,373)	-0.039	-0.037	-0.038	-0.035	-0.078	-0.06	-0.054	-0.052
Low-High LISA hotspot cluster of Community Facilities								
Full Sample (n=14,100)	0.094	0.077	0.076	0.069	0.077	0.058	0.057	0.052
Has Car (n=12,467)	0.112	0.086	0.086	0.084	0.058	0.026	0.024	0.025
No Car (n=1,624)	0.023	0.1	0.106	0.1	0.333	0.403	0.41	0.398
Rural Sample (n=3727)	0.037	-0.012	-0.001	0.004	-0.038	-0.08	-0.061	-0.06
Urban Sample (n=10,373)	0.115	0.121	0.12	0.101	0.131	0.12	0.118	0.101
Low-Low LISA hotspot cluster of Community Facilities								
Full Sample (n=14,100)	-0.053	-0.061	-0.06	-0.061	-0.019	0.005	0.009	0.004
Has Car (n=12,467)	-0.093	-0.107	-0.106	-0.108	-0.024	-0.004	0	-0.004
No Car (n=1,624)	0.565	0.424	0.419	0.352	0.532	0.327	0.338	0.245

Rural Sample (n=3727)								
Urban Sample (n=10,373)	-0.052	-0.061	-0.061	-0.059	-0.027	-0.004	-0.001	-0.003
Presence of community facilities within the LSOA								
Full Sample (n=14,100)	-0.025	-0.024	-0.021	-0.023	0.028	0.019	0.015	0.013
Has Car (n=12,467)	-0.017	-0.015	-0.012	-0.015	0.042	0.034	0.03	0.027
No Car (n=1,624)	-0.054	-0.079	-0.075	-0.058	-0.045	-0.101	-0.106	-0.081
Rural Sample (n=3727)	-0.11	-0.087	-0.092	-0.094	-0.064	-0.033	-0.048	-0.049
Urban Sample (n=10,373)	0.007	0.003	0.002	0	0.062	0.045	0.04	0.038
Culture								
0 to <200 metres mean distance to cultural venues								
Full Sample (n=14,100)	0.053	0.065	0.06	0.063	-0.021	-0.033	-0.05	-0.049
Has Car (n=12,467)	0.047	0.048	0.04	0.048	-0.045	-0.069	-0.09	-0.085
No Car (n=1,624)	0.332	0.437	0.474	0.461	0.242	0.463	0.482	0.454
Rural Sample (n=3727)	-0.223	-0.182	-0.222	-0.212	-0.165	-0.182	-0.233	-0.202
Urban Sample (n=10,373)	0.1	0.107	0.11	0.11	0.004	-0.009	-0.011	-0.014
200 to <400 metres mean distance to cultural venues								
Full Sample (n=14,100)	0.125	0.132	0.127	0.126	0.069	0.048	0.031	0.031
Has Car (n=12,467)	0.099	0.099	0.091	0.096	0.04	0.008	-0.012	-0.006
No Car (n=1,624)	0.509	0.58	0.618	0.599	0.447	0.627	0.645	0.601
Rural Sample (n=3727)	-0.12	-0.072	-0.112	-0.098	-0.194	-0.226	-0.276	-0.238
Urban Sample (n=10,373)	0.169	0.168	0.171	0.168	0.112	0.086	0.083	0.082
400 to <600 metres mean distance to cultural venues								
Full Sample (n=14,100)	0.074	0.089	0.083	0.082	0.035	0.033	0.016	0.014
Has Car (n=12,467)	0.034	0.037	0.03	0.034	-0.004	-0.024	-0.042	-0.038
No Car (n=1,624)	0.648	0.764	0.803	0.766	0.539	0.754	0.773	0.711
Rural Sample (n=3727)	-0.169	-0.105	-0.147	-0.137	-0.25	-0.259	-0.309	-0.275
Urban Sample (n=10,373)	0.119	0.122	0.123	0.123	0.087	0.076	0.073	0.071
600 to <800 metres mean distance to cultural venues								
Full Sample (n=14,100)	0.045	0.045	0.041	0.042	0.031	0.025	0.014	0.008
Has Car (n=12,467)	0.046	0.037	0.032	0.041	0.042	0.017	0.005	0.007
No Car (n=1,624)	0.066	0.095	0.129	0.117	-0.035	0.144	0.158	0.125
Rural Sample (n=3727)	-0.085	-0.06	-0.105	-0.107	-0.136	-0.173	-0.224	-0.213
Urban Sample (n=10,373)	0.035	0.036	0.037	0.045	0.043	0.038	0.038	0.036

At least 1 OA without access within 800-metres of Cultural Venues								
Full Sample (n=14,100)	-0.182	-0.17	-0.17	-0.168	-0.172	-0.135	-0.132	-0.134
Has Car (n=12,467)	-0.179	-0.167	-0.167	-0.166	-0.157	-0.126	-0.123	-0.125
No Car (n=1,624)	-0.256	-0.28	-0.274	-0.237	-0.323	-0.322	-0.317	-0.305
Rural Sample (n=3727)	-0.144	-0.137	-0.136	-0.143	-0.187	-0.155	-0.155	-0.163
Urban Sample (n=10,373)	-0.201	-0.19	-0.19	-0.18	-0.167	-0.128	-0.122	-0.119
High-High LISA hotspot cluster of Cultural venues								
Full Sample (n=14,100)	-0.078	-0.058	-0.061	-0.062	-0.136	-0.127	-0.141	-0.136
Has Car (n=12,467)	-0.04	-0.028	-0.03	-0.037	-0.084	-0.091	-0.105	-0.104
No Car (n=1,624)	-0.214	-0.202	-0.184	-0.127	-0.245	-0.291	-0.275	-0.24
Rural Sample (n=3727)	-0.005	0.022	0.023	0.042	-0.097	-0.1	-0.097	-0.069
Urban Sample (n=10,373)	-0.158	-0.138	-0.137	-0.127	-0.208	-0.162	-0.156	-0.144
High-Low LISA hotspot cluster of Cultural venues								
Full Sample (n=14,100)	0.016	0.033	0.039	0.052	-0.034	0.018	0.033	0.023
Has Car (n=12,467)	-0.018	-0.002	0.006	0.021	-0.072	-0.005	0.012	-0.003
No Car (n=1,624)	0.321	0.333	0.32	0.292	0.179	0.184	0.189	0.217
Rural Sample (n=3727)	1.3	1.474	1.466	1.643	-0.427	-0.095	-0.098	0.024
Urban Sample (n=10,373)	0.036	0.053	0.055	0.071	-0.029	0.024	0.033	0.024
Logged mean distance in kilometres to Cultural Venues								
Full Sample (n=14,100)	-0.065	-0.068	-0.063	-0.065	-0.048	-0.032	-0.019	-0.019
Has Car (n=12,467)	-0.082	-0.083	-0.076	-0.077	-0.046	-0.031	-0.016	-0.017
No Car (n=1,624)	0.003	-0.028	-0.035	-0.042	-0.017	-0.052	-0.054	-0.057
Rural Sample (n=3727)	-0.016	-0.019	-0.018	-0.036	-0.029	-0.007	-0.004	-0.023
Urban Sample (n=10,373)	-0.083	-0.081	-0.082	-0.08	-0.04	-0.031	-0.03	-0.027
Low-High LISA hotspot cluster of Cultural venues								
Full Sample (n=14,100)	-0.063	-0.056	-0.054	-0.049	0.046	0.032	0.04	0.041
Has Car (n=12,467)	-0.047	-0.05	-0.044	-0.04	0.12	0.078	0.09	0.091
No Car (n=1,624)	-0.079	-0.101	-0.095	-0.138	-0.319	-0.303	-0.291	-0.37
Rural Sample (n=3727)	0.031	0.026	0.047	0.055	0.116	0.063	0.096	0.096
Urban Sample (n=10,373)	-0.153	-0.145	-0.142	-0.134	-0.023	0.014	0.03	0.031
Low-Low LISA hotspot cluster of cultural venues								
Full Sample (n=14,100)	0.103	0.123	0.124	0.115	0.101	0.124	0.127	0.125
Has Car (n=12,467)	0.033	0.051	0.052	0.045	0.043	0.051	0.055	0.055

No Car (n=1,624)	0.42	0.402	0.398	0.373	0.433	0.488	0.487	0.445
Rural Sample (n=3727)								
Urban Sample (n=10,373)	0.114	0.131	0.132	0.124	0.102	0.127	0.128	0.127
Presence of Cultural venues within the LSOA								
Full Sample (n=14,100)	0.009	0.007	0.011	0.01	-0.034	-0.025	-0.025	-0.026
Has Car (n=12,467)	0.004	0.005	0.012	0.008	-0.046	-0.032	-0.031	-0.033
No Car (n=1,624)	0.069	0.034	0.033	0.039	0.096	0.078	0.077	0.075
Rural Sample (n=3727)	0.033	0.058	0.054	0.069	-0.028	0.015	0.003	0.009
Urban Sample (n=10,373)	0.021	0.016	0.016	0.013	-0.019	-0.014	-0.015	-0.018
Eating and drinking								
0 to <200 metres mean distance to Eating and drinking facilities								
Full Sample (n=14,100)	0.095	0.087	0.089	0.08	-0.051	-0.059	-0.041	-0.038
Has Car (n=12,467)	0.091	0.077	0.086	0.072	-0.039	-0.06	-0.033	-0.032
No Car (n=1,624)	0.262	0.26	0.235	0.237	0.083	0.107	0.093	0.081
Rural Sample (n=3727)	0.186	0.211	0.24	0.256	0.059	0.072	0.134	0.147
Urban Sample (n=10,373)	0.058	0.044	0.04	0.035	-0.098	-0.115	-0.102	-0.095
200 to <400 metres mean distance to Eating and drinking facilities								
Full Sample (n=14,100)	0.102	0.093	0.096	0.096	0.051	0.047	0.061	0.071
Has Car (n=12,467)	0.113	0.1	0.108	0.106	0.061	0.045	0.065	0.072
No Car (n=1,624)	0.11	0.11	0.088	0.087	0.099	0.144	0.134	0.147
Rural Sample (n=3727)	0.081	0.098	0.119	0.115	-0.064	-0.009	0.03	0.044
Urban Sample (n=10,373)	0.082	0.067	0.065	0.071	0.035	0.014	0.024	0.038
400 to <600 metres mean distance to Eating and drinking facilities								
Full Sample (n=14,100)	0.086	0.069	0.072	0.069	0.034	0.023	0.033	0.044
Has Car (n=12,467)	0.101	0.081	0.086	0.081	0.054	0.034	0.048	0.055
No Car (n=1,624)	0.07	0.069	0.06	0.06	-0.05	0.003	0	0.011
Rural Sample (n=3727)	0.132	0.11	0.125	0.122	0.113	0.074	0.103	0.109
Urban Sample (n=10,373)	0.055	0.034	0.033	0.034	-0.029	-0.037	-0.03	-0.017
600 to <800 metres mean distance to Eating and drinking facilities								
Full Sample (n=14,100)	0.057	0.025	0.028	0.026	0.084	0.041	0.049	0.06
Has Car (n=12,467)	0.055	0.02	0.025	0.02	0.082	0.034	0.045	0.053
No Car (n=1,624)	0.143	0.169	0.16	0.168	0.131	0.201	0.197	0.201
Rural Sample (n=3727)	0.232	0.184	0.198	0.198	0.241	0.193	0.216	0.226

Urban Sample (n=10,373)	-0.032	-0.065	-0.065	-0.065	-0.011	-0.066	-0.061	-0.047
At least 1 OA lacks access to Eating and drinking facilities within 800-metres of PWC								
Full Sample (n=14,100)	-0.025	-0.036	-0.037	-0.042	0.076	0.06	0.052	0.049
Has Car (n=12,467)	-0.03	-0.041	-0.043	-0.048	0.067	0.057	0.05	0.047
No Car (n=1,624)	0.004	0.032	0.04	0.042	0.061	0.057	0.055	0.039
Rural Sample (n=3727)	0.005	-0.002	-0.009	-0.014	0.176	0.155	0.136	0.138
Urban Sample (n=10,373)	-0.038	-0.052	-0.052	-0.058	0.039	0.024	0.018	0.012
High-High LISA hotspot cluster of Eating and Drinking venues								
Full Sample (n=14,100)	-0.163	-0.153	-0.149	-0.139	-0.368	-0.375	-0.362	-0.349
Has Car (n=12,467)	-0.16	-0.141	-0.135	-0.124	-0.419	-0.402	-0.386	-0.367
No Car (n=1,624)	-0.24	-0.198	-0.206	-0.176	-0.372	-0.341	-0.334	-0.319
Rural Sample (n=3727)	0.332	0.394	0.433	0.421	0.245	0.212	0.238	0.189
Urban Sample (n=10,373)	-0.287	-0.283	-0.282	-0.283	-0.492	-0.486	-0.481	-0.474
High-Low LISA hotspot cluster of eating and drinking venues								
Full Sample (n=14,100)	0.228	0.231	0.23	0.224	0.112	0.145	0.141	0.14
Has Car (n=12,467)	0.186	0.178	0.177	0.172	-0.039	0	-0.004	-0.005
No Car (n=1,624)	0.352	0.562	0.568	0.513	0.686	0.825	0.836	0.757
Rural Sample (n=3727)	-0.094	-0.085	-0.067	-0.08	-0.642	-0.729	-0.688	-0.61
Urban Sample (n=10,373)	0.215	0.198	0.197	0.199	0.126	0.162	0.159	0.163
Logged mean distance in kilometres to eating and drinking veneues								
Full Sample (n=14,100)	-0.022	-0.033	-0.03	-0.026	0.041	0.033	0.028	0.03
Has Car (n=12,467)	-0.032	-0.042	-0.041	-0.037	0.033	0.027	0.021	0.022
No Car (n=1,624)	-0.014	-0.019	-0.019	-0.023	0.028	0.023	0.02	0.014
Rural Sample (n=3727)	0.034	0.02	0.012	0.009	0.106	0.097	0.077	0.07
Urban Sample (n=10,373)	-0.032	-0.042	-0.04	-0.036	0.035	0.025	0.017	0.019
Low-High LISA hotspot cluster of Eating and drinking veneues								
Full Sample (n=14,100)	0.028	0.028	0.027	0.027	-0.25	-0.227	-0.222	-0.22
Has Car (n=12,467)	-0.027	-0.015	-0.014	-0.021	-0.306	-0.285	-0.28	-0.284
No Car (n=1,624)	0.385	0.335	0.325	0.39	-0.034	-0.02	-0.015	0.053
Rural Sample (n=3727)	0.141	0.148	0.139	0.12	0.027	-0.045	-0.036	-0.041
Urban Sample (n=10,373)	-0.059	-0.063	-0.062	-0.069	-0.344	-0.312	-0.305	-0.31
Low-Low LISA hotspot cluster of eating and drinking venues								

Full Sample (n=14,100)	-0.056	-0.087	-0.091	-0.084	-0.015	-0.08	-0.095	-0.093
Has Car (n=12,467)	0.088	0.068	0.062	0.062	0.088	0.05	0.037	0.037
No Car (n=1,624)	-0.713	-0.736	-0.735	-0.713	-0.663	-0.738	-0.756	-0.758
Rural Sample (n=3727)	0.544	0.44	0.433	0.417	0.215	0.247	0.259	0.254
Urban Sample (n=10,373)	-0.064	-0.089	-0.093	-0.088	-0.017	-0.074	-0.091	-0.089
Presence of Eating and drinking facilities within the LSOA								
Full Sample (n=14,100)	0.011	0.023	0.029	0.03	-0.028	-0.018	-0.008	-0.007
Has Car (n=12,467)	0.016	0.023	0.032	0.033	-0.015	-0.013	-0.001	0.001
No Car (n=1,624)	0.032	0.038	0.037	0.044	-0.064	-0.084	-0.085	-0.08
Rural Sample (n=3727)	-0.093	-0.065	-0.057	-0.058	-0.114	-0.102	-0.08	-0.075
Urban Sample (n=10,373)	0.032	0.038	0.04	0.042	-0.02	-0.012	-0.003	0
Education								
0 to <200 metres mean distance to Education facilities								
Full Sample (n=14,100)	-0.078	-0.049	-0.048	-0.052	-0.078	-0.009	-0.009	-0.016
Has Car (n=12,467)	-0.102	-0.063	-0.064	-0.067	-0.1	-0.012	-0.013	-0.02
No Car (n=1,624)	0.042	0.17	0.183	0.177	-0.032	0.167	0.176	0.174
Rural Sample (n=3727)	-0.556	-0.578	-0.616	-0.596	-0.292	-0.265	-0.315	-0.323
Urban Sample (n=10,373)	-0.081	-0.057	-0.056	-0.064	-0.115	-0.069	-0.074	-0.085
200 to <400 metres mean distance to Education facilities								
Full Sample (n=14,100)	-0.058	-0.038	-0.036	-0.039	-0.059	-0.003	0.002	-0.006
Has Car (n=12,467)	-0.07	-0.047	-0.045	-0.047	-0.062	-0.004	0.001	-0.004
No Car (n=1,624)	-0.006	0.116	0.133	0.141	-0.073	0.119	0.132	0.134
Rural Sample (n=3727)	0.104	0.09	0.09	0.085	0.064	0.072	0.082	0.079
Urban Sample (n=10,373)	-0.095	-0.079	-0.079	-0.084	-0.114	-0.076	-0.079	-0.089
400 to <600 metres mean distance to Education facilities								
Full Sample (n=14,100)	-0.018	-0.002	-0.002	-0.006	-0.019	0.035	0.037	0.029
Has Car (n=12,467)	-0.029	-0.013	-0.012	-0.016	-0.031	0.023	0.026	0.019
No Car (n=1,624)	0.04	0.167	0.183	0.188	0.046	0.222	0.23	0.232
Rural Sample (n=3727)	0.07	0.109	0.106	0.114	0.09	0.187	0.191	0.2
Urban Sample (n=10,373)	-0.067	-0.06	-0.06	-0.066	-0.092	-0.072	-0.074	-0.084
600 to <800 metres mean distance to Education facilities								
Full Sample (n=14,100)	0.013	0.031	0.029	0.03	-0.008	0.048	0.047	0.043
Has Car (n=12,467)	0.006	0.026	0.026	0.026	-0.011	0.047	0.049	0.045

No Car (n=1,624)	0.08	0.145	0.171	0.192	0.089	0.176	0.183	0.194
Rural Sample (n=3727)	0.058	0.098	0.096	0.101	0.06	0.138	0.139	0.147
Urban Sample (n=10,373)	-0.023	-0.018	-0.019	-0.02	-0.077	-0.044	-0.046	-0.054
At least 1 OA lacks access to Education facilities within 800-metres of PWC								
Full Sample (n=14,100)	0.126	0.118	0.117	0.12	0.108	0.091	0.089	0.094
Has Car (n=12,467)	0.098	0.091	0.09	0.093	0.087	0.075	0.074	0.078
No Car (n=1,624)	0.384	0.332	0.344	0.36	0.289	0.187	0.19	0.203
Rural Sample (n=3727)	0.085	0.093	0.098	0.102	0.11	0.116	0.118	0.121
Urban Sample (n=10,373)	0.132	0.124	0.124	0.126	0.089	0.07	0.073	0.075
High-High LISA hotspot cluster of Education venues								
Full Sample (n=14,100)	0.029	0.025	0.024	0.023	0.06	0.045	0.045	0.051
Has Car (n=12,467)	0.023	0.012	0.011	0.01	0.048	0.027	0.025	0.033
No Car (n=1,624)	0.126	0.185	0.187	0.16	0.227	0.289	0.298	0.277
Rural Sample (n=3727)	-0.035	-0.084	-0.085	-0.079	0.087	0.014	0.01	0.023
Urban Sample (n=10,373)	0.087	0.127	0.128	0.126	-0.007	0.025	0.031	0.035
High-Low LISA hotspot cluster of Education venues								
Full Sample (n=14,100)	0.127	0.114	0.115	0.125	0.142	0.149	0.152	0.156
Has Car (n=12,467)	0.011	0.01	0.011	0.021	0.046	0.064	0.066	0.072
No Car (n=1,624)	0.799	0.724	0.729	0.703	0.656	0.632	0.638	0.609
Rural Sample (n=3727)	-0.021	-0.02	-0.025	-0.026	-0.131	-0.115	-0.134	-0.135
Urban Sample (n=10,373)	0.141	0.125	0.126	0.137	0.168	0.171	0.174	0.181
Logged mean distance in kilometres to education facilities								
Full Sample (n=14,100)	0.017	0.009	0.003	0.001	0.007	-0.017	-0.028	-0.029
Has Car (n=12,467)	0.02	0.009	0.002	-0.002	-0.003	-0.031	-0.044	-0.046
No Car (n=1,624)	0	-0.013	-0.004	0.006	0.067	0.013	0.016	0.02
Rural Sample (n=3727)	-0.031	-0.033	-0.035	-0.03	-0.085	-0.102	-0.116	-0.112
Urban Sample (n=10,373)	0.03	0.021	0.021	0.018	0.027	0.008	0.009	0.007
Low-High LISA hotspot cluster of Education veneues								
Full Sample (n=14,100)	-0.203	-0.189	-0.186	-0.173	-0.238	-0.203	-0.198	-0.191
Has Car (n=12,467)	-0.201	-0.183	-0.18	-0.167	-0.301	-0.255	-0.251	-0.244
No Car (n=1,624)	-0.197	-0.234	-0.229	-0.199	0.168	0.108	0.121	0.148
Rural Sample (n=3727)	-0.15	-0.108	-0.101	-0.078	-0.123	-0.042	-0.031	-0.011
Urban Sample (n=10,373)	-0.26	-0.248	-0.247	-0.233	-0.345	-0.323	-0.32	-0.311

Low-Low LISA hotspot cluster of Education venues								
Full Sample (n=14,100)	-0.268	-0.241	-0.241	-0.236	-0.241	-0.124	-0.121	-0.114
Has Car (n=12,467)	-0.087	-0.05	-0.051	-0.058	-0.168	-0.016	-0.013	-0.016
No Car (n=1,624)	-1.572	-1.498	-1.507	-1.417	-0.948	-0.922	-0.923	-0.824
Rural Sample (n=3727)								
Urban Sample (n=10,373)	-0.272	-0.253	-0.253	-0.246	-0.267	-0.164	-0.166	-0.16
Presence of Educational facilities within the LSOA								
Full Sample (n=14,100)	0.006	0.011	0.014	0.016	-0.013	0.006	0.006	0.006
Has Car (n=12,467)	0.007	0.012	0.017	0.02	0.001	0.018	0.017	0.019
No Car (n=1,624)	0.017	0.018	0.018	0.002	-0.066	-0.017	-0.019	-0.037
Rural Sample (n=3727)	0.103	0.097	0.09	0.091	0.059	0.072	0.064	0.067
Urban Sample (n=10,373)	-0.006	-0.001	-0.001	0.002	-0.015	-0.001	0	0
financial services								
0 to <200 metres mean distance to Financial services								
Full Sample (n=14,100)	0.223	0.193	0.195	0.198	0.394	0.307	0.298	0.291
Has Car (n=12,467)	0.134	0.115	0.109	0.113	0.289	0.228	0.211	0.208
No Car (n=1,624)	0.962	0.932	0.949	0.922	1.293	1.111	1.12	1.107
Rural Sample (n=3727)	0.299	0.203	0.191	0.211	0.261	0.001	-0.025	0.009
Urban Sample (n=10,373)	0.217	0.195	0.199	0.198	0.401	0.358	0.348	0.34
200 to <400 metres mean distance to Financial services								
Full Sample (n=14,100)	0.212	0.182	0.182	0.182	0.271	0.197	0.194	0.189
Has Car (n=12,467)	0.146	0.126	0.124	0.124	0.189	0.137	0.132	0.127
No Car (n=1,624)	0.885	0.804	0.805	0.749	1.117	0.916	0.91	0.88
Rural Sample (n=3727)	0.416	0.372	0.376	0.385	0.645	0.504	0.509	0.52
Urban Sample (n=10,373)	0.184	0.159	0.16	0.157	0.225	0.188	0.183	0.179
400 to <600 metres mean distance to Financial services								
Full Sample (n=14,100)	0.218	0.183	0.183	0.189	0.331	0.25	0.251	0.252
Has Car (n=12,467)	0.206	0.181	0.181	0.187	0.313	0.253	0.253	0.253
No Car (n=1,624)	0.565	0.491	0.481	0.467	0.862	0.631	0.619	0.63
Rural Sample (n=3727)	0.294	0.23	0.23	0.234	0.415	0.259	0.261	0.262
Urban Sample (n=10,373)	0.187	0.165	0.165	0.169	0.311	0.275	0.274	0.279
600 to <800 metres mean distance to Financial services								
Full Sample (n=14,100)	0.063	0.018	0.02	0.015	0.097	0.003	0.009	0.01

Has Car (n=12,467)	0.035	-0.002	0.001	-0.005	0.076	-0.006	0.001	-0.001
No Car (n=1,624)	0.663	0.557	0.546	0.549	0.728	0.514	0.498	0.528
Rural Sample (n=3727)	-0.108	-0.19	-0.186	-0.189	-0.105	-0.263	-0.252	-0.255
Urban Sample (n=10,373)	0.195	0.172	0.173	0.163	0.286	0.244	0.246	0.251
At least 1 OA lacks access to Financial services within 800-metres of PWC								
Full Sample (n=14,100)	-0.14	-0.139	-0.139	-0.142	-0.177	-0.173	-0.166	-0.161
Has Car (n=12,467)	-0.11	-0.116	-0.116	-0.118	-0.118	-0.132	-0.127	-0.123
No Car (n=1,624)	-0.2	-0.226	-0.238	-0.219	-0.4	-0.408	-0.402	-0.368
Rural Sample (n=3727)	-0.256	-0.27	-0.281	-0.286	-0.457	-0.416	-0.429	-0.427
Urban Sample (n=10,373)	-0.095	-0.088	-0.088	-0.09	-0.091	-0.087	-0.077	-0.071
High-High LISA hotspot cluster of Financial facilities								
Full Sample (n=14,100)	-0.118	-0.137	-0.138	-0.126	-0.016	-0.065	-0.072	-0.08
Has Car (n=12,467)	0.035	0.03	0.024	0.026	0.012	-0.025	-0.036	-0.039
No Car (n=1,624)	-0.606	-0.7	-0.701	-0.666	-0.374	-0.474	-0.485	-0.491
Rural Sample (n=3727)	-0.038	-0.152	-0.172	-0.234	-0.004	0.004	-0.018	-0.04
Urban Sample (n=10,373)	-0.05	-0.067	-0.069	-0.051	0.036	-0.02	-0.029	-0.034
High-Low LISA hotspot cluster of Financial facilities								
Full Sample (n=14,100)	0.066	0.079	0.081	0.089	0.032	0.053	0.056	0.048
Has Car (n=12,467)	0.08	0.084	0.086	0.096	0.066	0.079	0.079	0.071
No Car (n=1,624)	-0.375	-0.337	-0.337	-0.32	-0.556	-0.561	-0.555	-0.511
Rural Sample (n=3727)	-0.008	0.005	0.017	0.018	0.118	0.166	0.174	0.144
Urban Sample (n=10,373)	0.089	0.102	0.102	0.12	-0.014	0.001	0.004	0.003
Logged mean distance in kilometres to financial services								
Full Sample (n=14,100)	-0.111	-0.103	-0.104	-0.107	-0.202	-0.17	-0.166	-0.163
Has Car (n=12,467)	-0.096	-0.091	-0.091	-0.092	-0.173	-0.15	-0.144	-0.142
No Car (n=1,624)	-0.16	-0.201	-0.21	-0.205	-0.284	-0.33	-0.33	-0.319
Rural Sample (n=3727)	-0.135	-0.11	-0.106	-0.111	-0.276	-0.195	-0.188	-0.192
Urban Sample (n=10,373)	-0.096	-0.086	-0.087	-0.09	-0.139	-0.127	-0.12	-0.118
Low-High LISA hotspot cluster of Financial facilities								
Full Sample (n=14,100)	-0.036	-0.05	-0.051	-0.044	0.143	0.119	0.121	0.11
Has Car (n=12,467)	-0.009	-0.013	-0.014	-0.005	0.235	0.225	0.226	0.216
No Car (n=1,624)	-0.146	-0.238	-0.249	-0.259	-0.504	-0.626	-0.622	-0.633
Rural Sample (n=3727)	-0.843	-0.93	-0.958	-0.955	-0.092	-0.216	-0.303	-0.359

Urban Sample (n=10,373)	0.085	0.072	0.073	0.081	0.227	0.197	0.202	0.193
Low-Low LISA hotspot cluster of Financial facilities								
Full Sample (n=14,100)	-0.214	-0.218	-0.213	-0.223	-0.266	-0.274	-0.259	-0.26
Has Car (n=12,467)	-0.296	-0.303	-0.297	-0.308	-0.361	-0.378	-0.364	-0.362
No Car (n=1,624)	0.363	0.395	0.384	0.412	0.33	0.297	0.315	0.324
Rural Sample (n=3727)	-0.43	-0.435	-0.413	-0.436	-0.587	-0.594	-0.559	-0.55
Urban Sample (n=10,373)	-0.189	-0.198	-0.195	-0.202	-0.225	-0.234	-0.22	-0.221
Presence of financial services within the LSOA								
Full Sample (n=14,100)	0.096	0.084	0.085	0.088	0.136	0.125	0.12	0.122
Has Car (n=12,467)	0.108	0.1	0.1	0.101	0.131	0.124	0.118	0.119
No Car (n=1,624)	0.008	-0.005	-0.004	0.022	0.146	0.159	0.158	0.186
Rural Sample (n=3727)	0.043	0.016	0.009	0.012	0.117	0.064	0.054	0.059
Urban Sample (n=10,373)	0.123	0.113	0.112	0.117	0.147	0.143	0.139	0.142
Food services								
0 to <200 metres mean distance to Food services								
Full Sample (n=14,100)	-0.287	-0.297	-0.29	-0.289	-0.299	-0.239	-0.231	-0.214
Has Car (n=12,467)	-0.256	-0.259	-0.257	-0.257	-0.325	-0.258	-0.256	-0.239
No Car (n=1,624)	-0.85	-0.877	-0.892	-0.868	-0.678	-0.592	-0.574	-0.586
Rural Sample (n=3727)	-0.438	-0.43	-0.425	-0.448	-0.479	-0.402	-0.403	-0.414
Urban Sample (n=10,373)	-0.333	-0.333	-0.332	-0.337	-0.243	-0.194	-0.205	-0.201
200 to <400 metres mean distance to Food services								
Full Sample (n=14,100)	-0.358	-0.364	-0.356	-0.354	-0.391	-0.34	-0.326	-0.315
Has Car (n=12,467)	-0.333	-0.336	-0.331	-0.33	-0.386	-0.328	-0.318	-0.306
No Car (n=1,624)	-0.836	-0.839	-0.856	-0.825	-0.824	-0.769	-0.758	-0.769
Rural Sample (n=3727)	-0.626	-0.623	-0.618	-0.624	-0.69	-0.663	-0.659	-0.658
Urban Sample (n=10,373)	-0.383	-0.377	-0.377	-0.381	-0.317	-0.273	-0.278	-0.282
400 to <600 metres mean distance to Food services								
Full Sample (n=14,100)	-0.258	-0.241	-0.234	-0.233	-0.367	-0.278	-0.262	-0.259
Has Car (n=12,467)	-0.252	-0.24	-0.234	-0.233	-0.358	-0.276	-0.262	-0.256
No Car (n=1,624)	-0.622	-0.606	-0.629	-0.629	-0.83	-0.756	-0.755	-0.792
Rural Sample (n=3727)	-0.294	-0.251	-0.249	-0.253	-0.493	-0.352	-0.354	-0.35
Urban Sample (n=10,373)	-0.318	-0.294	-0.294	-0.3	-0.306	-0.247	-0.247	-0.257
600 to <800 metres mean distance to Food services								

Full Sample (n=14,100)	-0.044	-0.008	-0.006	-0.005	0.006	0.11	0.114	0.114
Has Car (n=12,467)	-0.026	0.002	0.003	0.005	0.011	0.11	0.111	0.113
No Car (n=1,624)	-0.254	-0.235	-0.215	-0.225	-0.087	-0.13	-0.115	-0.147
Rural Sample (n=3727)	0.04	0.093	0.084	0.086	0.094	0.222	0.206	0.207
Urban Sample (n=10,373)	-0.248	-0.199	-0.199	-0.204	-0.163	-0.066	-0.068	-0.084
At least 1 OA lacks access to Food services within 800-metres of PWC								
Full Sample (n=14,100)	0.124	0.152	0.152	0.148	0.126	0.138	0.133	0.116
Has Car (n=12,467)	0.111	0.134	0.134	0.131	0.119	0.127	0.125	0.109
No Car (n=1,624)	0.314	0.421	0.448	0.449	0.295	0.348	0.346	0.336
Rural Sample (n=3727)	0.435	0.44	0.451	0.453	0.555	0.575	0.592	0.578
Urban Sample (n=10,373)	0.023	0.059	0.059	0.054	-0.022	-0.023	-0.024	-0.039
High-High LISA hotspot cluster of Food services venues								
Full Sample (n=14,100)	0.317	0.345	0.346	0.344	0.494	0.502	0.475	0.462
Has Car (n=12,467)	0.206	0.223	0.216	0.229	0.473	0.519	0.487	0.476
No Car (n=1,624)	0.406	0.541	0.552	0.554	0.381	0.467	0.446	0.454
Rural Sample (n=3727)	0.71	0.909	0.924	0.987	1.809	1.864	1.868	1.858
Urban Sample (n=10,373)	0.308	0.335	0.329	0.321	0.489	0.496	0.461	0.443
High-Low LISA hotspot cluster of Food services venues								
Full Sample (n=14,100)	-0.019	-0.046	-0.046	-0.041	0.124	0.085	0.087	0.084
Has Car (n=12,467)	-0.03	-0.06	-0.059	-0.056	0.087	0.042	0.044	0.042
No Car (n=1,624)	0.166	0.125	0.125	0.124	0.492	0.435	0.439	0.413
Rural Sample (n=3727)	0.122	0.092	0.1	0.111	0.364	0.334	0.351	0.339
Urban Sample (n=10,373)	-0.077	-0.1	-0.099	-0.1	0.035	-0.008	-0.006	-0.006
Logged mean distance in kilometres to food services								
Full Sample (n=14,100)	0.154	0.163	0.159	0.159	0.198	0.182	0.181	0.172
Has Car (n=12,467)	0.162	0.17	0.167	0.167	0.225	0.207	0.205	0.198
No Car (n=1,624)	0.138	0.166	0.168	0.171	0.041	0.039	0.045	0.041
Rural Sample (n=3727)	0.237	0.242	0.24	0.241	0.34	0.314	0.315	0.313
Urban Sample (n=10,373)	0.127	0.134	0.133	0.137	0.115	0.114	0.122	0.118
Low-High LISA hotspot cluster of Food services veneues								
Full Sample (n=14,100)	-0.029	-0.036	-0.034	-0.049	-0.089	-0.094	-0.105	-0.11
Has Car (n=12,467)	-0.175	-0.172	-0.172	-0.182	-0.266	-0.259	-0.264	-0.268
No Car (n=1,624)	0.533	0.524	0.533	0.501	0.717	0.824	0.796	0.751

Rural Sample (n=3727)	1.1	0.931	0.896	0.934	1.114	1	0.96	1.04
Urban Sample (n=10,373)	-0.086	-0.091	-0.094	-0.11	-0.13	-0.135	-0.154	-0.162
Low-Low LISA hotspot cluster of Food services venues								
Full Sample (n=14,100)	-0.043	-0.03	-0.029	-0.033	-0.021	0.015	0.023	0.025
Has Car (n=12,467)	-0.088	-0.074	-0.07	-0.079	-0.027	0.003	0.013	0.006
No Car (n=1,624)	0.377	0.302	0.296	0.32	0.092	0.147	0.147	0.196
Rural Sample (n=3727)	0.011	-0.025	-0.021	-0.001	-0.001	-0.077	-0.076	-0.069
Urban Sample (n=10,373)	-0.059	-0.039	-0.037	-0.044	-0.034	0.025	0.036	0.036
Presence of food services within the LSOA								
Full Sample (n=14,100)	-0.073	-0.073	-0.075	-0.079	-0.093	-0.106	-0.114	-0.115
Has Car (n=12,467)	-0.073	-0.071	-0.076	-0.079	-0.111	-0.121	-0.129	-0.13
No Car (n=1,624)	-0.163	-0.156	-0.15	-0.164	-0.081	-0.055	-0.059	-0.076
Rural Sample (n=3727)	-0.037	-0.027	-0.025	-0.023	-0.153	-0.138	-0.14	-0.147
Urban Sample (n=10,373)	-0.115	-0.114	-0.116	-0.122	-0.1	-0.118	-0.129	-0.132
Greenspace & recreation								
0 to <200 metres mean distance to Greenspace								
Full Sample (n=14,100)	0.157	0.203	0.2	0.194	0.258	0.264	0.258	0.227
Has Car (n=12,467)	0.132	0.184	0.18	0.175	0.212	0.224	0.217	0.191
No Car (n=1,624)								
Rural Sample (n=3727)	0.205	0.302	0.305	0.3	0.261	0.357	0.355	0.345
Urban Sample (n=10,373)	0.378	0.352	0.345	0.357	0.59	0.456	0.431	0.414
200 to <400 metres mean distance to Greenspace								
Full Sample (n=14,100)	0.147	0.184	0.181	0.178	0.273	0.28	0.279	0.253
Has Car (n=12,467)	0.161	0.206	0.206	0.203	0.284	0.302	0.304	0.283
No Car (n=1,624)	-0.188	-0.219	-0.221	-0.227	-0.156	-0.214	-0.219	-0.218
Rural Sample (n=3727)	0.061	0.134	0.15	0.147	0.062	0.142	0.165	0.154
Urban Sample (n=10,373)	0.389	0.356	0.349	0.365	0.639	0.507	0.486	0.476
400 to <600 metres mean distance to Greenspace								
Full Sample (n=14,100)	0.157	0.177	0.172	0.166	0.26	0.251	0.247	0.22
Has Car (n=12,467)	0.137	0.166	0.162	0.158	0.227	0.233	0.23	0.209
No Car (n=1,624)	0.064	0	0	-0.012	0.121	0.008	0.001	0.014
Rural Sample (n=3727)	-0.02	0.04	0.049	0.044	-0.006	0.056	0.069	0.062
Urban Sample (n=10,373)	0.412	0.36	0.352	0.366	0.633	0.48	0.459	0.451

600 to <800 metres mean distance to Greenspace								
Full Sample (n=14,100)	0.139	0.167	0.163	0.157	0.236	0.237	0.233	0.208
Has Car (n=12,467)	0.122	0.157	0.151	0.148	0.208	0.218	0.211	0.188
No Car (n=1,624)	0.523	0.381	0.381	0.382	0.577	0.424	0.417	0.467
Rural Sample (n=3727)	-0.064	-0.014	-0.008	-0.002	-0.04	-0.008	-0.001	0.01
Urban Sample (n=10,373)	0.458	0.412	0.404	0.423	0.645	0.521	0.504	0.495
At least 1 OA lacks access to Greenspace within 800-metres of PWC								
Full Sample (n=14,100)	0.052	0.035	0.033	0.029	-0.008	-0.024	-0.032	-0.031
Has Car (n=12,467)	0.07	0.054	0.049	0.046	-0.015	-0.026	-0.037	-0.038
No Car (n=1,624)	-0.061	-0.066	-0.048	-0.07	0.028	-0.016	-0.012	0.008
Rural Sample (n=3727)	0.033	0.026	0.017	0.027	-0.133	-0.161	-0.17	-0.149
Urban Sample (n=10,373)	0.109	0.066	0.067	0.066	0.149	0.137	0.14	0.142
High-High LISA hotspot cluster of Greenspace venues								
Full Sample (n=14,100)	0.006	0.03	0.03	0.03	-0.011	0.013	0.013	0.008
Has Car (n=12,467)	-0.027	-0.007	-0.005	-0.004	-0.025	-0.004	-0.005	-0.007
No Car (n=1,624)	0.216	0.242	0.248	0.235	0.053	0.102	0.114	0.072
Rural Sample (n=3727)	0.003	0.035	0.035	0.027	-0.031	0.017	0.022	0.007
Urban Sample (n=10,373)	-0.037	-0.017	-0.013	-0.015	-0.055	-0.042	-0.028	-0.036
High-Low LISA hotspot cluster of Greenspace venues								
Full Sample (n=14,100)	-0.254	-0.228	-0.224	-0.237	-0.375	-0.383	-0.38	-0.39
Has Car (n=12,467)	-0.226	-0.208	-0.204	-0.213	-0.308	-0.336	-0.33	-0.339
No Car (n=1,624)	0.169	0.267	0.259	0.239	-0.129	0.073	0.066	0.037
Rural Sample (n=3727)	-2.516	-2.738	-2.75	-3.038	-1.69	-1.895	-1.907	-2.162
Urban Sample (n=10,373)	-0.172	-0.136	-0.135	-0.149	-0.298	-0.296	-0.298	-0.305
Logged mean distance in kilometres to greenspace								
Full Sample (n=14,100)	0.012	-0.01	-0.01	-0.009	0.007	-0.004	-0.003	0.003
Has Car (n=12,467)	0.013	-0.003	-0.004	-0.001	0.007	0.003	0.004	0.009
No Car (n=1,624)	0.058	-0.014	-0.013	-0.025	0.122	0.033	0.035	0.043
Rural Sample (n=3727)	-0.057	-0.08	-0.084	-0.079	-0.086	-0.109	-0.111	-0.104
Urban Sample (n=10,373)	0.042	0.02	0.018	0.025	0.04	0.034	0.04	0.051
Low-High LISA hotspot cluster of Greenspace veneues								
Full Sample (n=14,100)	0.117	0.089	0.09	0.089	0.099	0.078	0.084	0.086
Has Car (n=12,467)	0.007	-0.025	-0.021	-0.02	-0.005	-0.022	-0.016	-0.012

No Car (n=1,624)	0.894	0.874	0.875	0.886	0.818	0.737	0.743	0.758
Rural Sample (n=3727)	-0.119	-0.148	-0.141	-0.157	-0.167	-0.177	-0.16	-0.189
Urban Sample (n=10,373)	0.352	0.329	0.332	0.329	0.318	0.295	0.308	0.317
Low-Low LISA hotspot cluster of Greenspace venues								
Full Sample (n=14,100)	0.118	0.102	0.101	0.098	0.018	-0.019	-0.021	-0.013
Has Car (n=12,467)	0.056	0.033	0.031	0.031	-0.025	-0.068	-0.073	-0.065
No Car (n=1,624)	0.55	0.586	0.586	0.575	0.384	0.452	0.451	0.468
Rural Sample (n=3727)								
Urban Sample (n=10,373)	0.133	0.121	0.12	0.117	0.032	-0.002	-0.007	0
Presence of greenspace and recreation within the LSOA								
Full Sample (n=14,100)	0.06	0.068	0.073	0.073	0.057	0.059	0.058	0.055
Has Car (n=12,467)	0.028	0.029	0.036	0.034	0.029	0.017	0.019	0.014
No Car (n=1,624)	0.231	0.276	0.278	0.296	0.228	0.279	0.274	0.275
Rural Sample (n=3727)	0.219	0.211	0.21	0.194	0.217	0.152	0.138	0.125
Urban Sample (n=10,373)	0.052	0.06	0.06	0.06	0.042	0.045	0.044	0.042
Health								
0 to <200 metres mean distance to Health Services								
Full Sample (n=14,100)	0.025	0.007	0.009	0.007	0.09	0.028	0.028	0.022
Has Car (n=12,467)	0.074	0.049	0.05	0.049	0.169	0.098	0.095	0.092
No Car (n=1,624)	-0.297	-0.247	-0.258	-0.234	-0.451	-0.453	-0.453	-0.416
Rural Sample (n=3727)	0.248	0.268	0.282	0.281	0.082	0.128	0.146	0.141
Urban Sample (n=10,373)	-0.045	-0.056	-0.055	-0.059	0.04	-0.025	-0.027	-0.033
200 to <400 metres mean distance to Health Services								
Full Sample (n=14,100)	0.069	0.058	0.059	0.06	0.051	0.019	0.02	0.015
Has Car (n=12,467)	0.09	0.072	0.073	0.074	0.09	0.05	0.052	0.046
No Car (n=1,624)	-0.113	-0.04	-0.048	-0.024	-0.252	-0.261	-0.263	-0.24
Rural Sample (n=3727)	0.049	0.036	0.037	0.037	0.055	0.051	0.054	0.038
Urban Sample (n=10,373)	0.013	0.011	0.011	0.014	-0.004	-0.041	-0.041	-0.042
400 to <600 metres mean distance to Health Services								
Full Sample (n=14,100)	-0.012	-0.029	-0.027	-0.025	-0.019	-0.038	-0.037	-0.04
Has Car (n=12,467)	-0.03	-0.044	-0.043	-0.042	-0.015	-0.027	-0.026	-0.03
No Car (n=1,624)	-0.033	-0.025	-0.029	-0.026	-0.218	-0.25	-0.247	-0.235
Rural Sample (n=3727)	0.05	0.038	0.05	0.051	0.066	0.069	0.082	0.068

Urban Sample (n=10,373)	-0.07	-0.081	-0.08	-0.078	-0.079	-0.104	-0.105	-0.105
600 to <800 metres mean distance to Health Services								
Full Sample (n=14,100)	0.115	0.094	0.096	0.1	0.1	0.071	0.075	0.078
Has Car (n=12,467)	0.103	0.085	0.087	0.089	0.106	0.078	0.082	0.083
No Car (n=1,624)	0.172	0.169	0.163	0.175	0.033	0.025	0.029	0.054
Rural Sample (n=3727)	0.374	0.335	0.339	0.346	0.361	0.332	0.337	0.334
Urban Sample (n=10,373)	0.005	-0.005	-0.004	0.001	-0.009	-0.037	-0.036	-0.028
At least 1 OA lacks access to Health services within 800-metres of PWC								
Full Sample (n=14,100)	0.081	0.086	0.086	0.089	0.099	0.121	0.126	0.134
Has Car (n=12,467)	0.083	0.095	0.096	0.097	0.094	0.12	0.125	0.13
No Car (n=1,624)	0.144	0.064	0.066	0.042	0.264	0.242	0.244	0.241
Rural Sample (n=3727)	0.134	0.147	0.151	0.152	0.147	0.126	0.132	0.137
Urban Sample (n=10,373)	0.071	0.074	0.073	0.076	0.086	0.112	0.116	0.126
High-High LISA hotspot cluster of Health services venues								
Full Sample (n=14,100)	0.184	0.208	0.215	0.198	0.165	0.139	0.136	0.137
Has Car (n=12,467)	0.18	0.2	0.21	0.2	0.196	0.166	0.178	0.174
No Car (n=1,624)	-0.256	-0.117	-0.111	-0.09	-0.389	-0.285	-0.316	-0.254
Rural Sample (n=3727)								
Urban Sample (n=10,373)	0.152	0.176	0.174	0.148	0.168	0.142	0.128	0.122
High-Low LISA hotspot cluster of Health services venues								
Full Sample (n=14,100)	-0.027	-0.037	-0.039	-0.043	0.017	-0.006	-0.012	-0.016
Has Car (n=12,467)	0.009	0.004	0.003	-0.001	0.052	0.036	0.031	0.026
No Car (n=1,624)	-0.242	-0.282	-0.278	-0.265	-0.056	-0.11	-0.105	-0.1
Rural Sample (n=3727)	-0.202	-0.182	-0.188	-0.179	-0.263	-0.243	-0.249	-0.23
Urban Sample (n=10,373)	0.056	0.035	0.036	0.03	0.169	0.118	0.121	0.113
Logged mean distance in kilometres to health services								
Full Sample (n=14,100)	-0.004	0.007	0.004	0.004	0.007	0.022	0.015	0.018
Has Car (n=12,467)	-0.02	-0.007	-0.011	-0.011	-0.015	0	-0.008	-0.006
No Car (n=1,624)	0.18	0.163	0.172	0.172	0.197	0.231	0.234	0.24
Rural Sample (n=3727)	-0.074	-0.063	-0.067	-0.064	-0.043	-0.049	-0.054	-0.046
Urban Sample (n=10,373)	0.028	0.035	0.034	0.036	0.017	0.046	0.046	0.05
Low-High LISA hotspot cluster of Health services veneues								
Full Sample (n=14,100)	0.016	0.007	0.007	-0.012	0.042	0.05	0.047	0.034

Has Car (n=12,467)	-0.025	-0.011	-0.012	-0.034	0.022	0.045	0.043	0.031
No Car (n=1,624)	0.095	0.02	0.018	0	-0.098	-0.083	-0.09	-0.096
Rural Sample (n=3727)	0.247	0.024	-0.013	0.006	-0.478	-0.695	-0.801	-0.735
Urban Sample (n=10,373)	-0.02	-0.027	-0.028	-0.051	0.019	0.03	0.025	0.006
Low-Low LISA hotspot cluster of Health services venues								
Full Sample (n=14,100)	-0.273	-0.238	-0.244	-0.249	-0.359	-0.27	-0.286	-0.275
Has Car (n=12,467)	-0.253	-0.233	-0.24	-0.239	-0.318	-0.255	-0.275	-0.259
No Car (n=1,624)	-0.532	-0.451	-0.419	-0.422	-0.936	-0.768	-0.745	-0.767
Rural Sample (n=3727)	-0.099	0.04	0.015	-0.011	-0.128	0.119	0.088	0.086
Urban Sample (n=10,373)	-0.565	-0.582	-0.582	-0.584	-0.705	-0.705	-0.707	-0.69
Presence of Health services within the LSOA								
Full Sample (n=14,100)	0.06	0.041	0.042	0.042	0.051	0.023	0.024	0.021
Has Car (n=12,467)	0.095	0.077	0.078	0.078	0.075	0.056	0.056	0.055
No Car (n=1,624)	-0.196	-0.167	-0.168	-0.164	-0.185	-0.196	-0.195	-0.204
Rural Sample (n=3727)	0.149	0.143	0.148	0.147	0.115	0.137	0.147	0.147
Urban Sample (n=10,373)	0.025	0.008	0.008	0.007	0.024	-0.019	-0.021	-0.024
public transport T1								
200 to <400 metres mean distance to Public Transport								
Full Sample (n=14,100)	-0.063	-0.044	-0.048	-0.047	-0.103	-0.079	-0.084	-0.083
Has Car (n=12,467)	-0.057	-0.042	-0.044	-0.041	-0.101	-0.079	-0.083	-0.081
No Car (n=1,624)	-0.03	0	0	0.008	0.013	0.025	0.016	0.025
Rural Sample (n=3727)	0.037	0.056	0.066	0.075	0.069	0.072	0.083	0.097
Urban Sample (n=10,373)	-0.087	-0.074	-0.075	-0.074	-0.167	-0.135	-0.132	-0.132
400 to <600 metres mean distance to Public Transport								
Full Sample (n=14,100)	-0.269	-0.251	-0.257	-0.251	-0.28	-0.242	-0.257	-0.253
Has Car (n=12,467)	-0.248	-0.234	-0.241	-0.242	-0.262	-0.224	-0.241	-0.238
No Car (n=1,624)	-0.822	-0.747	-0.732	-0.651	-0.72	-0.715	-0.718	-0.651
Rural Sample (n=3727)	-0.052	-0.01	-0.003	0.011	-0.08	0.004	0.006	0.02
Urban Sample (n=10,373)	-0.692	-0.692	-0.692	-0.677	-0.572	-0.64	-0.637	-0.618
600 to <800 metres mean distance to Health Services								
Full Sample (n=14,100)	-0.164	-0.165	-0.165	-0.156	-0.024	-0.056	-0.066	-0.068
Has Car (n=12,467)	-0.077	-0.086	-0.09	-0.094	0.035	0.007	-0.004	-0.006
No Car (n=1,624)	-2.717	-2.528	-2.527	-2.372	-2.279	-2.385	-2.382	-2.305

Rural Sample (n=3727)	-0.108	-0.117	-0.093	-0.078	0.015	0.009	0.038	0.052
Urban Sample (n=10,373)	-1.172	-1.163	-1.156	-1.099	-0.729	-0.963	-0.95	-0.995
At least 1 OA lacks access to Public Transport within 800-metres of PWC								
Full Sample (n=14,100)	-0.071	-0.055	-0.055	-0.044	0.005	0.011	0.004	0.01
Has Car (n=12,467)	-0.032	-0.02	-0.022	-0.014	0.04	0.042	0.035	0.04
No Car (n=1,624)	-0.801	-0.791	-0.786	-0.745	-0.616	-0.615	-0.616	-0.585
Rural Sample (n=3727)	-0.071	-0.058	-0.053	-0.042	0.035	0.053	0.056	0.061
Urban Sample (n=10,373)	-0.158	-0.147	-0.146	-0.134	-0.108	-0.14	-0.143	-0.143
High-High LISA hotspot cluster of Public Transport								
Full Sample (n=14,100)	0.086	0.09	0.088	0.088	0.138	0.16	0.149	0.139
Has Car (n=12,467)	0.055	0.066	0.064	0.067	0.115	0.147	0.135	0.127
No Car (n=1,624)	0.255	0.155	0.166	0.178	0.198	0.077	0.077	0.071
Rural Sample (n=3727)	-0.036	-0.022	-0.027	-0.031	0.032	0.08	0.065	0.052
Urban Sample (n=10,373)	0.234	0.233	0.233	0.225	0.245	0.237	0.237	0.225
High-Low LISA hotspot cluster of Public Transport								
Full Sample (n=14,100)	0.088	0.132	0.134	0.131	0.187	0.157	0.167	0.156
Has Car (n=12,467)	0.156	0.193	0.195	0.189	0.171	0.148	0.156	0.149
No Car (n=1,624)	-0.236	-0.049	-0.057	-0.012	-0.108	-0.029	-0.019	-0.009
Rural Sample (n=3727)	1.984	2.111	2.096	2.023	1.616	1.757	1.741	1.709
Urban Sample (n=10,373)	-0.047	-0.003	-0.002	-0.006	0.077	0.044	0.051	0.035
Logged mean distance in kilometres to public transport								
Full Sample (n=14,100)	-0.072	-0.057	-0.063	-0.061	-0.104	-0.077	-0.083	-0.08
Has Car (n=12,467)	-0.051	-0.043	-0.049	-0.046	-0.082	-0.061	-0.068	-0.066
No Car (n=1,624)	-0.095	-0.066	-0.06	-0.066	-0.081	-0.046	-0.041	-0.036
Rural Sample (n=3727)	-0.042	-0.041	-0.035	-0.027	-0.015	-0.004	0.004	0.009
Urban Sample (n=10,373)	-0.097	-0.076	-0.077	-0.072	-0.159	-0.119	-0.113	-0.107
Low-High LISA hotspot cluster of Public Transport								
Full Sample (n=14,100)	0.157	0.153	0.152	0.151	0.169	0.187	0.184	0.177
Has Car (n=12,467)	0.087	0.09	0.089	0.089	0.143	0.166	0.163	0.155
No Car (n=1,624)	0.58	0.497	0.504	0.478	0.387	0.375	0.381	0.364
Rural Sample (n=3727)	0.014	0.013	0.016	-0.007	0.058	0.07	0.075	0.062
Urban Sample (n=10,373)	0.259	0.247	0.247	0.255	0.211	0.232	0.234	0.224
Low-Low LISA hotspot cluster of Public Transport								

Full Sample (n=14,100)	-0.052	0.002	0.001	-0.003	-0.102	-0.056	-0.056	-0.068
Has Car (n=12,467)	-0.052	-0.006	-0.008	-0.013	-0.078	-0.033	-0.035	-0.044
No Car (n=1,624)	-0.178	-0.06	-0.064	-0.059	-0.37	-0.236	-0.232	-0.247
Rural Sample (n=3727)	-0.268	-0.198	-0.166	-0.164	-0.925	-0.926	-0.897	-0.894
Urban Sample (n=10,373)	-0.05	0.008	0.007	0.002	-0.094	-0.045	-0.047	-0.065
Presence of public transport within the LSOA								
Full Sample (n=14,100)	0.211	0.24	0.243	0.232	0.183	0.173	0.174	0.175
Has Car (n=12,467)	0.136	0.167	0.173	0.159	0.171	0.16	0.165	0.165
No Car (n=1,624)	0.495	0.511	0.515	0.504	0.038	0.044	0.039	0.047
Rural Sample (n=3727)	0.121	0.287	0.297	0.305	-0.148	0.126	0.122	0.171
Urban Sample (n=10,373)	0.233	0.256	0.256	0.247	0.215	0.192	0.193	0.192
retail								
0 to <200 metres mean distance to Retail								
Full Sample (n=14,100)	-0.032	-0.009	-0.009	0.003	-0.057	-0.022	-0.024	-0.039
Has Car (n=12,467)	-0.134	-0.107	-0.109	-0.101	-0.164	-0.113	-0.12	-0.138
No Car (n=1,624)	0.299	0.279	0.265	0.263	0.328	0.329	0.318	0.315
Rural Sample (n=3727)	1.157	1.233	1.28	1.3	2.023	2.252	2.308	2.309
Urban Sample (n=10,373)	-0.079	-0.048	-0.048	-0.041	-0.123	-0.089	-0.09	-0.109
200 to <400 metres mean distance to Retail								
Full Sample (n=14,100)	0.017	0.037	0.039	0.044	0.012	0.014	0.014	0.024
Has Car (n=12,467)	0.132	0.157	0.156	0.156	0.136	0.15	0.147	0.154
No Car (n=1,624)	-0.407	-0.391	-0.389	-0.396	-0.504	-0.488	-0.486	-0.484
Rural Sample (n=3727)	0.285	0.241	0.235	0.279	0.152	0.089	0.07	0.128
Urban Sample (n=10,373)	-0.008	0.018	0.019	0.02	-0.002	0.005	0.003	0.009
400 to <600 metres mean distance to Retail								
Full Sample (n=14,100)	0.117	0.111	0.112	0.114	0.15	0.135	0.133	0.138
Has Car (n=12,467)	0.119	0.117	0.117	0.117	0.125	0.124	0.122	0.125
No Car (n=1,624)	0.066	0.068	0.071	0.057	0.185	0.165	0.171	0.164
Rural Sample (n=3727)	0.155	0.117	0.122	0.147	0.121	0.065	0.07	0.083
Urban Sample (n=10,373)	0.106	0.105	0.106	0.106	0.162	0.151	0.148	0.152
600 to <800 metres mean distance to Retail								
Full Sample (n=14,100)	-0.014	-0.001	0.002	0.003	-0.094	-0.076	-0.074	-0.069
Has Car (n=12,467)	-0.026	-0.011	-0.011	-0.011	-0.102	-0.08	-0.079	-0.078

No Car (n=1,624)	0.047	0.075	0.075	0.088	-0.003	0.033	0.037	0.066
Rural Sample (n=3727)	0.143	0.112	0.126	0.125	0.015	-0.059	-0.045	-0.022
Urban Sample (n=10,373)	-0.026	-0.01	-0.009	-0.009	-0.095	-0.069	-0.071	-0.068
At least 1 OA lacks access to Retail within 800-metres of PWC								
Full Sample (n=14,100)	-0.068	-0.07	-0.07	-0.072	-0.113	-0.095	-0.088	-0.091
Has Car (n=12,467)	-0.099	-0.107	-0.106	-0.103	-0.122	-0.118	-0.112	-0.11
No Car (n=1,624)	0.081	0.079	0.077	0.076	0.045	0.033	0.037	0.023
Rural Sample (n=3727)	-0.24	-0.159	-0.176	-0.205	-0.152	-0.052	-0.058	-0.084
Urban Sample (n=10,373)	-0.051	-0.058	-0.058	-0.058	-0.107	-0.095	-0.087	-0.086
High-High LISA hotspot cluster of Retail								
Full Sample (n=14,100)	-0.072	-0.07	-0.076	-0.087	0.045	0.014	-0.002	-0.001
Has Car (n=12,467)	-0.054	-0.04	-0.049	-0.069	0.182	0.128	0.108	0.107
No Car (n=1,624)	-0.21	-0.366	-0.37	-0.421	-0.543	-0.64	-0.648	-0.706
Rural Sample (n=3727)	0.247	0.155	0.143	0.208	-0.169	-0.257	-0.264	-0.085
Urban Sample (n=10,373)	-0.068	-0.059	-0.063	-0.072	0.08	0.053	0.038	0.041
High-Low LISA hotspot cluster of Retail								
Full Sample (n=14,100)	0.19	0.168	0.167	0.18	0.078	0.067	0.063	0.068
Has Car (n=12,467)	0.195	0.187	0.187	0.198	0.136	0.14	0.141	0.147
No Car (n=1,624)	0.036	0.04	0.038	0.038	-0.341	-0.255	-0.263	-0.275
Rural Sample (n=3727)	0.233	0.163	0.163	0.177	0.243	0.19	0.196	0.172
Urban Sample (n=10,373)	0.178	0.167	0.166	0.182	0.029	0.022	0.018	0.028
Logged mean distance in kilometres to retail								
Full Sample (n=14,100)	-0.025	-0.026	-0.036	-0.038	-0.02	-0.016	-0.027	-0.029
Has Car (n=12,467)	-0.031	-0.032	-0.042	-0.043	-0.026	-0.025	-0.037	-0.038
No Car (n=1,624)	-0.004	-0.019	-0.011	-0.008	0.046	0.022	0.027	0.03
Rural Sample (n=3727)	-0.051	-0.025	-0.024	-0.027	-0.055	-0.012	-0.008	-0.011
Urban Sample (n=10,373)	-0.025	-0.033	-0.034	-0.037	-0.029	-0.033	-0.031	-0.034
Low-High LISA hotspot cluster of Retail								
Full Sample (n=14,100)	0.133	0.146	0.149	0.155	0.127	0.143	0.149	0.151
Has Car (n=12,467)	0.135	0.133	0.136	0.144	0.16	0.156	0.164	0.166
No Car (n=1,624)	0.008	0.161	0.162	0.128	0.116	0.304	0.302	0.276
Rural Sample (n=3727)	0.135	0.061	0.04	0.058	0.495	0.349	0.312	0.359
Urban Sample (n=10,373)	0.126	0.141	0.142	0.152	0.113	0.132	0.135	0.14

Presence of retail within the LSOA								
Full Sample (n=14,100)	0.024	0.037	0.033	0.041	-0.004	-0.007	-0.013	-0.008
Has Car (n=12,467)	0.012	0.029	0.023	0.031	0.002	0.006	0	0.007
No Car (n=1,624)	0.087	0.107	0.109	0.088	-0.083	-0.035	-0.034	-0.062
Rural Sample (n=3727)	-0.047	-0.087	-0.085	-0.076	-0.056	-0.095	-0.095	-0.096
Urban Sample (n=10,373)	0.045	0.074	0.073	0.08	0.018	0.03	0.025	0.029