



Classifying the Older Population

UNDERSTANDING THE GEOGRAPHY OF OPPORTUNITIES AND CHALLENGES IN ENGLAND

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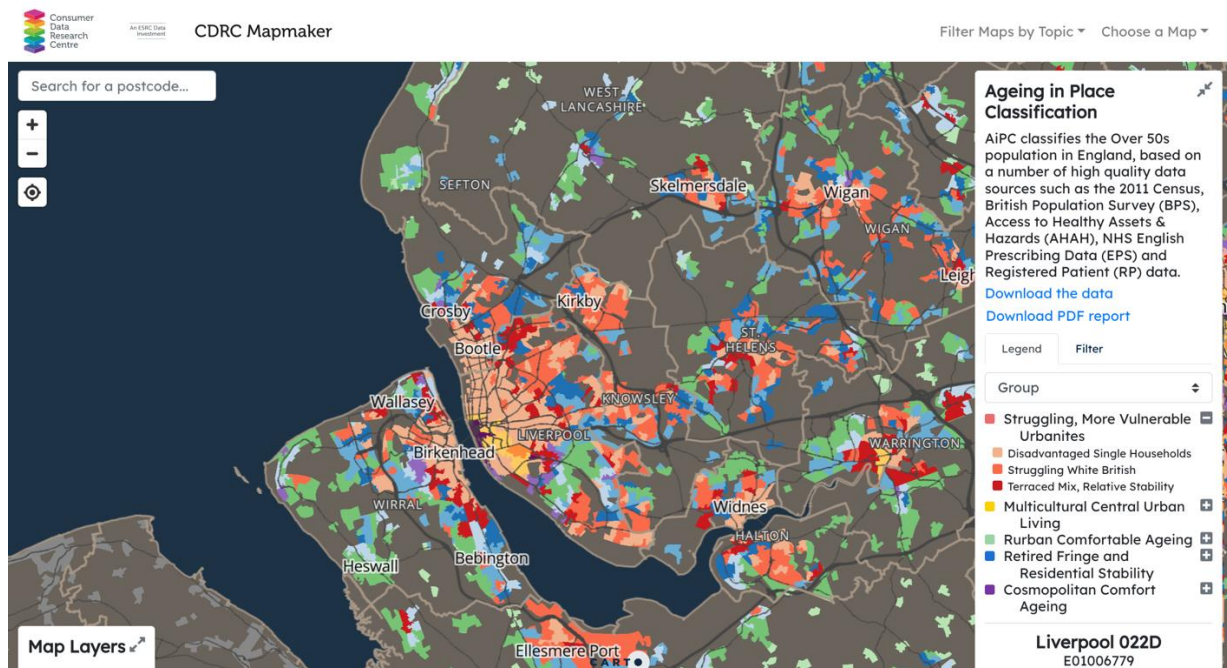
Map produced by authors (bottom picture)

Online material

The resulting Ageing in Place Classification (AiPC) is visualised on an interactive web map hosted on the Consumer Data Research Centre (CDRC) platform where members of the public are able to zoom in and out, pan around, and identify features such as individual clusters, LSOAs or postcodes and accompanying pen portraits (profiles of the identified clusters in the classification).

The AiPC classification can be accessed at the following web address:

<https://mapmaker.cdrc.ac.uk/#/ageing-in-place-classification>



Summary

Older people in England: the geography of challenges and opportunities

Research background

- The population of England is ageing. By 2041, approximately 26% of the UK's population will be aged 65 and over, with ages 50 and over likely comprising around half the adult population (ONS, 2018).
- This changing demographic character of the country represents a significant challenge. Developing places that are suitable for residents to 'age in place' will be one of the principal goals for policy makers over the coming decades. Providing decision makers with robust evidence will be an essential aspect of building the communities that can support this process of ageing in place.
- While it has been argued that the ageing population may present an untapped demographic dividend, it will equally challenge the fiscal sustainability of existing models of service provision. Response to the opportunity and challenge presented will be constrained by the current limited understanding of the differentiation within a population continues to present the ageing population as homogenous.
- It was from this perspective that the Nuffield Foundation supported researchers at the University of Liverpool by funding the project *Older people in England: the geography of challenges and opportunities* (2020-2022).

Research aims and objectives

- The overarching aim of this project is to better understand and support our older population by creating and demonstrating the utility of a bespoke multidimensional geodemographic classification of the older population in England; those aged 50+. Such a geodemographic classification will provide a unique policy resource that will capture the social and spatial heterogeneity of the older population in England by combining traditional and novel data sources.
- The key objectives are as follows: i) to build the Ageing in Place Classification (AiPC) and ii) to demonstrate the utility of AiPC through: a) an investigation of how accessibility to services for older people varies across the AiPC; b) a demonstration of how planning decisions in relation to housing need can be enhanced by applying the AiPC and c) an examination of whether application of the AiPC can enhance small area estimates of loneliness in England

The Ageing in Place Classification (AiPC) - understanding ageing in place:

- Just like any other generally definable social classification, older people are not a homogenous group. In order to understand variations in the population of older population the researchers developed a first in the UK bespoke geodemographic model, the ageing in place classification (henceforth, AiPC) which allows for a more

detailed understanding of the specific characteristics, needs, expectations and aspirations of older people.

- First, based on extensive literature review and consultations with our panel of experts, we identified nine inter-connected domains which are in line with the WHO Active Ageing Policy Framework. Measures for each domain were then generated, reflecting characteristics of older people and the places in which they live. The measures include: People, Housing, Work and education, Mobility, Financial Security, Digital, Health, Outdoor Space and Living Environment and Civic participation.
- To develop the AiPC we employed Census data and other novel sources of data at the small area level, such as the British Population Survey, NHS prescription data and house prices.
- We used a methodology based on previous geodemographic classifications studies, such as the OAC (Gale et al., 2016) and COWZ-EW (Cockings et al., 2020). A robust clustering algorithm, called 'k-means' ¹, was implemented to organise small geographical areas (Lower Super Output Areas) into categories (clusters) that share similar attributes across space (Singleton & Spielman, 2014).
- The AiPC resulted in 5 'Supergroups' and 13 nested 'Groups' that provide a more nuanced understanding of the characteristics of older people in England at small area level.
- The AiPC classification is visualised on an interactive, publicly available, web map hosted on the Consumer Data Research Centre (CDRC) platform where users are able to zoom in and out, pan around and identify particular features such as individual clusters, LSOAs or postcodes and accompanying pen portraits (profiles of the identified clusters in the classification).
- The characteristics of all clusters have been examined and given 'Pen Portrait' descriptions and names to depict their key characteristics. These names and descriptions were first proposed by the authors and evaluated through a ground-truthing exercise with the Advisory Group and experts.
- A more detailed understanding of the geography of the ageing population's characteristics and dwelling environments is essential to better target interventions and allocate resources. Using the AiPC the researchers were able to investigate the utility of the developed geodemographic classification through a series of research questions relating to the three following themes: neighbourhoods, housing and society. These three case studies were used to evaluate spatial variation in service accessibility across the geodemographic classification and the extent to which implementing our AiPC classification can enhance small area estimation of loneliness and housing satisfaction for an ageing population.

Neighbourhoods - ageing and the 20-minute city

- The idea that someone's daily needs should be met within an active travel distance has gained significant currency with policy makers the world over (Dunning, Calafiore &

¹ In this context, k-means clustering is a method to group different spatial areas given a set of different variables into multiple clusters.

Nurse, 2021). To guarantee a 20-minute city that is inclusive, specific attention needs to be paid to the geography of the population that is ageing in the area. This research, therefore, introduces a score that is specifically focused on the needs and characteristics of an ageing population.

- The 20-minute city concept is dependent upon the distance which its residents are able to walk in a relatively short time frame. This raises the question of equitable access for those older people whose mobility is more limited. To account for this we identified a realistic alternative understanding of the 20-minute city for the ageing population. Using Liverpool City Region (LCR) as a case study, we show how the interpretation of the 20-minute city 'narrows' when limited mobility/walking pace amongst older citizens is accounted for.
- When we consider a slower walking pace common to older citizens, we note that the maximum score found in the study area is only 69% of the necessary access to meet the ideal of a 20-minute city. Thus, older people are not currently able to access all necessary services within a 10-minute walk anywhere in Liverpool City Region.
- Four classes of relative accessibility were distinguished: areas with *very low*, *low*, *high* and *very high* access. Only a few very high access areas were identified in Liverpool City Region typically in a close proximity to town centres and local high streets, accompanied by a more extensive coverage of high access areas where people have at least half of the service categories accessible to them in a 10-minute walk. When the score is computed for people over 50 with reduced mobility, a striking reduction in *very high* and *high* access areas was noticeable.
- This has implications for decision makers with regards to the density and mixed-use character of developments and encourages a fuller understanding of what the 20-minute city means for an ageing population. Thus, the AiPC classification can be used as an important tool to effectively profile service users and their needs, serving as a mechanism to better target service provision for this demographic group.

Housing – estimating accommodation satisfaction in England

- The case study explores how the AiPC can support understanding of the ageing population satisfaction with their dwellings, by generating first-of-its-kind small area estimates (SAE) based on English Housing Survey (EHS) data.
- New insights into the small area geography of housing (un)suitability relative to the needs of an ageing population are provided by identifying drivers of housing (dis)satisfaction and employing the AiPC classification to the SAE model.
- The estimates show that the highest dissatisfaction with accommodation amongst the 50+ population is recorded in Supergroup 2, *Multicultural Central Urban Living*. These areas are mostly located in the central major urban centres and with higher cost of living, especially housing. At the other end of the spectrum Supergroup 3 and 4 (*Rurban Comfortable Ageing* and *Retired Fringe*, and *Residential Stability* respectively) record around 50% to 80% lower levels of dissatisfaction with accommodation amongst 50+ residents. Both Supergroups have a higher median age and are predominantly homeowners.

- A case study of the Liverpool City Region (LCR) was used to explore the geography of housing satisfaction amongst older residents in this specific area. Supergroup 2 (*Multicultural Central Urban Living*) has the highest share of dissatisfied residents compared to the national average. This suggests that the housing stock for older residents in Liverpool living in those areas might require more attention compared to other similar areas in England.
- To an extent, this can be explained by the rate of home ownership in these neighbourhoods, which is far below the national level for the same Supergroup (23% in LCR compared to 49% nationally). Older people in these areas are also more likely to be living with a long-term health condition (54% vs 44%) and these areas have a higher crime score (0.76 in LCR vs 1.06 nationally) measured by the Index of Multiple Deprivation (IMD).
- There are clear geographic variations in the suitability of the housing stock in LCR to encourage differences in ageing in place. Some neighbourhoods are relatively well-equipped to make this transition to an ageing population, while others may require more support.

Society - estimating loneliness in England

- Loneliness has been defined as a 'silent pandemic' (Jeste et al., 2020). Feeling lonely is associated with higher mortality, depression, and heart attacks (Gale et al. 2017). Loneliness is not only a tragic social phenomenon, but it also adds a significant cost to UK public spending. Some estimates suggest that loneliness could cost £2.5 billion for UK employers (New Economics Foundations, 2017) and it could cost £6,000 per person for older people (McDaid et al., 2017).
- To better understand the geography of loneliness, we draw on the AiPC and develop a small area estimation (SAE) model of the levels of loneliness across the 50+ population based on the English Longitudinal Study of Ageing (ELSA) survey data.
- The results show that large urban centres are the areas where loneliness in the 50+ population is more prevalent. On the one hand urban centres are exceptional nodes for human activities, whilst these are also the locations where aspects of deprivation may make ageing in place more difficult. However, these variations are not homogenous across space with more affluent areas in central neighbourhoods having low levels of estimated loneliness. Conversely, some suburban and rural-fringe areas near larger cities such as London, Birmingham, Liverpool and Manchester have levels of loneliness that are at least 50% higher than the national average.
- AiPC Supergroup 2 (*Multicultural Central Urban Living*) and 1 (*Struggling, More Vulnerable Urbanites*) have around 50% to 100% higher than average levels of older people feeling lonely, whilst the more rural AiPC Supergroup 3 has a lower level of loneliness. We identified marital status and health conditions as two key factors driving loneliness. Environmental factors such as crime and income deprivation are also positively associated with higher level of loneliness among ageing population.
- Finally, the digital engagement is almost proportionally correlated with lower levels of loneliness across all the AiPC Supergroups, suggesting that the AiPC can provide relevant insights into loneliness to support policy makers. For example, Supergroup 3 (*Rural/Rural Urban Fringe, Comfortable Ageing*) and Supergroup 5 (*Retired Fringe and Residential Stability*) have the best access to information, services and social media,

and also show the lowest levels of loneliness. While we do not suggest that there is a direct link between lower levels of loneliness and higher level of digital engagement, this hint might suggest implementation of policies to improve digital access for ageing population, especially when almost a third of the 65+ have never used the internet (Age UK, 2016).

Recommendations

1. Our first recommendation is that when considering questions of ageing population from a policy perspective geography matters. Older people are often homogenised as a dependent burden, however effective planning for services provision and targeted interventions depend on recognition of the heterogeneity of these demographics and their uneven spatial distribution.
2. Research shows that general-purpose geodemographic classifications can be successfully applied to provide evidence-based policy guidelines and interventions (e.g. Singleton and Spielman, 2014; Moon et al., 2019), however we argue that within the ageing population context, a bespoke classification can offer richer insights to support specific applications or focus on these demographics. As such the AiPC classification provides a valuable tool to equip policy makers, planners and service providers with a better understanding of the social and spatial variation in the characteristics, behaviours and needs within the older population.
3. The AiPC offers an opportunity to contrast similar population-place structures in different parts of England. There is substantial policy discourse at present regarding Levelling Up, which is normally considered at the local authority scale. The AiPC provides for national comparisons that are predicated on older person specific geodemographics, to help define what Levelling Up might look like spatially for this demographic.
4. We also recommend that any approach which seeks to understand spatial patterns of the ageing population employ our bespoke geodemographic classification. We have provided evidence that AiPC has been beneficial and enhanced the synthetic estimates of housing satisfaction and loneliness for older people at small area level. We believe that AiPC can also be applied within other contexts related to older people to further expand our understanding of multiple challenges and opportunities and their spatial variation.

1. Introduction

1.1 Research background

The population of England is ageing. By 2041, approximately 26% of the UK's population will be aged 65 and over, with ages 50 and over likely comprising around half the adult population (ONS, 2018). Concurrently, the success of the economy will increasingly be linked to an ageing workforce: the proportion of workers aged between 50 and State Pension Age (SPA) is projected to increase by 9% to 35% over the next 30 years (Government Office for Science, 2016). The dramatically shifting age-structure of England will have a significant impact on health and wellbeing, and is already challenging the fiscal sustainability of strained models of service provision. It is therefore crucial to develop a robust evidence base that can support effective and efficient planning and policy interventions. As the social, economic, and environmental requirements of an older population will be significantly different from those previously encountered (RTPI, 2004: 2), effective planning and policy intervention will follow from a better understanding of the nature and geography of the older population. However, while population ageing is often demonised as a looming crisis wherein older people are homogenised as a dependent burden, the characteristics, behaviours and needs of the older demographic are not uniform, tending to vary spatially (Skinner et al., 2014). Challenging binary divisions between the young (able) and old (infirm) is therefore critical.

Multiple emerging policy agendas, such as *ageing-in-place* (Bartlett and Carrol, 2011), calls for employment reforms for age-adjusted flexible working patterns and age-appropriate healthcare for older workers (see Ilmarinen, 2006) are contributing to the realisation of age-friendly societies. Associated policies typically promote healthy, active lifestyles alongside sustained age-appropriate economic activity while also enabling older populations to live within the community for longer, rather than moving away to residential care. Their success hinges on appropriate local service provision responding to local needs, and appropriate housing. Understanding the characteristics and geography of the older population, including the older workforce, will substantively enhance policy-makers ability to meaningfully tailor and target specialised policy interventions. Effective planning for 'whole life-course' neighbourhoods therefore depends on recognition of the heterogeneity of the older population and their uneven spatial distribution. Carefully targeted interventions in local service provision and the built environment (e.g. housing) will be incumbent upon a fine-grained understanding of the dynamics of place-based ageing, yet such an understanding is currently lacking.

It is, therefore, essential to "develop tools to equip policy makers, planners and service providers with a better understanding of the social and spatial variation in the characteristics, behaviours and needs within the older population" (Darlington-Pollock et al., 2020, p.4). Singleton and Spielman (2014) demonstrate that the social and spatial heterogeneity of population or a particular group of people can be facilitated by using a multidimensional geodemographic classification. Such classifications provide a more detailed understanding of the geography of the entire or particular group of population, including their socio-economic characteristics and environments they live in, which is essential to better target interventions and allocate resources. Geodemographic classifications are built with cross-sectional data and organise neighbourhoods into clusters based on similarity of their multidimensional attributes

across space (Singleton & Spielman, 2014). However, research implementing geodemographics to the ageing population in England is virtually non-existent.

1.2 Aims and objectives

The overarching aim of this project is to better understand and support our older population by creating and demonstrating the utility of a bespoke multidimensional geodemographic classification of the older population in England aged 50+. This unique policy resource combines traditional and novel data sources that capture the social and spatial heterogeneity of the older population in England.

The key objectives of this project are as follows:

- i) To build the Ageing in Place Classification (AiPC) by using cross-sectional data to provide new insights that can be used to support service planning and policy development related to the ageing population.
- ii) To demonstrate the utility of the AiPC through:
 - a) an investigation of how accessibility to the relevant services for older people varies for the AiPC geodemographic groups within the concept of the 20-min city
 - b) an exploration of how planning for housing needs can be enhanced by applying the AiPC to improve understanding older people's housing satisfaction and needs.
 - c) an examination of whether application of the AiPC can develop a more nuanced understanding of the characteristics and contexts of the older population and social isolation by enhancing small area estimates of loneliness in England.

1.3 Structure of the report

The main research output of this study is the bespoke classification of older people aged 50+ in England – the Ageing in Place Classification (AiPC). Chapter 2 of this report provides relevant background and justification for such a classification and outlines the methodology applied to develop the AiPC. Geodemographic classifications organise geographical areas into clusters that share similar characteristics across multidimensional variable space (Singleton & Spielman, 2014). In Chapter 2 we also provide the differential characteristics of each cluster and sub-cluster referred to as 'pen portraits' and in the final section summarise the 'ground truthing' exercise used to validate the study results. The AiPC classification allows then the researchers to test its utility within the context of a series of research questions relating to the following three research themes: neighbourhoods, housing and society.

In Chapter 3, we investigate the application of the AiPC classification to neighbourhoods by computing accessibility scores to relevant services for older people within the 20-min city context. The relationship between neighbourhoods, housing and society is critical for urban planning to ensure that older people are supported to age in the places that they choose to. One key extension to this classification is to understand how the AiPC relates to other key public policy plans, such as the need to support active travel and access to key services for older people. Thus, the AiPC represents a major opportunity to consider the relationship between groups of older people, mobility, and access to services as part of the 20-minute city concept, in the hope of supporting urban planning for older people.

In Chapter 4 we explore the housing theme by initially estimating housing (dis)satisfaction at the national scale and then focusing on Liverpool City Region as a case study. Housing is one of the key pillars helping people to 'age in place' (WHO, 2007). A satisfactory home is essential to support both physical health and mental wellbeing, with dwelling conditions being a significant predictor of the psychological well-being of older people (Fernández-Portero et al., 2017). However, the geography of housing satisfaction is little understood and there is no direct measure of the phenomenon at a small area level. In this chapter, we employ the AiPC alongside other variables to build a model that estimates housing satisfaction in England at the LSOA level. We then investigate the relationship between the estimates and the AiPC supergroups and groups and test whether understanding diverse spatial patterns in accommodation satisfaction can be enhanced by employing the AiPC, which offers detailed profiling of older people.

In Chapter 5 we focus on the society theme by using the AiPC to demonstrate how a bespoke classification can enhance understanding of older people's vulnerability by exploring spatial patterns of loneliness. Research shows that feeling lonely is associated with higher mortality (Luo et al., 2012), depression (Gale et al., 2018) and heart attacks (Thurston et al., 2009) and it also adds a significant cost to public spending. In this study we generate synthetic estimates of loneliness for 50+ years old in England at small area level using a small area estimation (SAE) technique and test the extent to which the AiPC can enhance these estimates. We also explore the utility of the AiPC as a policy tool within the above context, in particular whether it can be used to flexibly identify targeted interventions based on the ageing population profiles.

Chapter 6 provides a summary and the conclusions of the research, arguing that the AiPC is a novel contribution to understanding the geography of older people in England and has multiple and significant policy implications.

2. The Ageing in Place Classification (AiPC) - Understanding Ageing in Place

2.1 Introduction

Geodemographic classifications organise areas into categories sharing similar attributes across multidimensional variable space (Singleton & Spielman, 2014). The integration of “geo”, implies the place and environment where people live, with “demographics”, indicating the various sociodemographic characteristics of households or individuals (Leventhal, 2016; Xiang et al., 2018). There are various geodemographic classifications worldwide, and broadly, they can be classified as either general-purpose e.g. UK Output Area Classification (OAC) (Gale et al., 2016) or bespoke classifications (e.g. Classification of Workplace zone Population (COWZ) (Cockings et al., 2020). General-purpose classifications typically cover the general population and their characteristics at small area level. They are designed for use across a range of applications, although their generalist approach means they cannot always offer rich insights into all particular groups of interest (Gray et al., 2021).

Bespoke classifications, on the other hand, have been developed to support specific applications or focus on a particular group of people such as abovementioned working population or engagement with the Internet in the UK (e.g. Internet User Classification (Singleton et al., 2020). Bespoke classifications often use novel data from a range of sources, not limited to typically used Census data, to enrich insights and enhance their applicability. For example, to construct the bespoke classification of older population in England we used British Population Survey to estimate their digital engagement with finance, shopping and social networking.

To better understand the social and spatial heterogeneity within the older population and thereby support effective policy development and targeted service provision, we argue that developing an open access, multidimensional geodemographic classification of the older population in England at a small area level is pivotal. The urgency to develop a such classification was increased by marginalisation of older people in policy and public rhetoric, and the public health crisis exacerbated by the COVID 19 pandemic (Darlington-Pollock et al., 2021). We argue that development of a bespoke classification of older people in England would facilitate a more nuanced understanding of the heterogeneity of this demographic group. Though a cross-sectional snapshot, such classification can provide valuable insights into the nature of need, vulnerability and opportunity in a population which will continue to age. This understanding provides a robust basis for effective planning and policy interventions.

2.2 Methodological approach

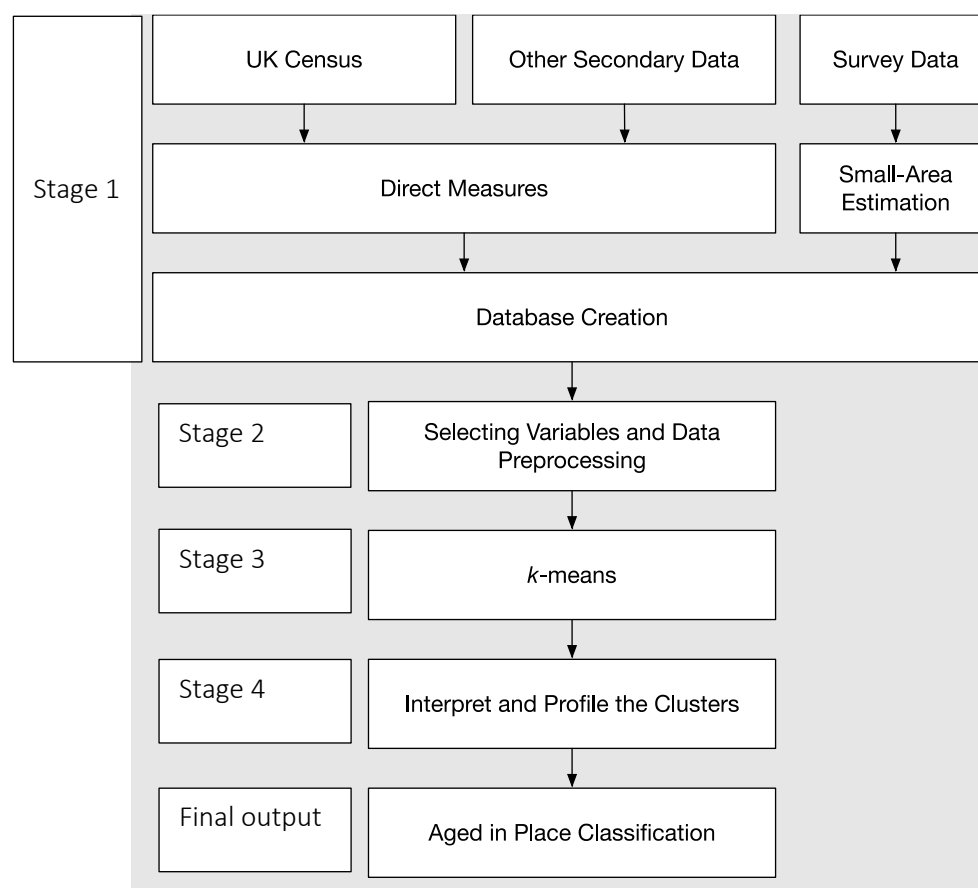
The methodology employed to develop AiPC is based on previous approaches that have been used in other geodemographic classifications studies, such as the OAC (Gale et al., 2016), COWZ-EW (Cockings et al., 2020) and IUC (Singleton et al., 2020). There are four key stages in our methodological approach shown in Figure 2.1.

In stage 1 we focussed on identifying key domains related to older people and the places in which they live based on a review of relevant literature, and validated through discussion with an advisory panel of experts (full list is available in the Acknowledgments section). Then a number of variables were obtained from various data sources to reflect different characteristics of the domains identified.

In stage 2 we statistically evaluated all generated variables to select the final set of variables that were used in the model. The applied tests included examination of their distribution, spatial coverage and patterning, as well as correlation between variables. Sensitivity analysis was also performed to measure the impact of variables on the cluster forming process (Gale et al., 2016).

In stage 3 the final set of variables was initially normalised and standardised to ensure that all contributed equally to the clustering process. Then by employing a k-means clustering model we generated a series of clusters and nested sub-clusters that represent the grouping of small areas with similar characteristics of older people and their living environment.

Figure 2.1 Flow chart of methodology employed to create AiPC



Source: Yang, Dolega and Pollock-Darlington (2022)

Finally, in stage 4 we identified the unique characteristics of all clusters and sub-clusters and created their profiles - the so-called "Pen portraits". The final output – AiPC classification was

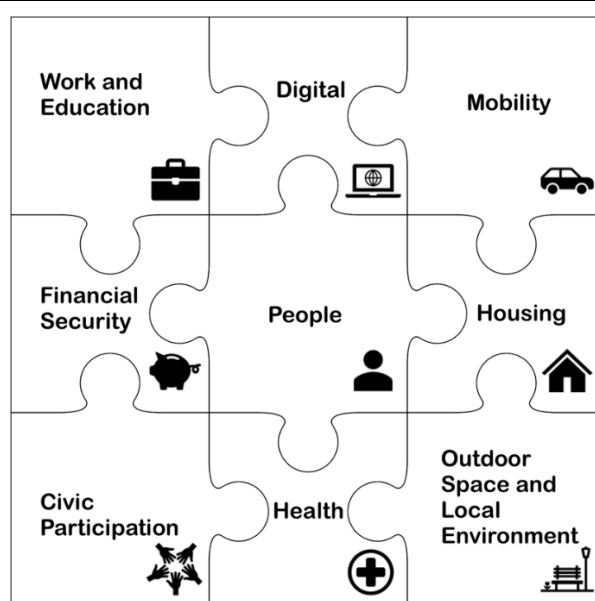
also mapped to help the end-users to understand and utilise the product more effectively. The AiPC classification is visualised on an interactive web map hosted on the Consumer Data Research Centre (CDRC) platform where members of public are able to zoom in and out, pan around and identify particular features such as individual clusters, LSOAs or postcodes and accompanying pen portraits (profiles of the identified clusters in the classification). Several advisory group meetings and consultations were conducted to ensure the various choices in the above steps were methodologically robust and theoretically grounded. Central to the consultation exercise was identifying variables that best captured relevant characteristics of older people and the places they live, pertinent to their experience of old age and ageing.

2.2.1. Relevant domains and variables

Based on extensive literature review and consultations with our panel of experts, nine interconnected domains were identified shown in Figure 2.2. These include People; Housing; Work and education; Mobility; Financial Security; Digital; Health; Outdoor space and living environment; and Civic participation. They reflect characteristics of older people and the places in which they live and they are broadly consistent with the World Health Organization (WHO) age-friendly communities' framework and the WHO Active Ageing Policy Framework. Within each of the nine domains, a number of candidate indicators were generated and considered as inputs, with the majority of the variables sourced from the 2011 Census.

We used the UK Census Local Characteristics tables which provide the greatest level of detail including the age dimension. The study has focussed on only the ageing population using a threshold of 50 years old which makes a significant difference to many other geodemographic classification studies (e.g. OAC) where the whole resident population is used as the denominator of the variables. In contrast, AiPC uses the number of older people in each LSOA as the denominator, which helps to uncover the unique features of this age group rather than masking the interesting patterns smoothed by all ages.

Figure 2.2. Domains of the AiPC classification



Source: Yang, Dolega and Pollock-Darlington (2022)

Importantly, to enhance our classification we also used a number of other secondary data sources to capture the additional characteristics in the above domains. The key datasets included NHS prescription data to calculate dementia treatment prescribing rate and British Population Survey to estimate digital engagement of older people at small area level.

NHS prescription data from January 2015 to December 2019 were used to estimate the prescribing pattern of dementia treatment medication in England. The data contain records of the prescriptions issued by each GP practice, including the ID of the practice, the prescription BNF code, chemical substance and quantity (the number of items prescribed), and the year and month of the prescription. However, the information about individual patients of each prescription is not available, and therefore the prescribing rate at lower super output area (LSOA) level had to be estimated based on the counts of patients and their home address LSOA registered at each GP using a transformation approach suggested by Comber et al. (2021). It should also be noted that dementia is highly associated with age, but this work does not produce age-standardised dementia medication prescribing rates due to data limitations. Therefore, the result can only indicate places with higher levels of prescribing for dementia medications not adjusted by age. To estimate the digital engagement of older people we used the British Population Survey (BPS) which contains information about people's sociodemographic characteristics, internet access and engagement to obtain the estimates at small area level and a novel Small Area Estimation (SAE) technique that leverage Spatial Microsimulation (SMS) and a Machine learning model developed by (Singleton et al., 2020). Only data for those aged over 50 in England was selected and used in the following modelling framework.

In addition to the abovementioned estimates, we also used other complementary information related to ageing population to enhance our understanding of their experience of ageing, to that offered by the Census. In our model we employed the Access to Health Assets and Hazards (AHAH) dataset and Journey Time Statistics (JTS) to describe (physical) access to different services and locations, air quality and green space. Index of Multiple Deprivation (IMD) scores were used to obtain information on older people's income deprivation, housing quality and local crime rates. Also, a median house price indicator derived from ONS HPSSA (Mean house prices by middle layer super output area) dataset was used and finally, we used the Ordnance Survey POI (points of interests) data to estimate the capacity for civic activity as a proxy for civic participation.

2.2.2. Variables selection and pre-processing

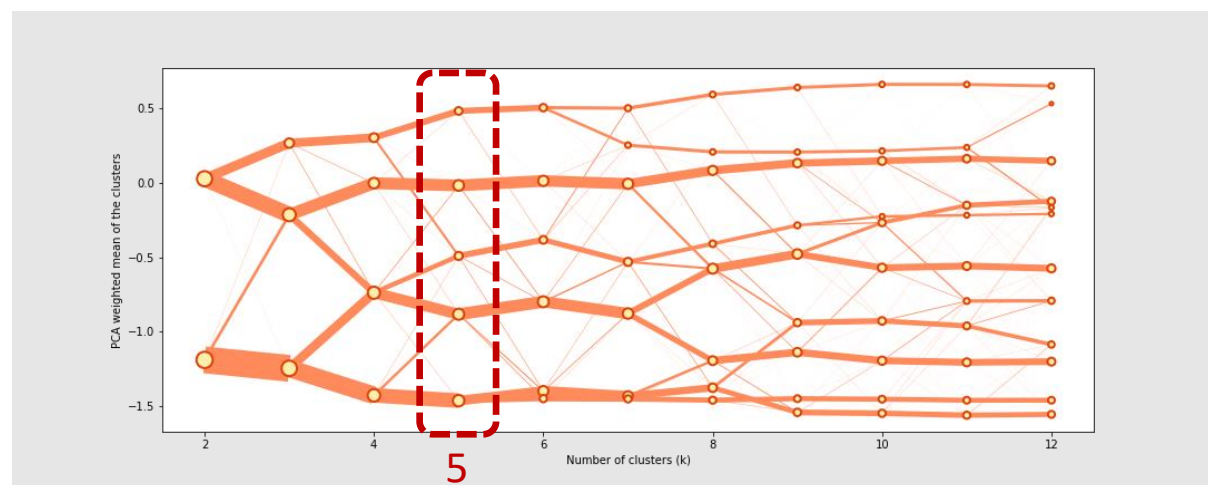
The selection of the final set of variables was based on a number of selection criteria applied in previous approaches used for building geodemographics classifications (e.g. Cockings et al., 2020; Gale et al., 2016). This included the selection of variables that (1) fell within the scope of the classification; (2) were of good quality and representativeness; (3) varied the most between areas, and (4) were not strongly correlated with each other to avoid unnecessary weight in the classification. First, the descriptive statistics such as mean, median, quantile values, standard deviation, skewness index, histograms, normal probability plots and maps at various geographical scales were examined (Cockings et al., 2020). Then we removed or combined a number of variables that were highly correlated and conducted a cluster-based sensitivity analysis to identify variables that had the greatest impact, either positive or negative, on cluster formation (Liu et al., 2019). After a careful examination, an initial set of over 150

variables was reduced to a final set of 71 variables, covering all the nine domains shown in Figure 2.2. The final set of variables is provided in Supplementary Table 1.1 in Appendix 1. Before running the clustering models, the input variables were standardised and normalised to reduce some undesirable impact in their raw format (Cockings et al., 2020; Gale et al., 2016).

2.2.3. K-means clustering analysis

Although different clustering algorithms can be used to create geodemographic classifications we followed the approach adopted by (Gale et al., 2016) and Cockings et al., (2020) to develop the OAC(Gale et al., 2016) and COWZ-UK classifications respectively - we used a *k*-means clustering to create the AiPC. It is a method that groups areas based on a measure of similarity: the areas within clusters are very similar while clusters are as distinct as possible from one another. The results comprise a two-tier classification. Tier 1 results - the main clusters referred to as *supergroups* and the nested sub-clusters - Tier 2 results, referred to as *groups*. Figure 2.3 shows the clustergram used to determine the most suitable number of clusters in the Tier 1. This visual tool plots different potential *k* values with the weighted mean of their first principal components (Schonlau, 2002) demonstrating at which point (number of *k*), the clusters are well separated in the input variable space (the y axis). Figure 2.3 suggests that—splitting the dataset into 5 clusters ($k = 5$) is most appropriate for the Tier 1 classification, which produces five distinctive clusters – these are the *AiPC supergroups*.

Figure 2.3: Clustergram of the Tier 1 classification



Source: Yang, Dolega and Pollock-Darlington (2022)

Each of the identified Tier 1 clusters was then subset and again examined using clustergram to determine the number of sub-clusters (*AiPC groups*) in Tier 2.

2.2.4. Cluster profiles

The characteristics of all clusters in Tier 1 and Tier 2 have been examined and their profiles, referred to as 'Pen Portraits' created. Each cluster was assigned a name to depict their key characteristics. The principal features of each *supergroup* (main cluster) and *group* (sub-cluster) were summarised based on their mean z-scores, which is shown in a range of radar plots (Figure 2.4 and Appendix 2) and bar plots (Figures 2.7 – 2.24), and their description is provided in Section 2.4. The z-score value of 0 denotes the England's average, while higher values indicate higher than average and vice-versa. When creating these profiles often the highest

and lowest z-scores computed for each variable are helpful in identifying the key and principal feature of the cluster.

It has been acknowledged by Gale et al. (2016) and Vickers and Rees (2011) that this process, especially the naming, is challenging and needs to: (i) accurately reflect the input variables; (ii) be consistent throughout the hierarchy; (iii) remain neutral; and (iv) avoid duplicating names/labels with other classifications (Cockings et al., 2020). To maximise the utility of the names and pen portraits for end-users of this classification, the creation of the pen portraits was done in consultation with the expert advisory group and a ground-truthing exercise (description of the process is provided in Section 2.5). Names and pen portraits were first proposed by the authors, and then evaluated through a ground-truthing exercise and advisory board consultation. The revised names and descriptions taking into consideration feedback and suggestions from the ground truthing exercise were then developed and are presented in Table 2.1 below.

2.3 The Aging in Place Classification (AiPC)

The AiPC consists of two tiers. Tier 1, the *Supergroups*, contains five clusters providing the most generic descriptions of the older population (aged 50 and over) and their living environments. Tier 2, the *Groups*, further differentiates within the five clusters of Tier 1 giving an additional 13 clusters (Table 2.1). The nested *Groups* in Tier 2 present more detailed descriptions of the people and places they represent and supplement the detail provided in the parent group.

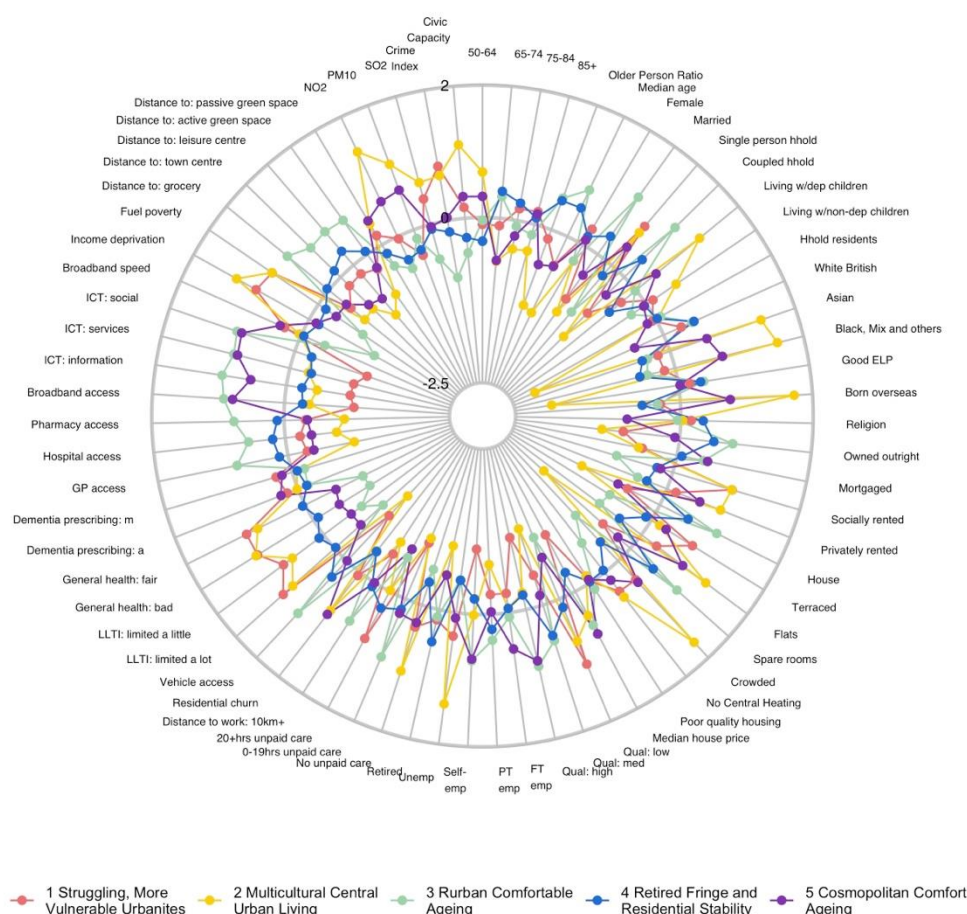
Table 2.1 AiPC hierarchy and cluster names

Supergroups	Groups
1. Struggling, More Vulnerable Urbanites	1.1 Disadvantaged Single Households 1.2 Struggling White British 1.3 Terraced Mix, Relative Stability
2. Multicultural Central Urban Living	2.1 Inner City Diverse Living 2.2 Peripheral Constrained Diverse Living
3. Rurban ² Comfortable Ageing	3.1 Rural Comfortable Ageing 3.2 Ageing in the Affluent Fringe
4. Retired Fringe and Residential Stability	4.1 Retired Country and Coastal Living 4.2 Comfortable Rural/Suburban Ageing Workers and Retirees 4.3 Constrained Semi-Rural Ageing and Retirement
5. Cosmopolitan Comfort Ageing	5.1 Cosmopolitan Family Ageing 5.2 Coastal Later Aged Retirees 5.3 Cosmopolitan Ageing

Source: Yang, Dolega and Pollock-Darlington (2022)

² This term denotes predominantly rural and urban fringe areas

Figure 2.4. Mean z-scores depicting key characteristics for AiPC Supergroups



Source: Yang, Dolega and Pollock-Darlington (2022)

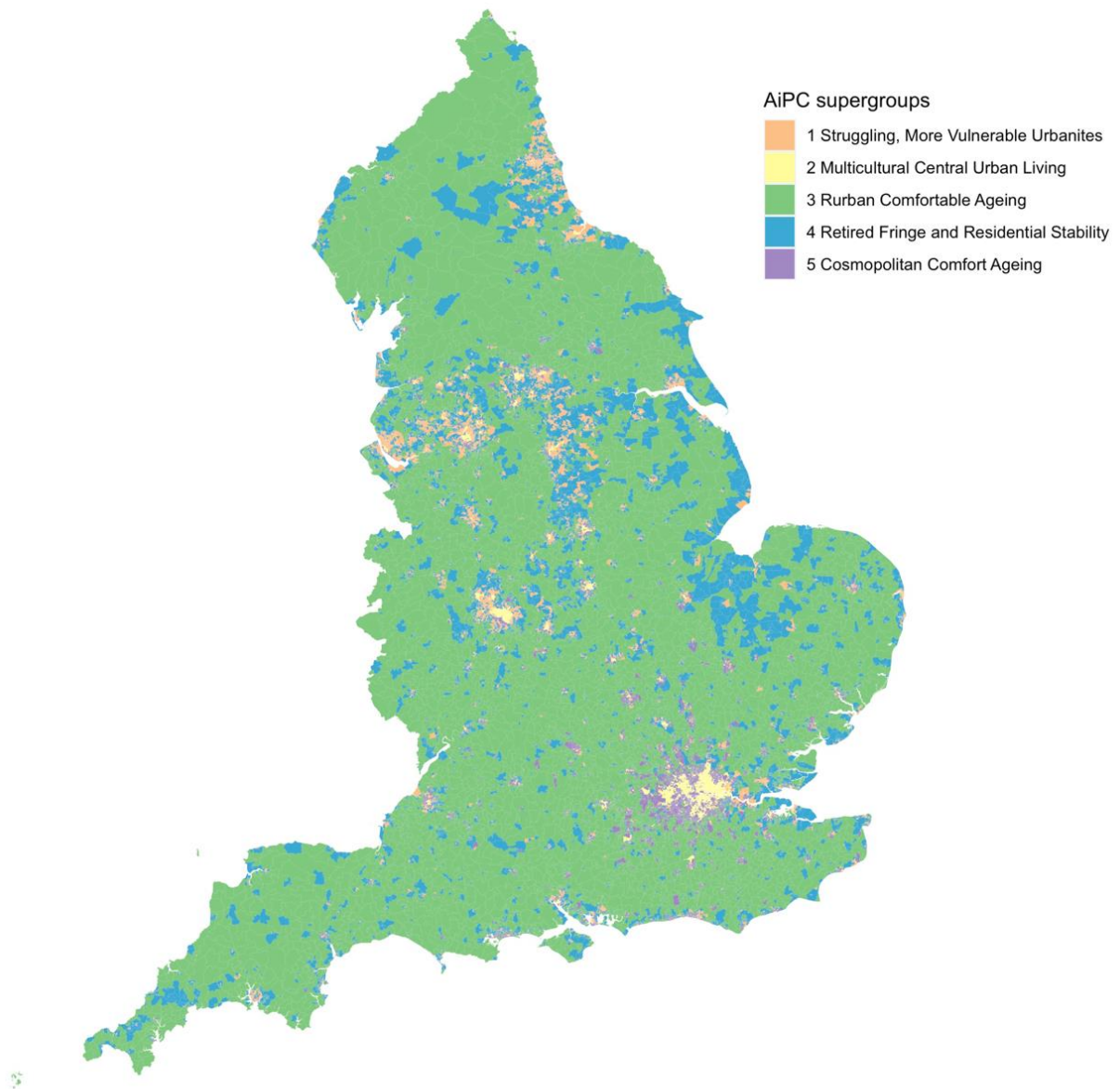
Table 2.2 shows the summary key characteristics for the supergroups including size, percentage of population aged 50+ and average age. It is clear that cluster 3, ‘Rurban Comfortable Ageing’, shown in green on a map below (Figure 2.5) is the largest and oldest cluster, comprising 8,802 LSOAs, 32.6% of the population of England aged 50 and over, and with a median age of 45.37. This contrasts starkly with cluster 2, ‘Multicultural Central Urban Living’, which is the smallest and youngest cluster, comprising 3,905 LSOAs, only 7.7% of the older people, and with a median age of 30.50. It is of note that this cluster is the most ethnically diverse given that the ethnic minority population of England are relatively youthful. Figure 2.5 and Figure 2.6 show spatial distribution of the Supergroups and Groups respectively.

Table 2.2. Supergroup summary characteristics – size, age, and age-structure

Supergroup (cluster)	1	2	3	4	5
Number of LSOAs	7,507	3,905	8,802	8,194	4,436
Percentage of England's population aged 50+	20.2%	7.7%	32.6%	27.9%	11.5%
Mean median age	36.25	30.50	45.37	43.20	36.11
Mean Older Person ratio	0.25	0.13	0.35	0.34	0.20

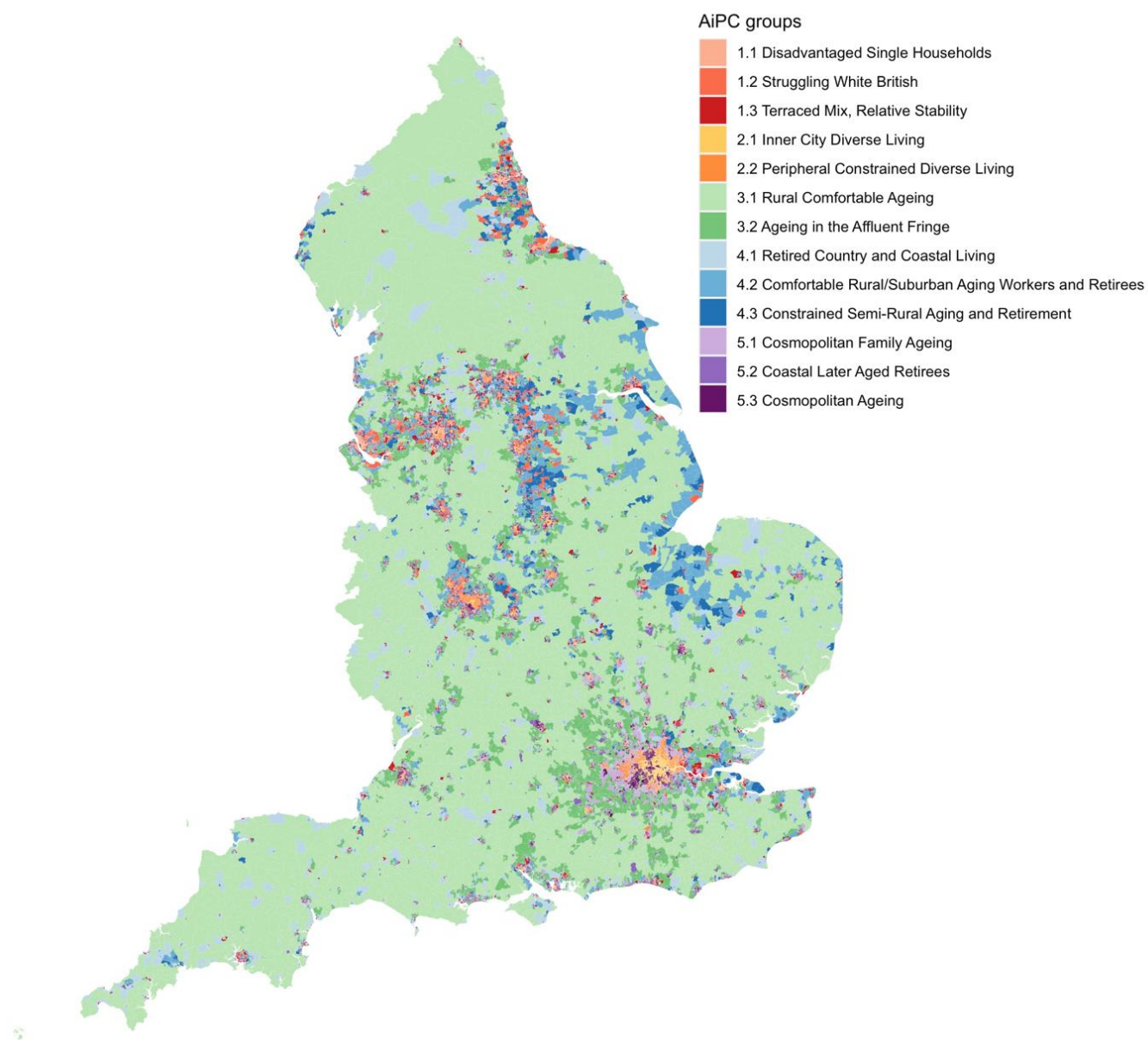
Source: Yang, Dolega and Pollock-Darlington (2022)

Figure 2.5: Map of AiPC supergroups (Tier 1)



Source: Yang, Dolega and Pollock-Darlington (2022)

Figure 2.6: Map of AiPC groups (Tier 2)

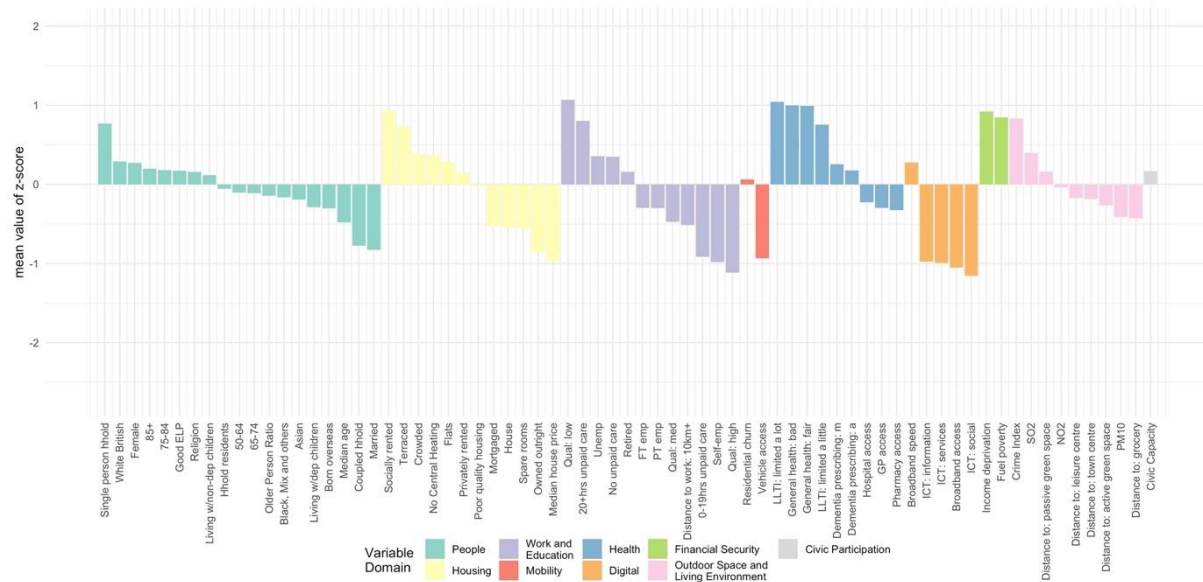


Source: Yang, Dolega and Pollock-Darlington (2022)

2.4 Pen Portraits

Supergroup 1: Struggling, More Vulnerable Urbanites

Figure 2.7 Mean z-scores, 'Struggling, More Vulnerable Urbanites'

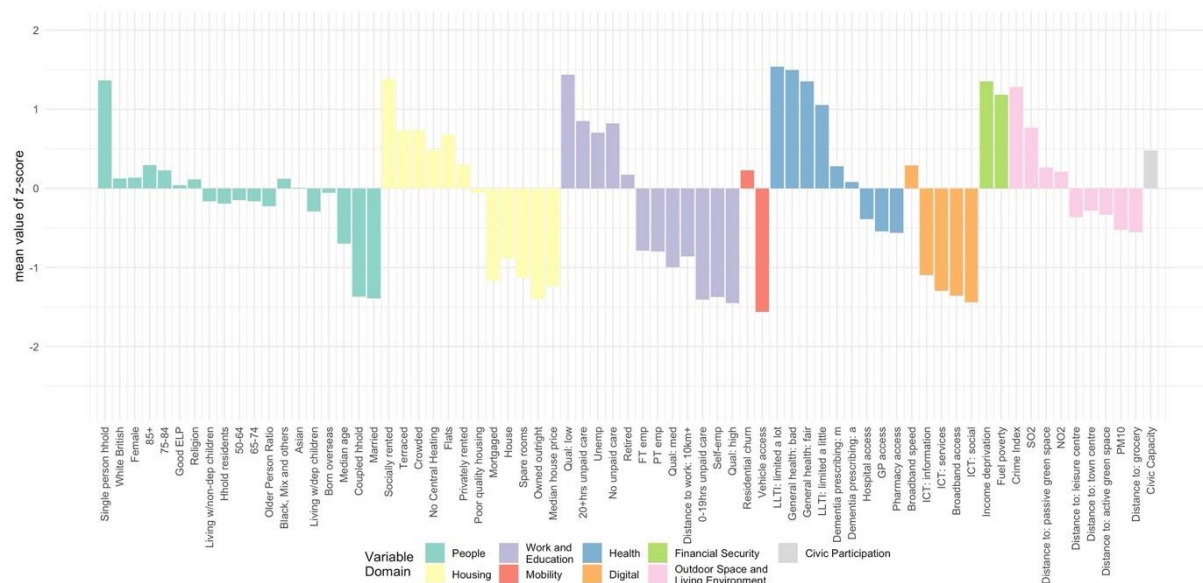


Source: Yang, Dolega and Pollock-Darlington (2022)

Note: Variables ranked within domain by mean z-score. All future bar charts retain this ranking. The population of this supergroup tend to live in urban and semi-urban areas, predominantly concentrated around major cities of the Midlands, Yorkshire and the Humber, North West and North East. Residents tend to be female, living in single-person households, and to live in terraced housing or flats, with above average representation in socially rented accommodation. They are more likely to live in income deprived households and experience fuel poverty. Residents are characterised by the lowest levels of educational attainment and internet engagement, provide high levels of unpaid care, suffer from poor health, and see the highest prescribing rates of medications for more advanced dementia conditions. The areas are characterised by the lowest median house prices and crime rates tend to be higher (Figure 1.7).

Group 1.1: Disadvantaged Single Households

Figure 2.8 Mean value of z-scores, 'Disadvantaged Single Households'

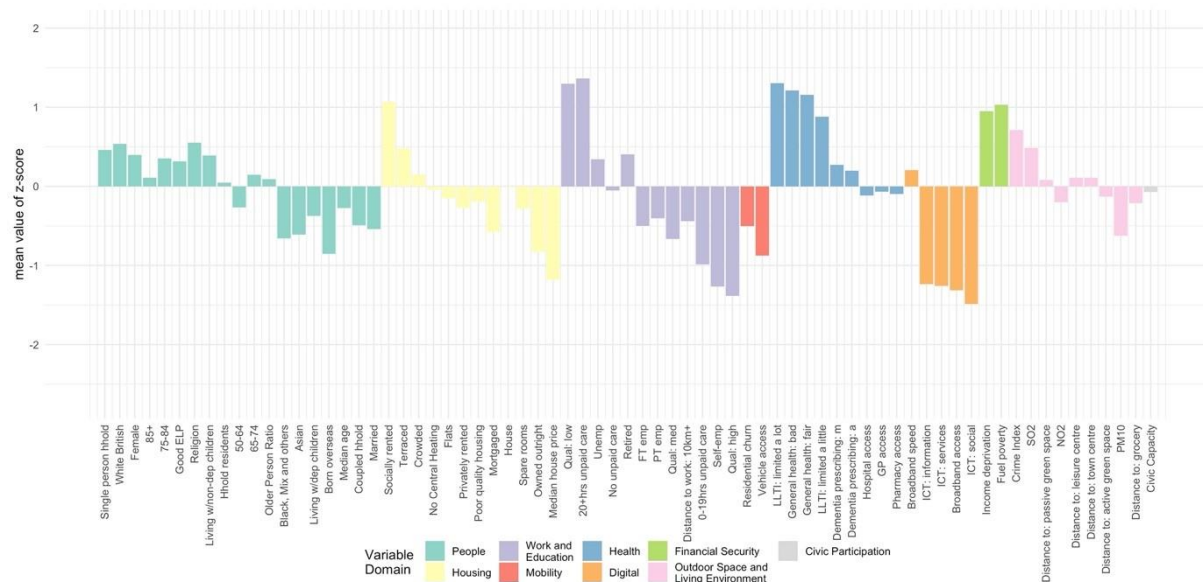


Source: Yang, Dolega and Pollock-Darlington (2022)

Shares a similar age-structure to parent group, with the highest proportion of people aged 85+ despite the lowest median age at 34.68. A relatively more diverse population than the parent group but with similarly high proportions in single-person households and socially rented accommodation. Households are less likely to have spare rooms and most likely to experience income deprivation and fuel poverty. This group are the least educated and least likely to engage digitally, but with the highest capacity for civic engagement (Figure 1.8).

Group 1.2: Struggling White British

Figure 2.9 Mean value of z-scores, 'Struggling White British'



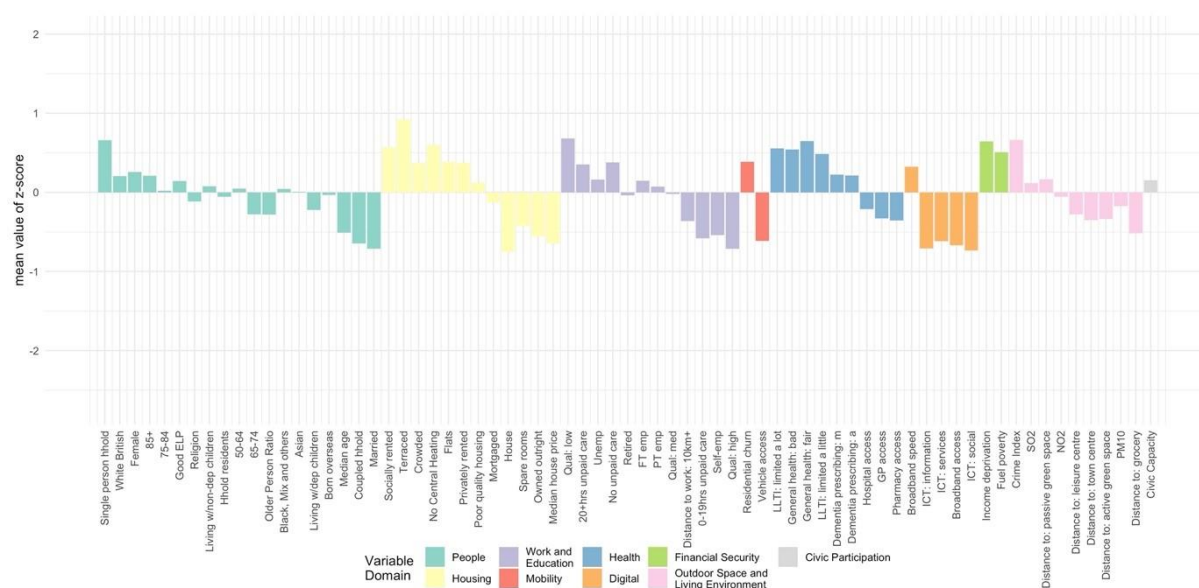
Source: Yang, Dolega and Pollock-Darlington (2022)

Median age slightly higher than parent group (37.75) and with a slightly higher proportion aged 65-74. Higher proportion of White British than the parent group, and relatively more likely to

identify with a religion. Though below the national average, they are more likely to live in detached/semi-detached houses or bungalows than parent group and, overall, more likely to provide unpaid care. As this group tend to locate at semi-urban (urban fringe) areas, travel distances to local amenities and health services tends to be greater than the other two groups (Figure 1.9).

Group 1.3: Terraced Mix, Relative Stability

Figure 2.10 Mean value of z-scores, 'Terraced Mix, Relative Stability'

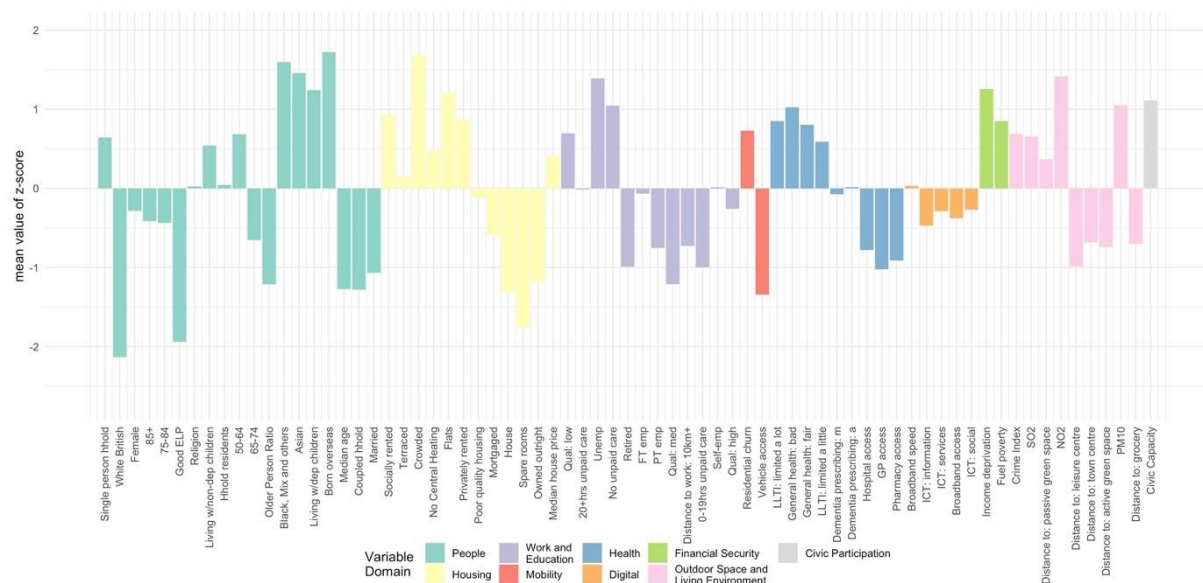


Source: Yang, Dolega and Pollock-Darlington (2022)

This group is slightly younger than the parent group, with a slightly higher proportion aged 50-64. They are characterised by higher levels of educational attainment, employment and digital engagement than the parent group, and are more likely to own their own home, enjoy more financial security and are less likely to be in poor health. Though living in challenging circumstances compared to the national average, this group are relatively better off than the two sister groups (Figure 2.10).

Supergroup 2 Multicultural Central Urban Living

Figure 2.11 Mean value of z-score, 'Multicultural Central Urban Living'

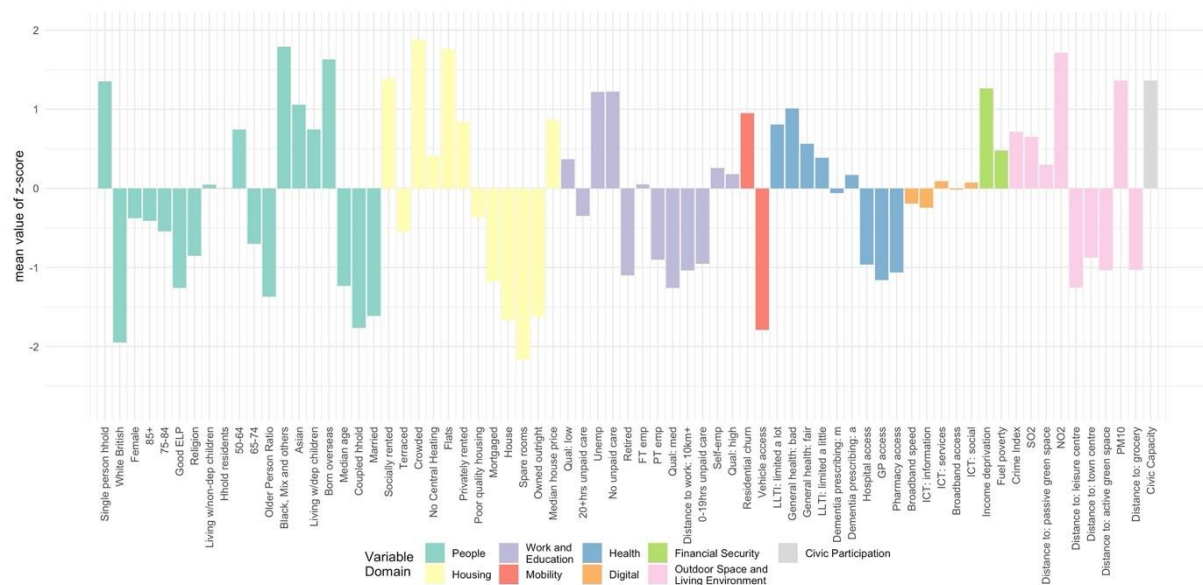


Source: Yang, Dolega and Pollock-Darlington (2022)

The population of this supergroup tend to live in city centres, with concentrations in major cities. This is the youngest and most ethnically diverse group, with higher-than-average proportions of residents born overseas, and of Asian, and Black, Mixed and Other ethnicities. There are also notably lower levels of English language proficiency. Residents are more likely to live in rented accommodation, particularly flats, and unlikely to have any spare rooms. The proportion of households without central heating is above the national average, and households in this group are the most likely to experience income deprivation and fuel poverty. Nevertheless, median house prices are relatively high – typical of their central location. This group has the lowest proportion of retirees, likely reflecting the younger age structure with a high proportion aged 50-64. However, employment rates are below average (though rates of self-employment are similar), and this group has the highest rates of unemployment. The proportion of single-person households and living with children is higher than the national average, vehicle ownership is low, and residents tend to have relatively low levels of education. Though less likely to provide unpaid care, likelihood of poor health and disability are also relatively high compared to the national average. Proximity to the city centre means distances to amenities and health services are amongst the shortest while density of civic assets is the highest (Figure 2.11).

Group 2.1: Inner City Diverse Living

Figure 2.12 Mean value of z-scores, 'Inner City Diverse Living'

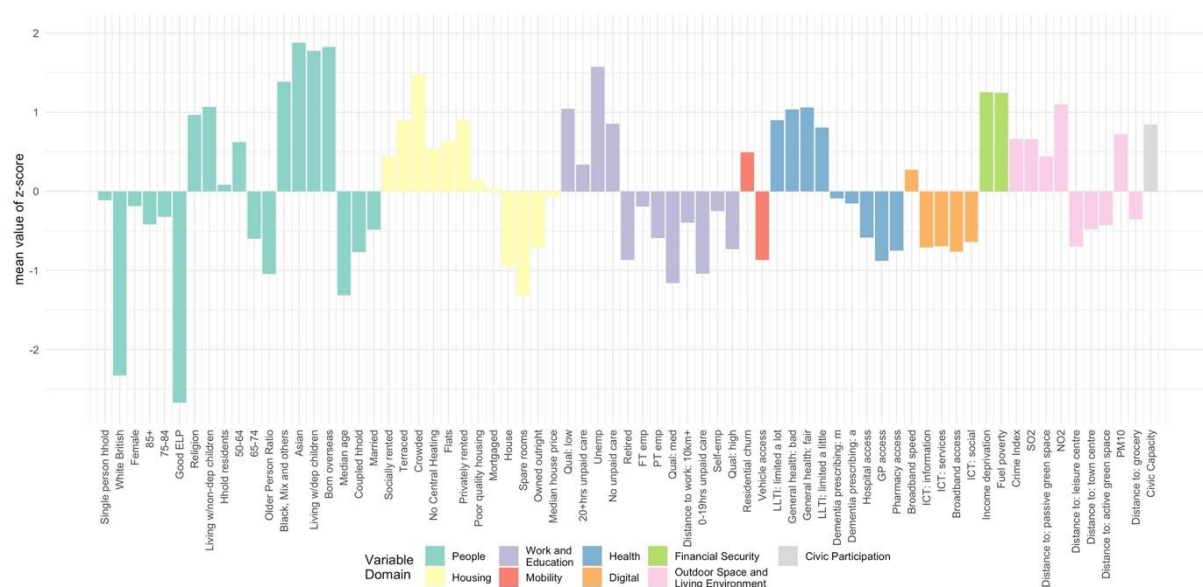


Source: Yang, Dolega and Pollock-Darlington (2022)

This group tend to concentrate within inner city areas, with higher median house prices than the parent group. Residents are far more likely to live in socially rented accommodation, concentrating in flats and less likely to have spare rooms. It is an ethnically diverse cluster, but as compared to the parent group with relatively lower proportions of Asian ethnicities and higher proportions of Black, Mixed and Other ethnicities. Though residents are more likely to live in income deprived households, they have a lower risk of fuel poverty. Given proximity to the city centre, the low levels of vehicle ownership and short distances to services and amenities is unsurprising (Figure 2.12).

Group 2.2: Peripheral Constrained Diverse Living

Figure 2.13 Mean value of z-scores, 'Peripheral Constrained Diverse Living'

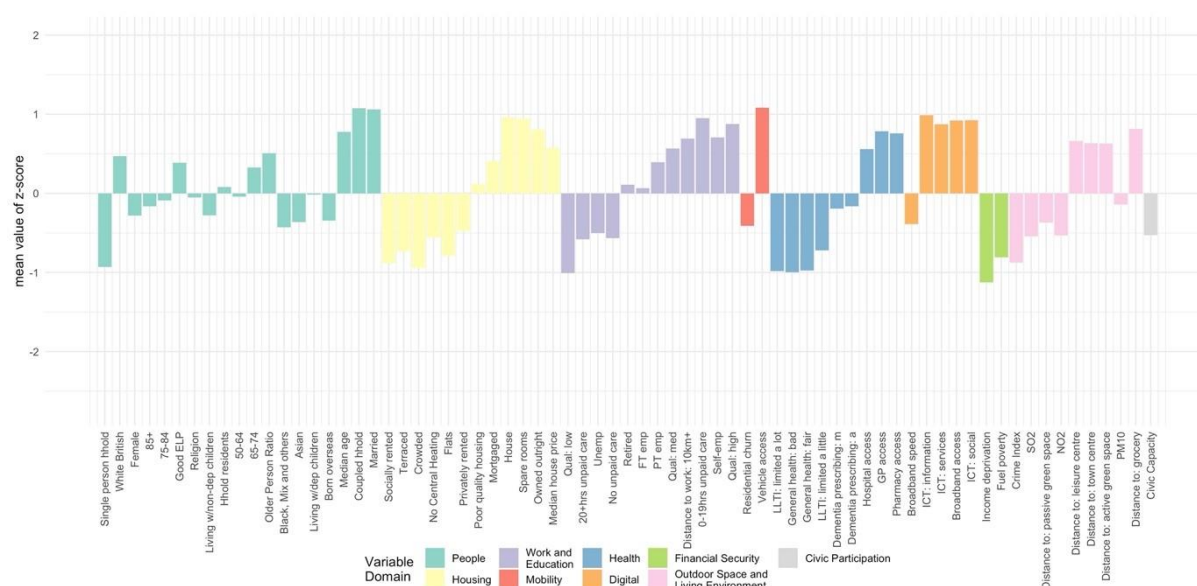


Source: Yang, Dolega and Pollock-Darlington (2022)

This group concentrates on the periphery of town and city centres, with notably lower median house prices than the parent group. Residents are more likely to be of Asian ethnicity and to identify with a religion than in any other cluster reported, and residents have the lowest levels of English language proficiency. They are more likely to be living as a couple or married than the parent group, residing in terraces, detached/semi-detached housing, or bungalows, either mortgaged or owned outright. However, housing quality is poorer than the parent group, and households are at greater risk of fuel poverty. Rates of self-employment are lower while there are a higher proportion of retirees (Figure 1.13).

Supergroup 3 Rurban Comfortable Ageing

Figure 2.14 Mean value of z-score, 'Rural and Suburban Comfortable Ageing'

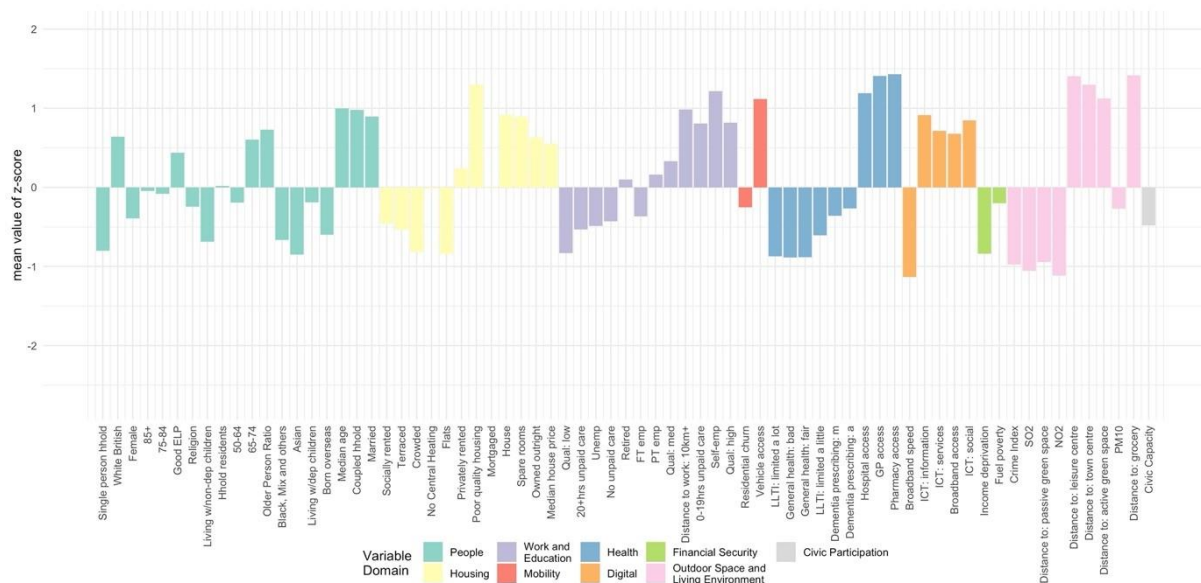


Source: Yang, Dolega and Pollock-Darlington (2022)

The population of this supergroup predominantly live in rural, or rural-urban fringe areas. This is the largest and oldest supergroup: it has the highest ratio of older people to younger people, and the highest median age reflecting the concentration of older people in more rural areas. Residents are the most likely to be married and/or living as a couple. There is a high proportion of White British residents, with lower-than-average representation of ethnic minorities. This group are most likely to own their properties outright and tend to live in detached/semi-detached housing or bungalows, and with spare rooms. This group are the least likely to experience fuel poverty or to live in income deprived households. They tend to be in better health than the other supergroups and are most likely to provide between 0-19 hours of unpaid care a week. They are relatively more likely to be either in self- or part time employment and tend to have medium or higher levels of educational attainment. This is the most digitally engaged group of older people. Their geography means that though they benefit from better air quality and lower crime rates, distance to services and amenities are amongst the highest. Accordingly, this group are the most likely to have access to a vehicle (Figure 1.14).

Group 3.1: Rural Ageing

Figure 2.15 Mean values of z-scores, 'Rural Ageing'

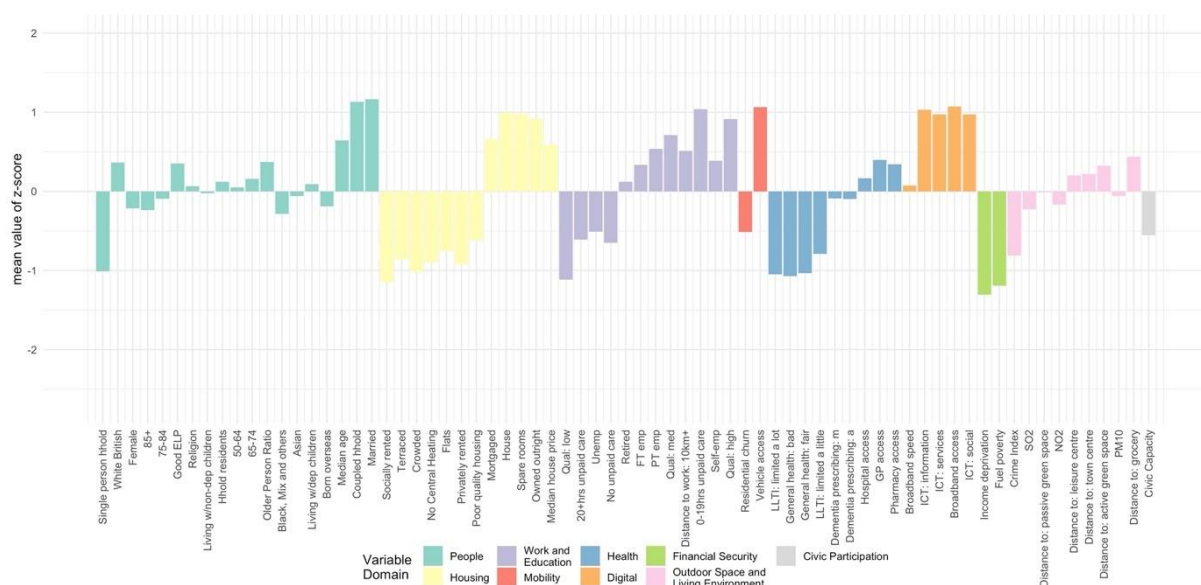


Source: Yang, Dolega and Pollock-Darlington (2022)

This group concentrate in rural areas, with the highest travel distances to healthcare facilities, services and amenities. This group have less financial security than the parent group, are more likely to live in privately or socially rented accommodation and less likely to have a mortgage. Though this group tend to have central heating, the housing quality is relatively poor. Of those working, more are in self-employment than the parent group. Digital engagement is slightly lower than in the parent group, with notably lower proportions of people with broadband access at home and a lower broadband speed available (Figure 2.15).

Group 3.2: Ageing in the Affluent Fringe

Figure 2.16 Mean value of z-scores, 'Ageing in the Affluent Fringe'

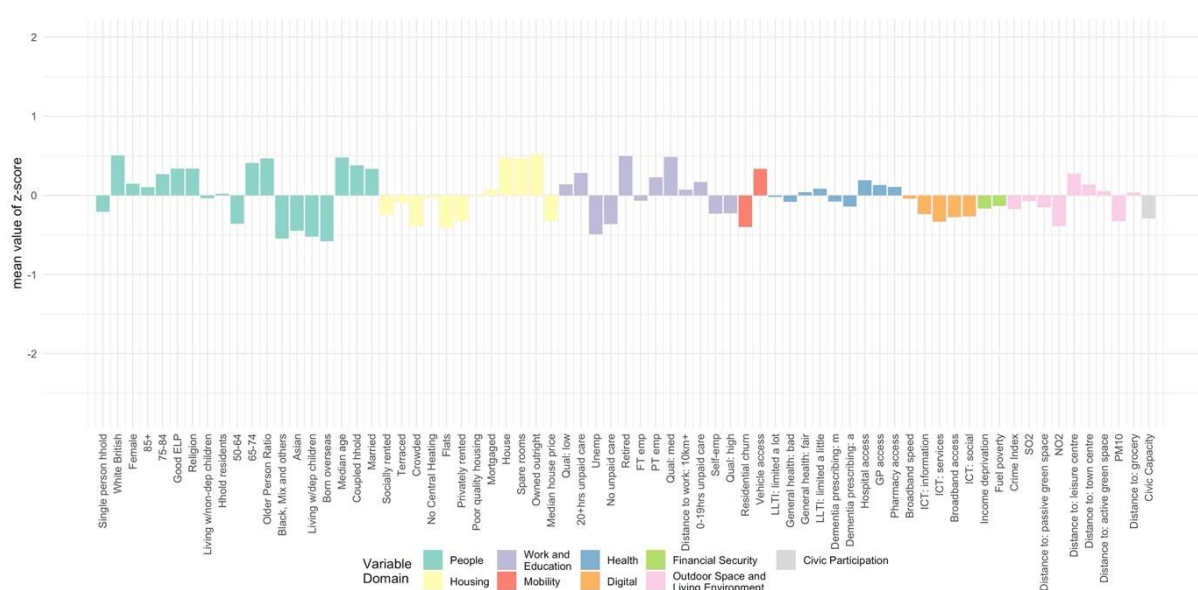


Source: Yang, Dolega and Pollock-Darlington (2022)

Members in this groups tend to reside in more affluent areas on the urban-rural fringe and are less likely to experience financial hardship than the parent group. Housing tends to be of good quality with detached/semi-detached housing and bungalows dominating the dwelling types. Higher proportions are married, living as a couple, and/or with children. This group has the highest level of digital engagement across different online activities of all clusters, and experience relatively better health than the parent group (Figure 2.16).

Supergroup 4 Retired Fringe and Residential Stability

Figure 2.17 Mean values of z-scores, 'Retired Fringe and Residential Stability'



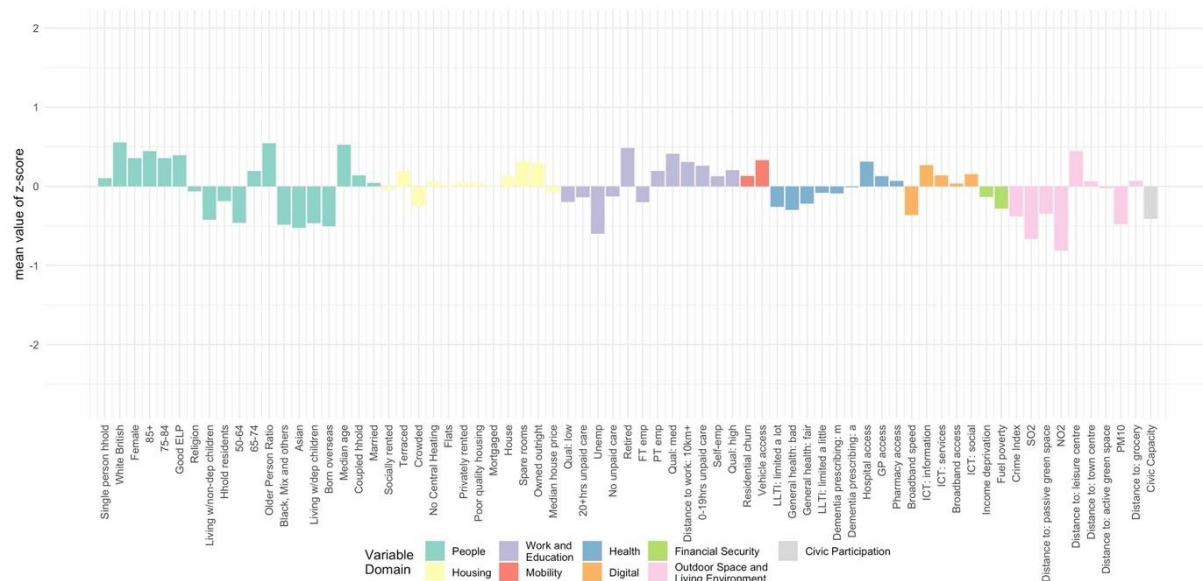
Source: Yang, Dolega and Pollock-Darlington (2022)

The population of this supergroup are concentrated in rural suburbs of smaller cities and towns, and coastal areas particularly to the East.

Residents of these areas are more likely to be between 65 and 84 with the highest proportion of retirees found across all clusters. They are predominantly UK-born White British, are most likely to own their property outright and are likely to have spare rooms. This group represents a very stable population, with the lowest levels of residential mobility indicated across all clusters. However, the remaining characteristics in each domain are otherwise very close to the national average (Figure 2.17).

Group 4.1: Retired Country and Coastal Living

Figure 2.18 Mean value of z-scores, 'Retired Country and Coastal Living'

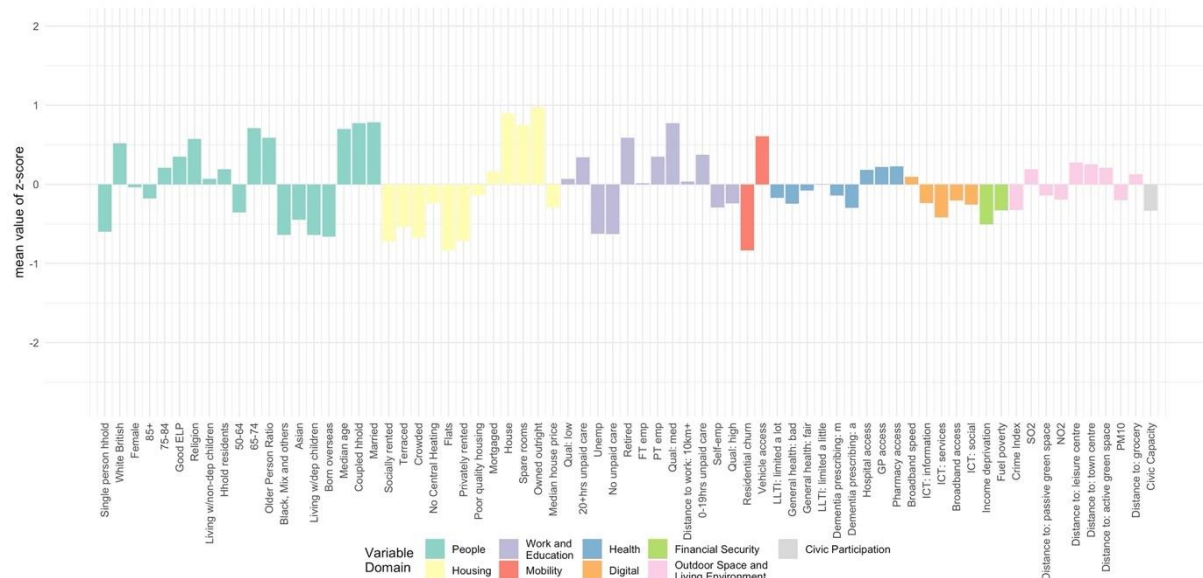


Source: Yang, Dolega and Pollock-Darlington (2022)

Relative to the parent group, there are more people aged 75-84 and 85 and over in this group, and residents have a slightly higher tendency to higher levels of educational attainment and being self-employed. Residents also have a higher probability of living in communal establishments (rather than a household) and are less likely to identify with a religion. Despite notably lower broadband speeds, levels of digital engagement are relatively high. As many areas in this group are in coastal areas and further from larger urban areas, members of this group benefit from significantly better air quality, but also have high levels of vehicle access and longer distance commutes (Figure 2.18).

Group 4.2: Comfortable Rural/Suburban Ageing Workers and Retirees

Figure 2.19 Mean values of z-scores, 'Comfortable Rural/Suburban Ageing Workers and Retirees'

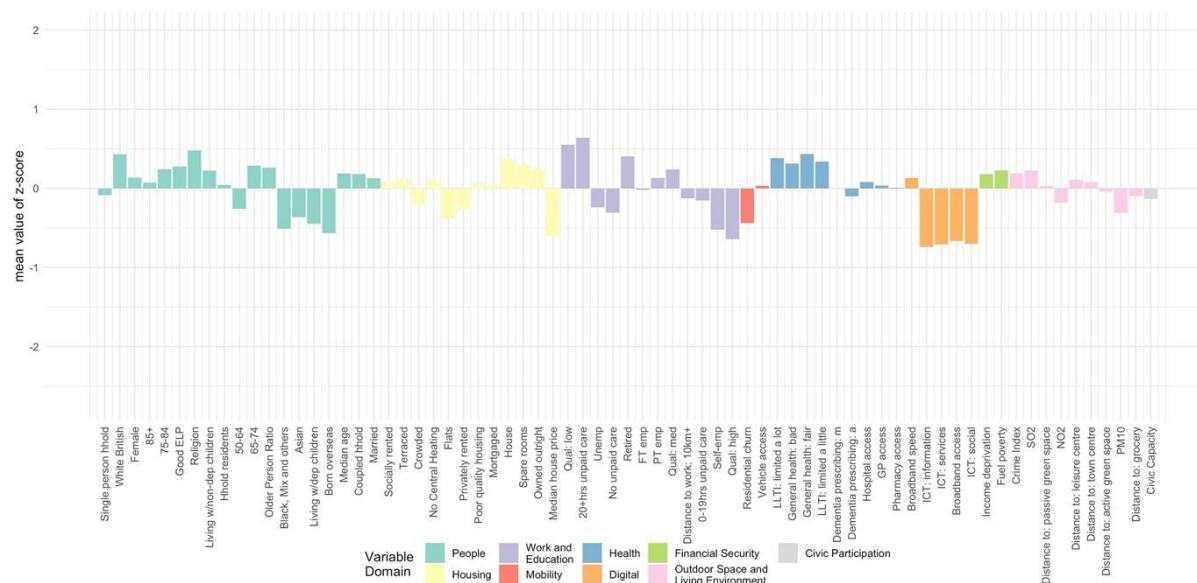


Source: Yang, Dolega and Pollock-Darlington (2022)

A slightly younger age-structure relative to the parent group, with a higher proportion aged 50-64 and 65-74. Residents are likely to be married or living as a couple, with a low proportion of single person households. They tend to own their property which is more likely to be detached /semi-detached housing or a bungalow, and less likely to be overcrowded. Of those working, there are slightly more people in part-time employment. These areas are very stable, experiencing the lowest level of residential churn within this supergroup (Figure 2.19).

Group 4.3: Constrained Semi-Rural Ageing and Retirement

Figure 2.20 Mean values of z-scores, 'Constrained Semi-Rural Ageing and Retirement'

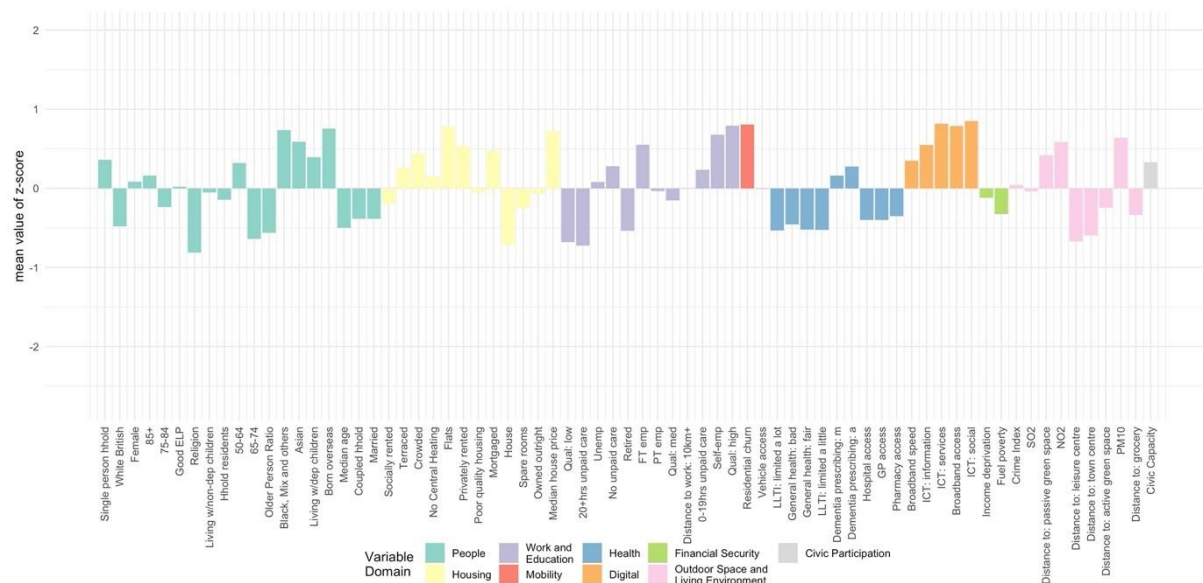


Source: Yang, Dolega and Pollock-Darlington (2022)

This group may be living in relatively more constrained circumstances than the parent group: they have relatively lower levels of educational attainment, are more likely to be unemployed, provide more than 20 hours of unpaid care a week, and tend to have poorer health outcomes. This group are much less likely to engage with the internet and more likely to be affected by household income deprivation and fuel poverty. The areas experience higher crime rates and the median house price is lower (Figure 2.20).

Supergroup 5: Cosmopolitan Comfort Ageing

Figure 2.21 Mean values of z-scores, 'Cosmopolitan and Coastal Ageing'



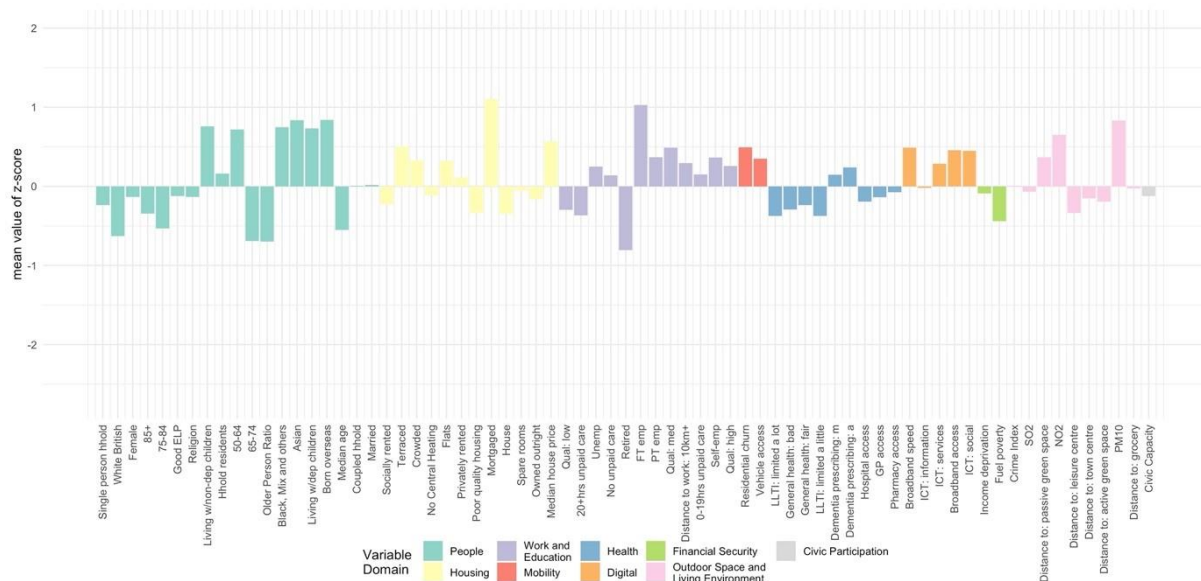
Source: Yang, Dolega and Pollock-Darlington (2022)

The population of this supergroup are concentrated in periphery of major cities, or in the suburbs of towns, particularly around London and the South East. These areas are characterised by the highest median house price (mean value of £362,158.90).

Residents are highly educated and likely to be either in full-time employment or self-employed. They do not provide many hours of unpaid care, and are likely to live in property with a mortgage or shared ownership. There is also a higher proportion of people living in privately rented accommodation. Housing type tends towards terraced houses or flats, and there is an above-average rate of living in a crowded property. Though members of this group tend to have better health outcomes overall, there is a higher prescribing rate of dementia medications. People have access to high-speed broadband and like to engage with the internet, especially for shopping, banking and social use. These communities have the highest level of residential churn, and it is notable that there is also a relatively low ratio of older people to younger people in the local populations (Figure 2.21).

Group 5.1: Cosmopolitan Family Ageing

Figure 2.22 Mean z-scores, 'Cosmopolitan Comfort Ageing'

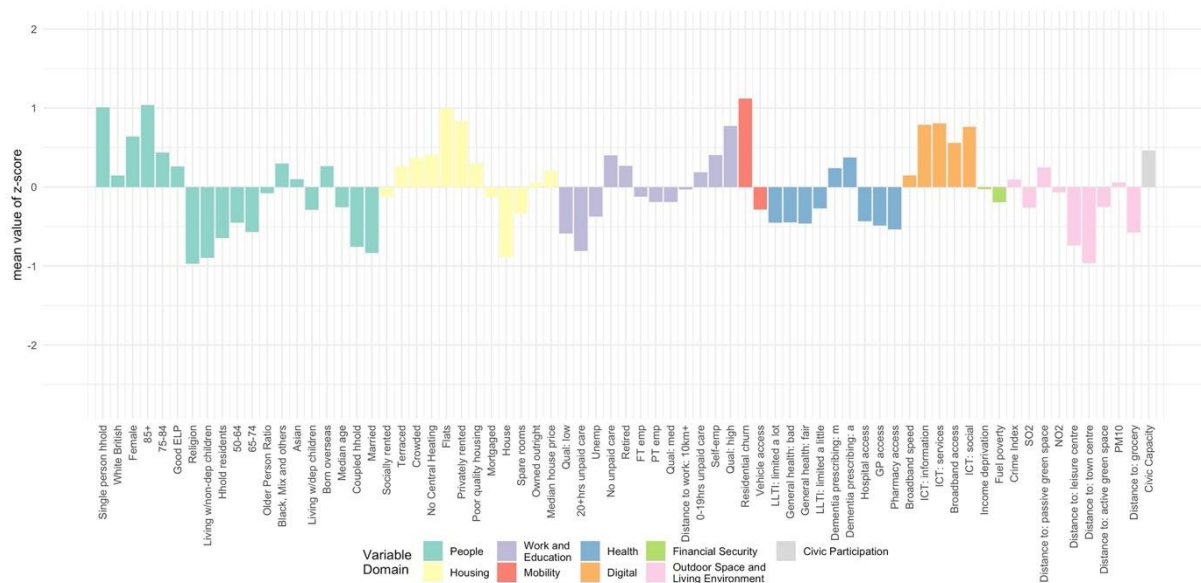


Source: Yang, Dolega and Pollock-Darlington (2022)

This group has slightly higher proportion of ages 50-64 than the parent group with people more likely to live in mortgaged properties, particularly detached/semi-detached housing. A higher proportion of this group have lower levels of educational attainment relative to the parent group, and there is also greater representation of people born overseas and from Asian ethnicities. Single person households are relatively less common and residents are more likely to be living with children, married and/or living as a couple. This group is most prevalent in London and across the South East (Figure 2.22).

Group 5.2: Coastal Later Aged Retirees

Figure 2.23 Mean values of z-scores, 'Coastal Later Aged Retirees'

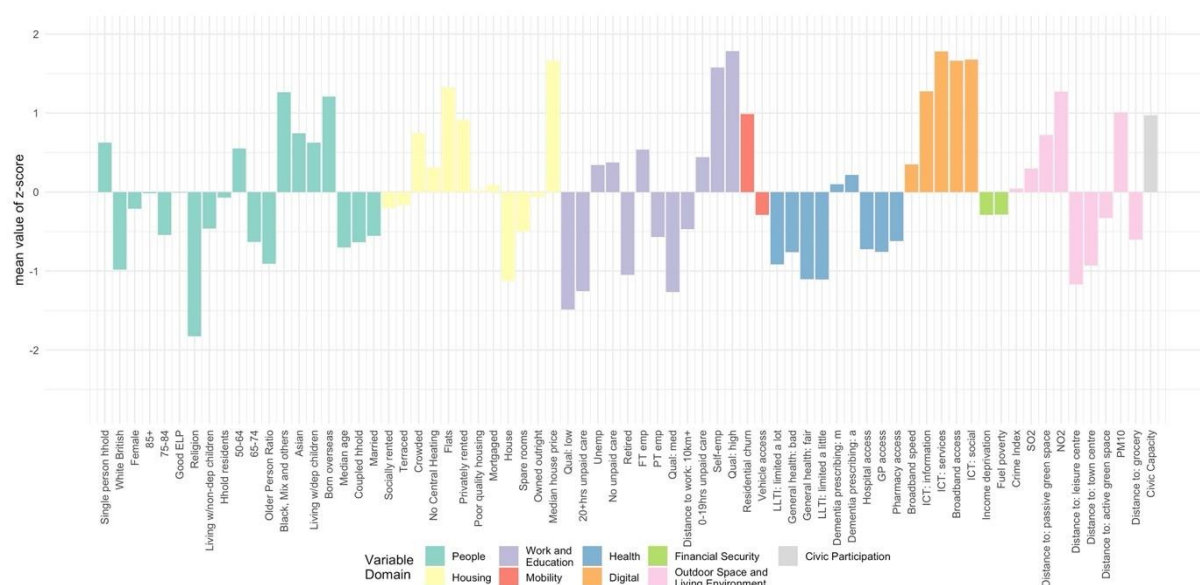


Source: Yang, Dolega and Pollock-Darlington (2022)

Compared to the parent group, there are notably higher proportions of White British residents in these areas, with much lower representation of ethnic minorities or residents born overseas. Residents are also notably older, both than the average national population for ages 85 and over, and the parent group for 75 and over. They are likely to be female, living in single-person households and retired. However, there is also a higher proportion living in communal establishments than many other areas. These areas tend to have relatively high levels of residential mobility, are much less prevalent in London and more often found in towns on the Southern coast (Figure 2.23).

Group 5.3: Cosmopolitan Ageing

Figure 1.24 Mean values of z-scores, 'Cosmopolitan Ageing'



Source: Yang, Dolega and Pollock-Darlington (2022)

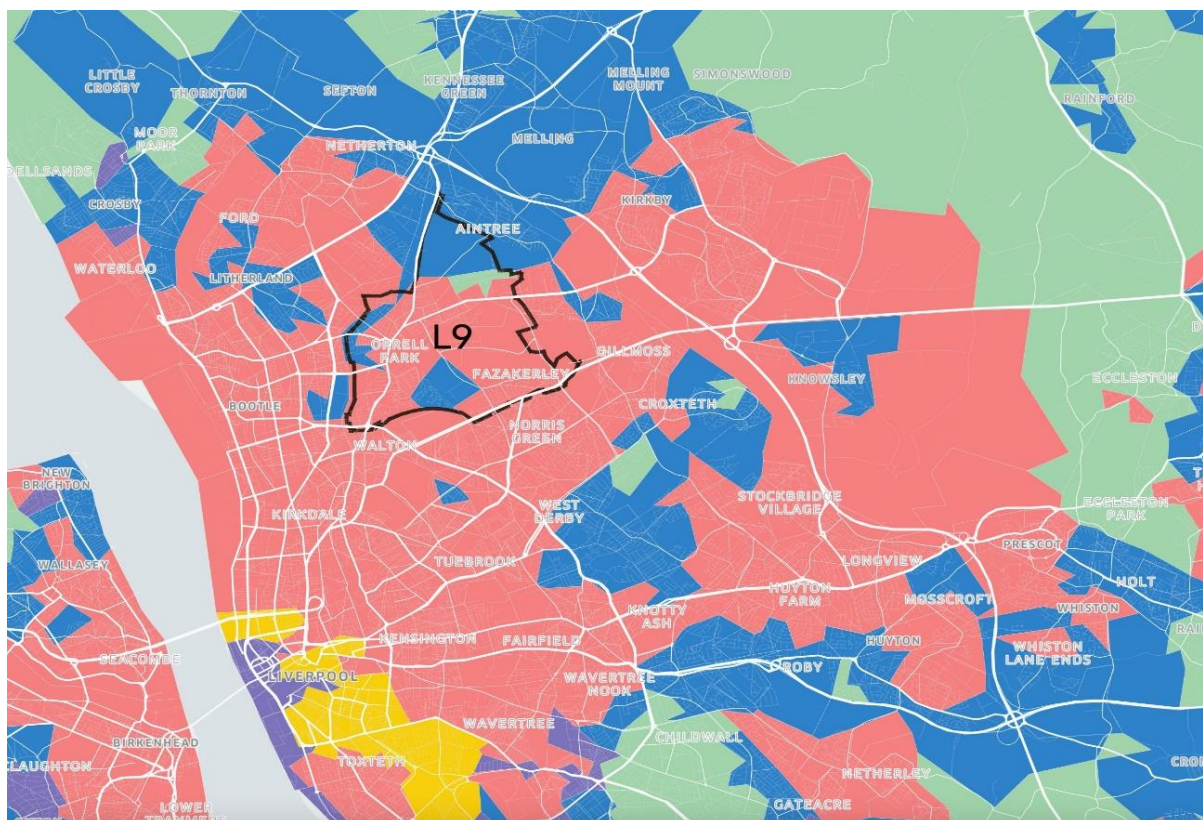
Residents are highly educated, less likely to be retired, and slightly younger than the parent group. Ethnic minorities, particularly Black, Mixed and Other ethnicities and those born overseas are more highly represented in this group. Residents are more likely to live in crowded households, particularly flats. These areas concentrate in London, but are also found in other affluent suburbs of major cities. The median house price in these areas is very high, but the centrality means residents benefit from good proximity to a range of amenities and civic assets (Figure 2.24).

2.5 Ground-truthing

A final stage of creating the bespoke geodemographics involved a ground-truthing validation exercise to understand better whether the clusters and the corresponding descriptions (names and pen portraits) were appropriately representing the real world. We followed the approach used in the work of Vickers and Rees (2011) where a panel of peer reviewers were invited to validate the results for the areas they know well. Participants were asked to provide up to 3 postcode districts, and then maps showing the AiPC *supergroups* in those areas were sent back to each participant respectively. Figure 2.25 is an example of the postcode district of “L9” where each AiPC *supergroup* is shaded with different colours on the map.

The correspondence between colours and supergroups were unknown to the participants. After reading the names and pen-portraits descriptions of the supergroups, participants would provide their answers to match each colour to the supergroups. Respondents were asked to complete this “matching exercise” task based on their knowledge of the demographic, socioeconomic characteristics of older people and the environment in the local areas. They were also invited to provide additional comments, which were used to further inform evaluation and improvement of the AiPC.

Figure 2.25: Map for ground-truthing the areas around postcode “L9”, which covers parts of North Liverpool



Source: Yang, Dolega and Pollock-Darlington (2022)

A total of 56 non-duplicate locations (postcode districts) were provided by a panel of 25 peer reviewers, consisting of 9 internal and 16 external participants. The internal reviewers (from the University of Liverpool) were familiar with geography and urban planning, while the external participants were scholars, other expert users of geodemographic classification, practitioners and members of the public. The responses were distributed across England, covering all regions in England with slightly more samples in the North West and London. The responses were analysed and their accuracy rates (%) for different supergroups, shown in Table 2.3, calculated.

Table 2.3: Accuracy rate (%) of the responses by supergroups and participants

Supergroup	External	Internal	All
1: Struggling, More Vulnerable Urbanites	87.5	66.7	80
2: Multicultural Central Urban Living	75	50	66.7
3: Rurban Comfortable Ageing	78.6	55.6	69.6
4: Retired Fringe and Residential Stability	60	50	56.5
5: Cosmopolitan Comfort Ageing	66.7	87.5	73.9

Source: Yang, Dolega and Pollock-Darlington (2022)

The results and feedback were then discussed in a series of consultations with a panel of experts and end-users including gerontologists, geriatricians, scholars, local authority policy makers and community workers to make further changes to finetune the ‘Pen Portraits’ names and descriptions. For instance, the initial (old) name of supergroup 4: “Retired Fringe and Residential Stability” had the lowest accuracy rate with only 56.5% of participants providing accurate response. It became apparent that using geography in the cluster name was confusing to some respondents. Despite many LSOAs in this cluster located in coastal areas, a non-coastal and suburban distribution was also substantial and therefore, the cluster name was altered to ‘Retired Fringe and Residential Stability’ to better reflect its characteristics. Changes were also made to the initial names of clusters 3 and 5 and their descriptions, addressing issues raised by the respondents.

2.6 Summary

In this chapter we present the key research output of this study – the AiPC classification of population aged 50+ in England. We build on existing advances in the developments of open source geodemographics and employ both conventional and novel data sources. The AiPC depicts a multidimensional and distinctive features of ageing population at small area level and has been developed in consultation with an expert advisory panel including gerontologists, geriatricians, scholars, local authority policy makers and community workers. The AiPC classification containing 5 distinctive clusters referred to as *Supergroups* and 13 nested sub-clusters referred to as *Groups* and it is available as an open source data product to maximise its utility for end users.

Developing a fine-grained understanding of the characteristics and geography of England’s ageing population at a small area level is critical to better understand the needs of these diverse demographics. As such, we believe that our classification can facilitate more efficient service planning and policy development, ensuring services are targeted to those most in need rather than on assumptions based on age alone. Such approach may miss those most in need while using a multidimensional bespoke classification of older people would mitigate against that. To the best of our knowledge, the Ageing in Place Classification developed in this study is the first bespoke geodemographic classifications of older people in the UK, although ageing population is of increasing importance in many countries. The closest previous attempt was developed by Hunter (2016) creating an older people geodemographic classification in Australia although, their model was constructed purely based on the Australian Census data.

3. Neighbourhoods - Aging and the 20-minute city

3.1 Introduction

The relationship between neighbourhoods, housing and society is critical for urban planning and ensuring that older people are supported to age in the places that they choose to. One key extension to this classification is to understand how this classification relates to other key public policy plans, such as the need to support active travel and access to key services for older people. This chapter explores this extension through bespoke analysis of the 20-minute city in Liverpool City Region using the AiPC.

Older citizens have the same rights and needs for access to services as younger people, even if their mobility decreases. Yet, this presents a complex challenge for those planning cities and their regions. Planners need to know the structure of the population they are planning for, the location of services which they need to access and the structures of transport between the two. Modelling decreasing speeds of active travel are necessary in order to avoid painting a picture of ease of access to services when they are not actually reachable within a reasonable travel distance.

Active travel has gained in prominence since COVID-19 changed the structure of transport for many cities and the mobility patterns of households as they were encouraged to stay at home (Nurse and Dunning, 2021). However, this impetus is part of a longer-term trajectory and need to move away from reliance on carbon-based personal transport and recognition of the role of active travel in supporting healthier lifestyles (Dunning, Calafiore & Nurse, 2021). At the time of writing, the concept of the 20-minute city has risen in prominence internationally to “brand” active travel as a mechanism to access one’s daily needs (Moreno, 2021). The assumption underpinning the 20-minute city is that active travel is possible and broadly equitable across different groups. To date there has been no attention paid to the specific needs of older people in relation to the concept of the 20-minute city and the relationship between reduced mobility and the service needs of older people.

Of key significance for this project is the relationship between groups of older people. Whilst, every individual has unique characteristics which comprise their mobility capability it is possible to discern patterns of mobility behaviour in aggregate populations, including older people (Gonzalez, Hidalgo & Barabási, 2008). Thus, the AiPC represents a major opportunity to consider the relationship between groups of older people, mobility, and access to services as part of the 20-minute city concept, in the hope of supporting urban planning for older people.

We next provide a precis of evidence of the 20-minute city concept for people over 50 years old with the bespoke AiPC for a single case study, Liverpool City Region, in Northwest England. The AiPC is paramount to understanding the geographic potential for intersectionality with active travel accessibility of services. The AiPC provides a heuristic tool to understand the distribution of different types of older people across Liverpool City Region, which can then be

linked to how easy it is for those groups to access services through a ten-minute walk at reduced mobility speeds.

3.2 Background - Ageing and the 20-minute city

The 20-minute city draws on previous planning ideas, such as: Howard's 'Garden City'; Jacob's mixed land use; Perry's neighbourhood unit concept and New Urbanism's walkable neighbourhoods and urban liveability (Gower and Grodach, 2022). It makes some large promises about enhancing sustainability, liveability and health of citizens through active travel access to services without the need for carbon-based transport (Moreno et al., 2021). Yet, to make this ideal a reality, urban planners need to be able to locate services or provide active travel infrastructure in the right places to support access in a 20-minute round trip.

20-minute city planners need to know the relationship between three attributes: the location of the population, the location of services, and access between population and services. Planners have been attempting to adjust one of these to support the 20-minute city in cities internationally, from Bogotá (Guzman et al., 2021) to Singapore (Manifesty and Park, 2022), although this challenge should not be underestimated (Dunning and Nurse, 2021). Yet, no one has to date attempted to understand the impact of an ageing population on the 20-minute city or the need to understand older people's heterogeneity.

With a specific focus on older people, there is a sizeable evidence base which suggests that there are benefits to people being able to age in place, i.e., not moving to access specific services for older people (Dobner et al., 2016). Whilst we acknowledge the counterargument that older residents should be supported to move if their aspirations lie elsewhere and not assumed to want to 'age in place' (Vasara, 2015), we consider the reverse also to be true, that older residents should be supported to remain in place, if their aspirations are to stay local. If this is accepted, then the urban planner needs to find a mechanism to bring services within an accessible distance of the dwellings that older people live in.

The architect of re-branding these active travel concepts as the 20-minute city, Carlos Moreno, argued that service needs could be summarised by access to six functions: living, working, commerce, healthcare, education, and entertainment (Moreno et al., 2021). According to the World Health Organization (WHO) (2007) there are six determinants of active ageing: Economic determinants; Health and social services; Behavioural determinants; Personal determinants; Physical environment; and Social determinants. Intersectionality will also have a prevailing positive or negative impact. Among the topics that the WHO studies in its report, a great emphasis is placed on the type of services that an ageing population might need. Outdoor spaces, transportation and access to community support and health services are some specific types of services that the WHO also highlights as essential. However, they also consider how social participation, social inclusion and civic participation might also be fostered by different types of services in the context of walkable neighbourhood (e.g., access to community spaces, charity associations, community markets).

An ideal 20-minute city would provide for the everyday needs of its citizens within 10-minutes' active travel of the home (Sustrans, 2020). There are strong sustainability and equality arguments that the primary active travel mode should be considered a 10-minute walk for

planning purposes (e.g., Calafiore et al., 2022). The accessibility of key services is driven by various factors related to social and spatial heterogeneity of ageing population, which tend to impact the ability to walk safely to amenities within the 20-min city. These typically include their age (both chronological and functional), mobility, health, digital engagement and living environments. The AiPC represents an opportunity to link these discussions of group mobility to a clear explanation of the geographic variation in the demographic structure of older people.

Chronological ageing is different from functional ageing with regards to mobility. Research and policy frequently conflate ‘older people’ as all simultaneously experiencing the same vulnerabilities and limited mobilities (Darlington-Pollock et al., 2021). Most of the issues that planners are seeking to address in relation to ageing are really functional issues and not chronological ageing. It is also the case that functional ageing may intersect with other vulnerabilities, including socially determined access to support mechanisms and financial wellbeing, thus having a compounding or confounding impact on overall mobility and limiting urban access (Ziegler, 2012).

There are many more influences on route choice than the quickest route, on how and why people will choose to walk or not walk to local services, such as stimulating environments, shade and surface type (e.g. Hillnhütter, 2021). The literature on walking behaviours and experiences is deep, much of which covers intersectional understandings of the walker’s emotions and behaviour, combined with the material conditions of the walking environment (e.g., Rose, 2017; Campbell, 2010). Planning needs to engage with these material conditions and diverse urban practices and experiences to ensure a high quality of walking space within the city. There is, however, also a need for planning to engage with proximity as a core concept in the 20-Minute City, without which concepts like the flâneur and dérive are limited to aesthetic choices and not everyday needs. It is the attribute of proximity for functional ageing which we focus on in this article, to support planning to measure urban performance and identify weaknesses (following Balsas, 2004).

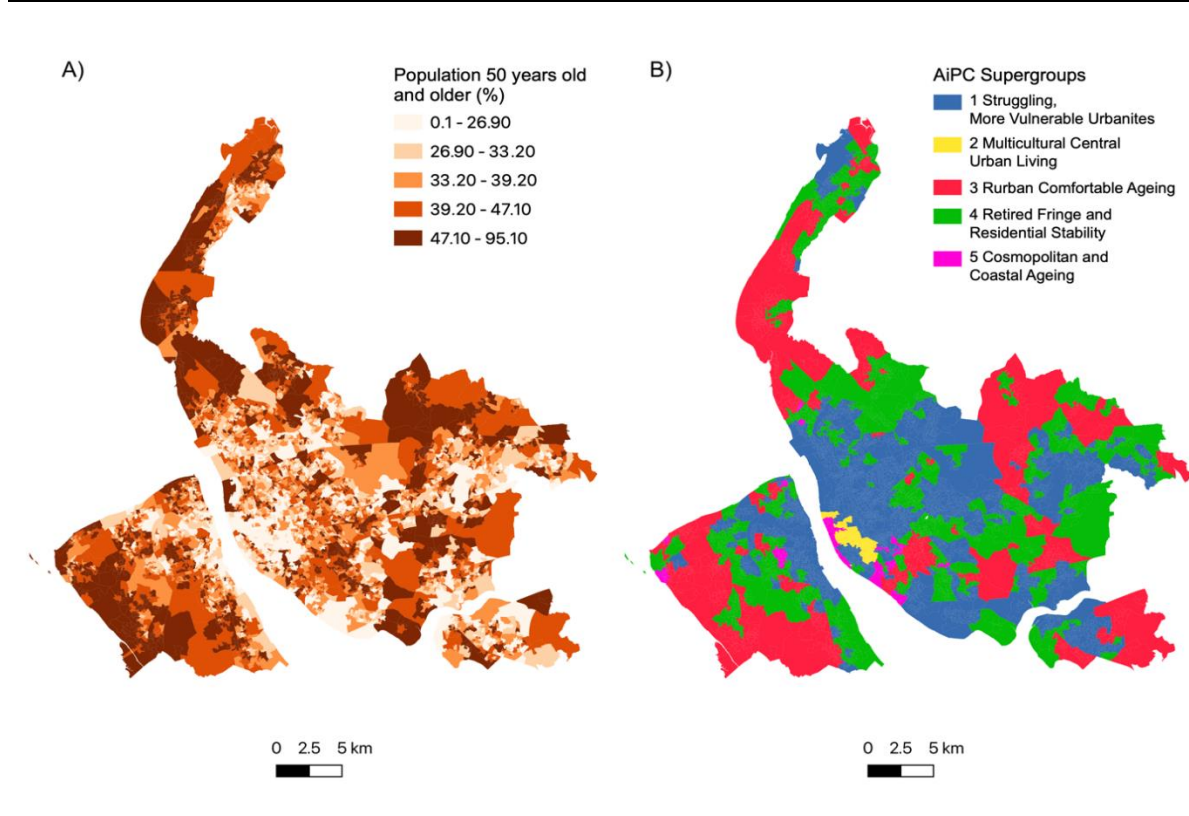
Whilst dwellings, services and access are all within the purview of the urban planner, there is often concern with the suggestion that people should move home in order to access services, as many older people prefer to age in place (Atkins, 2017). As such, the logic of the 20-minute city is that everyday services cannot be centralised; they cannot require citizens to travel more than 10-minutes to the urban core (or periphery). This means that where services have historically been clustered in the urban core, a process of service decentralisation is needed to enable citizens to walk to these services (Caselli et al., 2022). This decentralisation mirrors the argument for greater land use mix, but with the focus on the location of service provision rather than land use. Nevertheless, there is some evidence that more mixed land uses correlate with greater walking rates (Im and Choi, 2020). Application in practice of the 20-minute city is too new to determine empirically if greater service provision changes long term walking behaviour, but borrowing from the logic of land use mix, the hypothesis is that if services are brought closer to dwellings, then the 20-minute city could promote a modal shift to walking.

3.3 Study design - Liverpool City Region

This research is concerned with service accessibility for the older population living in Liverpool City Region (LCR). In recent years the general public and politicians have expressed support for

enhancing active travel (Sustrans, 2020, Anderson 2020, LCRCA, 2020). LCR comprises six local authorities: Liverpool, Wirral, Sefton, Knowsley, St Helens and Halton. It is located in Northwest England and is populated by over 1.5million people, of which approximately 0.55 million are 50+ years old. The ageing population is approximately 37% of the LCR population. Figure 3.1 shows that the proportion of older people aggregated LSOA vary from below 25% in Liverpool city centre and other central locations to well above 50% in some rural and coastal areas, especially in the boroughs of Sefton and Wirral.

Figure 3.1. Maps showing: the percentage of people 50 years and older in Liverpool City Region; the Ageing in Place Classification Supergroups



Source: 2011 Census; Yang, Dolega and Pollock-Darlington (2022)

Table 3.1 – Population aged 50 years old and older (share and median age) in Liverpool City Region and England by AiPC Supergroup

Supergroup Name	Population		Median Age	
	LCR (%)	England (%)	LCR	England
1 Struggling, More Vulnerable Urbanites	44.6	20.2	55	53
2 Multicultural Central Urban Living	1.0	7.7	53	52
3 Rurban Comfortable Ageing	19.5	32.6	59	60
4 Retired Fringe and Residential Stability	32.8	27.9	56	59
5 Cosmopolitan and Coastal Ageing	2.1	11.5	54	52
<i>Total/Median</i>	100	100	56	54

Source: 2011 census; Yang, Dolega and Pollock-Darlington (2022)

Table 3.1 compares various characteristics of ageing population aggregated by the AiPC supergroups (for a full description of the supergroups see Yang et al, 2022) for LCR and England, clearly shows that this claim is supported by data. Whilst the median age of ageing populations are broadly in line with each other, there is a clear disparity between LCR and England in car ownership and proportion of people falling within those AiPC supergroups that are linked to higher deprivation levels. The most staggering difference is in the supergroup 1 with 44.6% of ageing population in LCR classified as *Struggling, More Vulnerable Urbanites*, compared to 20.2% in England. Older populations falling within this supergroup tend to live in urban and semi-urban areas, predominantly concentrated around major northern UK cities and be characterised by high income deprivation, fuel poverty, lowest level of educational attainment and are most likely to suffer from health problems. Conversely, in LCR the representation of *Rurban Comfortable Ageing* and *Cosmopolitan and Coastal Ageing* supergroups are significantly below the national average. Only 19.5% of older people in LCR were classified as *Rurban Comfortable Ageing* and 2.1% as *Cosmopolitan and Coastal Ageing*, compared to the respective national averages at 32.6% and 11.5%. Residents of these supergroups predominantly live in suburban and rural-urban fringe areas, are more affluent, have better education and general health; they also have access to high-speed broadband and like to engage with the internet.

3.2.1 The 20-minute city for an ageing population – analytical approach

The concept of the 20-minute city in the context of LCR has previously been operationalised in Calafiore et al. (2022), generating accessibility scores at postcode level based on needs aimed at being generalisable to the population as whole. However, as argued above, to guarantee a 20-minute city that is inclusive, specific attention needs to be paid to the growing proportion of the population that is ageing in the area. Therefore, working with Alessia Calafiore, Alex Nurse and Richard Dunning from the original work, this research introduces a score that is specifically focused on the needs and characteristics of an ageing population.

The bespoke model is defined on a selection of those services that are especially needed by the older population. It also accounts for a decreased walking speed, which is more likely when ageing.

We identified services that are likely to be relevant for older people from across service categories, then tested this selection through a panel of stakeholders and experts. The initial list of services was amended and enriched by ranking all service categories and domains (see Supplementary Table 3.1 in Appendix 3 for a full list of services). We grouped these services in relation to the 20-minute city concept, giving 18 categories and 92 types. We then modelled the shortest walk time between each postcode and service type using Open Trip Planner through R, giving every output area a binary score of 1 if that service can be walked in 10 minutes, and a score of 0 if not. We can then aggregate binary service scores to give a composite score.

The overall score at service category for each Output Area can range from 0 with no access to services to 18 with access to all service categories and is the result of summing the proportion of service types accessible in 10-minute walk for each category. As such for each service category the computed score, can range from 0 to 1, depending on how many service types satisfy the 10-minute walk condition. For example, if all service types belonging to a particular service category are reachable in a 10-minute walk, then the category will score 1. Conversely,

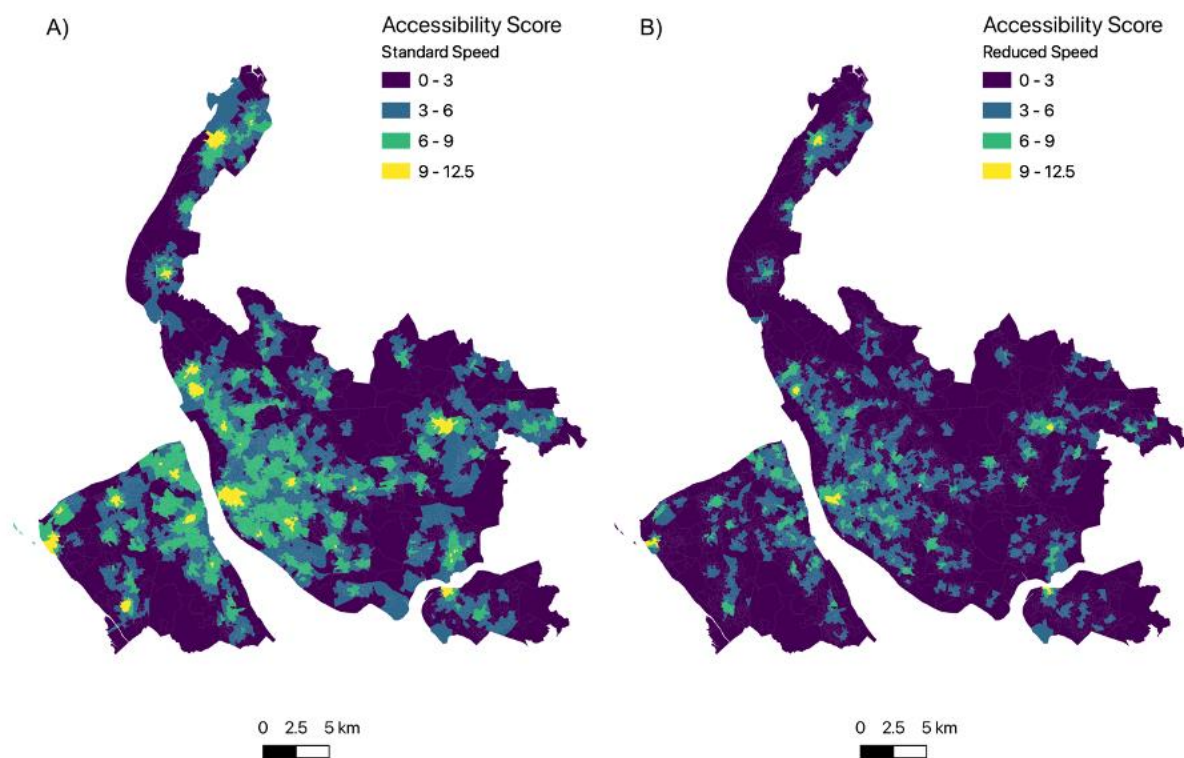
if there is no single service type reachable in a 10-minute walk, it will score 0, and if half service types can be accessed the score for that category will be 0.5 and so on. We must also note that the weight of types that underpin the final score depends on how many types are present within the same service category. For example, *Specialised Food* has 9 types, therefore each type that can satisfy the 10-minute condition adds 1/9 (0.11) to the final score, while under *Essential Food* the only 2 types add 0.5 each.

Functional ageing is one factor that may affect the velocity at which people walk, though the rate of walking speed reduction is highly variable (Guralnik et al., 2001). Consequently, to account for such variations the access to services score in this study is computed assuming different walking speeds. Two walking speeds are employed: 1.2 meters per second (“standard walking speed”) and 0.9 meters per second (“reduced walking speed”). The former is representative of 60+ year olds (Schimpl et al., 2011), while the latter is the estimated speed at which people with mobility challenges walk at (following Fitzpatrick et al., 2006 and Duim, 2017). Evidently in reality, people’s walking speeds will be highly variable, as such this illustrates what services might be reached if people walked at particular speeds.

Once the score is calculated for the two walking speeds, we investigate similarities and differences across the various ageing population geodemographics. We do not assume that all people in each category will experience a lower walking speed but illustrate how their accessibility will change ‘if’ their mobility decreases. As discussed in Section 2.2, geodemographics are able to capture demographic heterogeneity into meaningful population segments. Applied to the 20-minute city for the ageing population, geodemographics characterising older people and their environment holistically provide a rich description of the service users which can help policy-makers in developing more targeted plans. Through mapping and descriptive statistics, we therefore explore the relationship between walking speeds, geodemographics of the ageing population and the bespoke access to services score developed as described above.

3.4 Results: How does access to 20-minute services change through the functional ageing process?

Figure 3.3a and 3.3b: Maps showing the accessibility score for “Standard Walking Speed” and “Reduced Walking Speed” groups of people aged 50 years and over.



Source: Dunning et al., forthcoming

Figures 3.3a and 3.3b show how the walk access to services score varies across space in LCR. We note that the maximum score found in the study area is 12.5, a value well below the theoretical high point of 18, that could be reached when all service categories needed are accessible in a 10-minute walk.

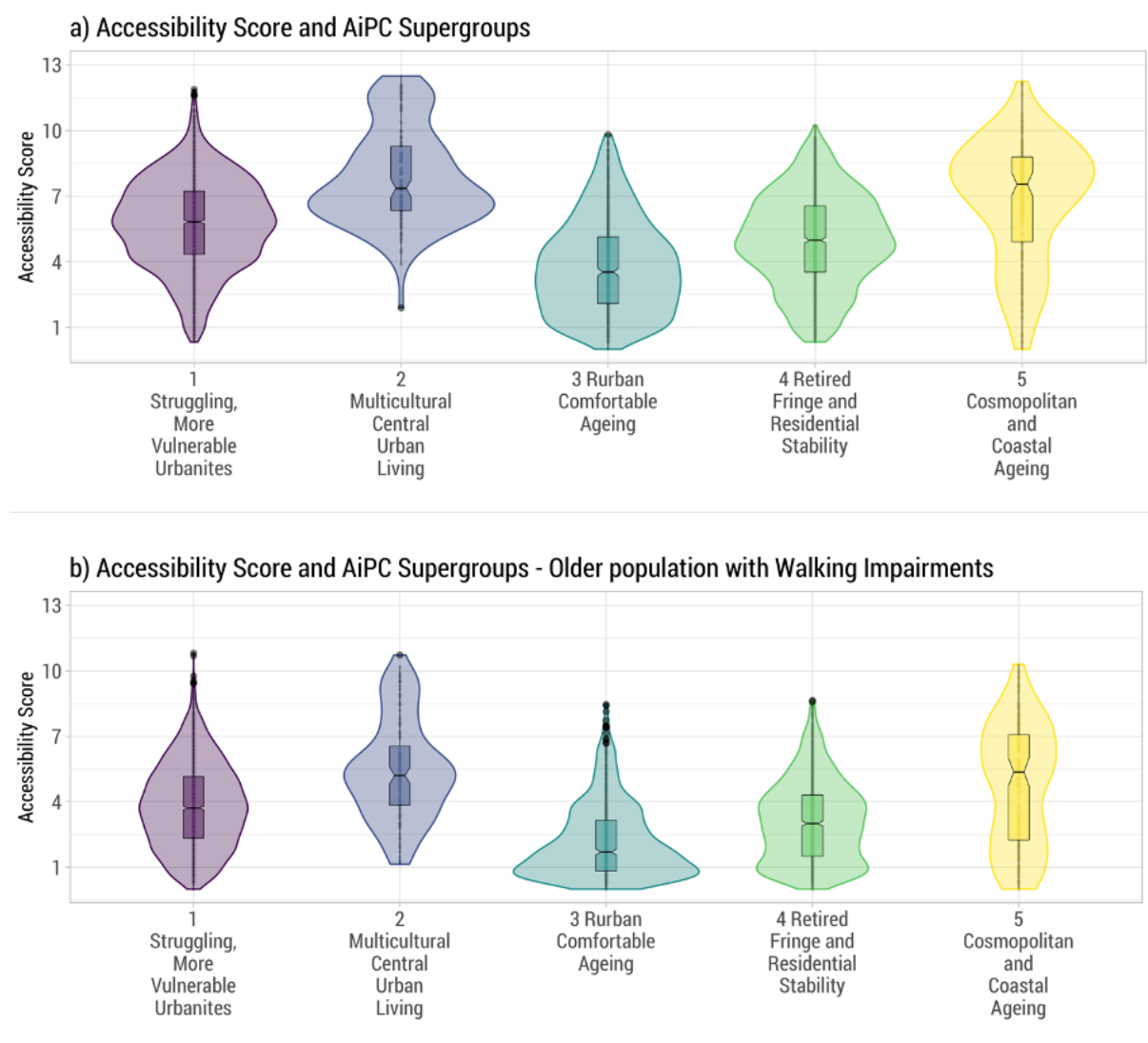
For visualisation purposes 4 classes can be distinguished in the two maps: 0-3 corresponding to areas with *very low access*, 3-6 corresponding to areas with *low access*, 6-9 corresponding to areas with *high access*, 9-12.5 corresponding to areas with *very high access*. Only a few very high access areas, coloured in yellow, are visible in Map 3a, accompanied by a more extensive coverage of high access areas shown in green where people have at least half of the service categories accessible to them in a 10-minute walk. When the score is computed for people with reduced mobility (see Map 3b), a striking reduction in yellow and green (very high and high access) areas is noticeable.

The very high scores are typically found in city and town centres and high streets, where most retail, leisure and entertainment amenities are located. These correspond to 4.16% and 0.57% of the whole LCR output areas for people without and with reduced mobility respectively. High access is also visible in proximity to very high access areas, denoting an appreciable degree of spatial clustering. These areas can be considered as neighbourhoods that are not necessarily city or town centres but should be able to retain population mobility for most of their basic needs. The percentage of OAs falling in the low access class, shown in purple, ranges from 35.31% for the 1.2 m/s walking speed to 11.02% for the reduced walking speed (0.9 m/s). We can see that in Map 3a these are more peripheral areas, often located in the outskirts of urban

areas, while in Map 3b purple areas cover most urban spaces, denoting the wider extent to which people with reduce mobility can feel as living in peripheral areas. Black areas with very low access cover 17.10% of all LCR OAs in Map 3a, with a staggering increase to 45.27% in Map 3b.

Along with looking at the spatial distribution of the access to services score for the two walking speeds implemented, this study also aims at investigating and comparing how walk access varies across different geodemographic groups. Accordingly, Figure 3.4 shows the score's distributions for each AiPC geodemographic supergroup, 4a with a walking speed of 1.2 m/s and 4b with a walking speed of 0.9.

Figure 3.4a and 3.4b Violin plots of the Ageing in Place Classification Supergroups and “Standard Walking Speed” and “Reduced Walking Speed”



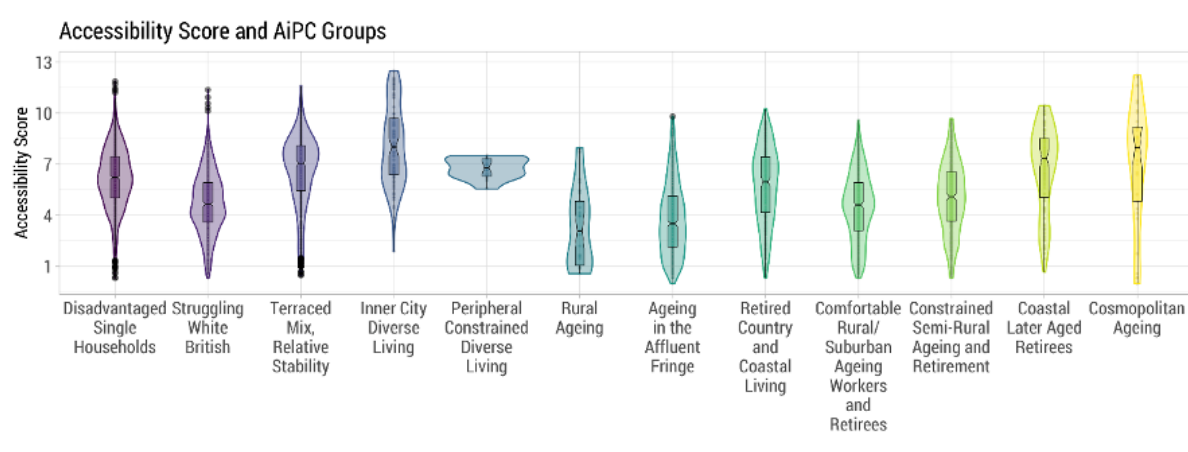
Source: Dunning et al., forthcoming

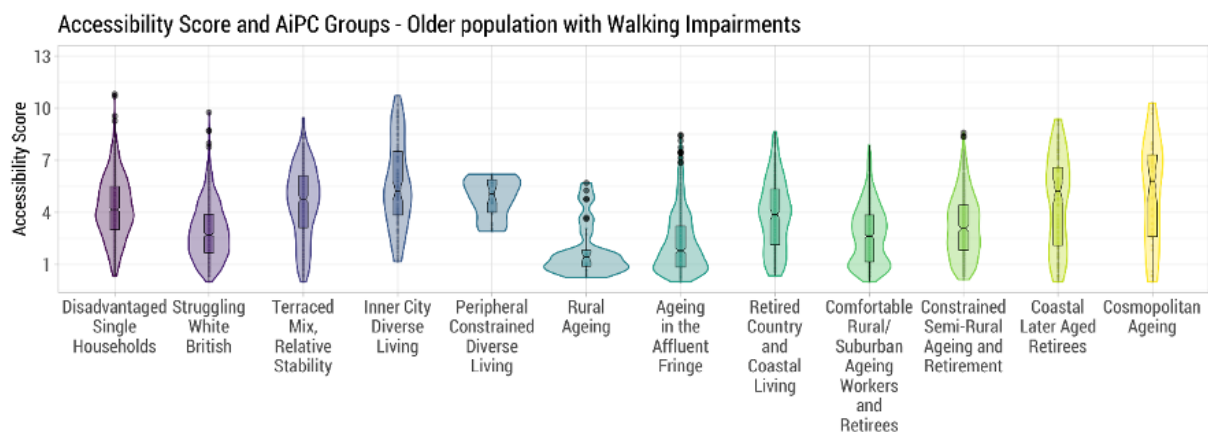
Comparing the distributions in Figure 3.4a with those in Figure 3.4b we note that the score is generally lower for all geodemographic classes when calculated on reduced walking speed.

Population with reduced mobility living in the areas with the highest access approximately have 10% - corresponding to 1.8 points in the score - less access to services than those without reduced mobility. Furthermore, based on the median score, the supergroups are ranked equally for both people with, and without, reduced mobility. Specifically, the *Cosmopolitan and Coastal Ageing*, and the *Multicultural Central Urban Living* supergroups are those with the highest median access – with a median score of 7.5 and 7.3 respectively for those with no reduced mobility and 5.4 and 5.3 for those with reduced mobility -- followed by the *Struggling and Vulnerable People* supergroup and the *Retired Fringe and Residential Stability* – with a median score of 5.8 and 4.9 for those with no reduced mobility and 3.7 and 3 for those with reduced mobility. The supergroup with the lowest access is the *RUrban Comfortable Ageing* with a median score of 3.5 for those with no reduced mobility and only 1.7 for those with reduced mobility.

Analysing the shapes of these distributions, we note that while the score distributes quite similarly for the *Struggling, More Vulnerable Urbanites* and *Multicultural Central Urban Living* supergroups, other population segments show different shapes. Specifically, we can see that the score distributions for the *RUrban Comfortable Ageing* and *Retired Fringe and Residential Stability* supergroups tend to be more flattened towards their lower end for those with reduced mobility when compared with the “standard” (i.e. 50+) walking speed; this means that within these population segments those that also have reduced mobility see a more sizeable lowering of accessible services. On the contrary, the score distribution for the *Cosmopolitan and Coastal Ageing* supergroup shows a higher concentration of observations towards the top end when computed with the “standard” 50+ walking speed, meaning that people without reduced mobility in this population segment not only benefit from higher access overall but it is also more likely for them that the OAs where they live in are of high or very high access.

Figure 3.5a and 3.5b Violin plots of the Ageing in Place Classification Groups and “Standard Walking Speed” and “Reduced Walking Speed”





Source: Dunning et al., forthcoming

3.5 Summary

This research has shown that when an adjusted walking speed is used, to illustrate the difference between older residents with lower mobility, there is a major reduction in the number of services that the population can access. The diminution resulting from just a 25% speed reduction is clear, with many areas accessing three or fewer service types. Whilst a reduction is intuitive, the scale of reduction is surprising with the vast majority of Liverpool City Region not close to the 20-minute city ideal for lower walking speeds. The AiPC shows that this reduction in accessibility from decreasing mobility is not evenly distributed between groups within the older population of LCR.

After modelling the distribution of access to services by different groups, planning will need to grapple with the fact that reduced mobility for some groups is likely to have a more sizeable impact upon access to services than on other groups. This will raise equity questions about the prioritisation of new or improved infrastructure and services. In our analysis, rural and affluent older households have less access to services by walking for 10 minutes than more urban and less affluent households. Whilst this may represent choice-based housing moves in which households prioritise other spatial attributes of the home than walking access, such as particular forms of green space and neighbourhood aesthetic attributes, it comes with the cost of car dependence, particularly for those who do not use active travel modes with longer ranges (e.g. cycling). The housing search literature suggests however, that households who have higher quality neighbourhoods are less likely to seek a move elsewhere (Clark and Huang, 2003). As such, if 20-minute city planning were to support weaker neighbourhoods, there may be less movement into peripheral locations at different stages of the life course, not just for older people, but would simultaneously (in Liverpool City Region) support household groups that are already less disadvantaged with regards 20-minute city analysis.

This development of a 20-minute city accessibility analysis for older people has shown that 20-minute city planners need to account for variation in mobility between groups and provides a first model to support this planning.

4. Housing - estimating accommodation satisfaction in England

4.1 Introduction

Housing is one of the key pillars helping the older population to ‘age in place’ (WHO, 2007). A satisfactory home is essential to support both physical health and mental wellbeing, with dwelling conditions being a significant predictor of the psychological well-being (Fernández-Portero et al., 2017). Architectural features of accommodation, such as the type of dwelling (e.g. flats vs. bungalows) or overcrowding conditions might influence the ability of the ageing population to adapt to changing needs driven by functional ageing and/or physical impairments.

Research shows that housing can impact mental wellbeing among older people in different ways. A large number of variables have been shown to impact accommodation satisfaction, e.g. tenure, gentrification or crime rate (Elsinga and Hoekstra, 2005). Furthermore, they have been shown to vary by age with housing condition, for example, being more important for older than younger people (Zhang et al., 2018). It represents a sense of financial security or insecurity, potentially causing and alleviating higher stress levels (Rowley and Ong, 2012). This is especially important for the ageing population given the larger share of residents being retired and living on a fixed income than the whole population. Geographical and socio-economic phenomena, such as fuel poverty, high rate of inflation or gentrification might also adversely impact some of this demographic group. Besides, as life progresses housing needs may change including resizing (Lord et al., 2019). Research shows that over 57% of the houses occupied by people aged 55+ are under occupied (Pannell et al., 2012) signaling how family houses have become instead de facto couple or single person accommodations (Griffith, 2011). Though policy responses to this have been ill-conceived and misunderstood the role of space within homes in supporting careers, extended families, hobbies and memories (Gibb, 2015). Thus, it is necessary to understand how older people perceive their actual dwellings, their overall satisfaction and how this varies within the older population.

Determining the spatial and social patterns driving accommodation satisfaction is essential to mitigate existing problems and plan for more effective housing policies for these demographics. Understanding accommodation satisfaction at small area level is essential, yet no granular national estimates exist in England, leaving policymakers, housing developers and researchers without a granular understanding of the phenomena. Although the English Housing Survey (EHS) is a nationwide survey that measures multiple characteristics including accommodation satisfaction, the survey covers only a small portion of the total number of LSOAs in England and as a result, there is no direct measure of the phenomenon in almost two thirds of the country. Relying on EHS data, we built a model to estimate household satisfaction with their accommodation at LSOA level in England. This allows us to fully map accommodation (dis)satisfaction nationwide and furthermore determine key factors influencing accommodation (dis)satisfaction. Finally, we also explore whether the understanding of diverse spatial patterns in accommodation satisfaction could be enhanced by employing the

Ageing in Place Classification (AiPC), which offers profiling of older people at small area level based on their socio-economic characteristics and environments they live in.

4.2 Background

‘Ageing in Place’ refers to a broader set of theories that point towards creating effective conditions to allow older people to age well in the accommodation and areas where they live. Indeed, housing is one of the eight key determinants of wellbeing and health in the ageing in place policy framework established by the WHO (2007). As older people spend more time at home due to reductions in mobility, lack of work commuting and general slower lifestyle the characteristics of the accommodation can affect both physical and mental health. For instance, poor quality accommodation can increase mortality and worsen general health conditions (House of Commons, 2018). The NHS has estimated that the associated health costs are around £624 million per annum (Age UK, 2019). Research indicates that this can be associated with tenure with previous studies showing how home ownership is associated with better health status even when we control for the individual characteristics of the household, such as income or wealth (Hiscock et al., 2003).

Ageing can bring new challenges which may require adaptations to the existing accommodation. For instance, research shows that only 60% of the 65+ population live disability free (Horsfield, 2017). On the one hand this may indicate that this may require more living space, as in general, overcrowding conditions can be challenging but on the other hand, larger and especially energy inefficient accommodation might be a financial burden rather than resource for residents with a fixed or low income. Indeed, fuel poverty is currently a major issue among senior residents in England (Abdi et al., 2021) and is predicted to become more severe.

Almost a third of the senior population would like to move to another dwelling (House of Commons, 2018) which is largely driven by the fact that older people require adaptations to the existing accommodation. Changes can include both their physical characteristics (single-story ground floor houses vs. multistory houses) or area characteristics. Area characteristics such as crime level, pollution, or access to local services, play also crucial role in determining certain level of accommodation satisfaction. Crime increases the sense of insecurity and impacts mental wellbeing (Buffel et al., 2012). Substantial urban redevelopment, including gentrification, can also have a negative impact on accommodation satisfaction by altering the demographics of the neighborhood, thus the inherent social capital built by the ageing population which is a foundational element to effectively ‘age in place’ (Lewis and Buffel, 2020). These socio-economic factors and their spatial patterns at small area-level might effectively contribute to predicting where accommodation needs are met.

The AiPC offers a robust tool to differentiate across various characteristics of ageing population and environments they live in and as such we test whether including this information in a small area estimation (SAE) model to generate synthetic estimates of housing satisfaction would be beneficial. In fact, the use of the AiPC within this context might be particularly helpful to identify socio-economic groups which share common traits across England and might require similar intervention from policymakers. This would create an efficient instrument to have a glimpse of the larger factors driving accommodation satisfaction as well as their spatial

patterns. Better understanding of where dissatisfaction with the existing accommodation is prevalent and what are the spatial patterns associated with that is crucial when assessing housing needs for an ageing population. Existing surveys do not allow us to understand how accommodation satisfaction varies in the population aged 50 years old and older across the whole of England on a small geographical scale. Furthermore, the sampled population for each LSOA might be extremely small making any granular understanding that relies exclusively on survey data unfeasible and undesirable. To counter these limitations in survey data, statisticians and social scientists have used small area estimation.

4.3 Methodological approach

4.3.1. Data

The English Housing Survey (EHS, 2008-14; <https://doi.org/10.5255/UKDA-SN-6923-6>) is a multiyear survey measuring different characteristics in the broader housing context managed by the Department for Levelling Up, Housing and Communities (previously the Ministry of Housing, Communities & Local Government). The survey includes an interview with households and physical inspection and is hosted by the UK Data Services (UKDS). Access to some of the geographical location of the respondents, although aggregated at LSOA level is deemed sensitive and therefore access to the data is safe guarded. This required researchers to obtain access to those data in a 'safe environment' controlled by UKDS where all analyses were performed, except for computing the housing satisfaction estimates. A series of pre-processing steps have been completed using EHS survey data including combining different yearly surveys from 2009 to 2015 and excluding data not containing geographical information at LSOA level. We also removed values with no responses on accommodation satisfaction, people aged below 50 years old and responses from Welsh LSOAs. To make our model more robust, we further filter out LSOAs with less than 2 responses per area. Our final dataset contains 15,983 responses across 20.58% of the total 32,844 LSOAs in England. The distribution of the responses across LSOA appears to be random across the space and thus representative of the whole England (Supplementary Figure 4.1 in Appendix 4).

To measure area-level characteristics, we used the Index of Multiple Deprivation (IMD) 2015 score and some individual IMD domains including 'Crime' and 'Barriers to Housing and Services'. The 'Crime' domain measures the risk of personal or material victimization while the 'Barriers to Housing and Services' domain measures the physical and financial accessibility of housing and local services, this includes proximity to local services and issues relating to access to housing such as affordability.

4.3.2. Small area estimation

Small area estimation (SAE) is a well-established technique that generates synthetic data based on survey data. The idea is that survey level data is used to generate a model that predicts a desired variable. The model learns from the survey responses and subsequently predicts the outcome variable. In more statistical terms, the model is fitted based on the survey predictors and then is used to get new estimates. SAE is a simple and yet effective concept, although there are numerous limitations. In order to obtain the estimates, the predicting model needs to rely on robust dataset (e.g. national censuses) that contains information across all areas of interest. Without this constraint, it wouldn't be possible to leverage the survey-fitted model into a broader context using the predictors available at the larger scale. In the context of this

research, the larger reliable dataset is the latest available national Census (2011) at the LSOA level. We used a logistic regression model to predict the probability of being satisfied or not with the existing accommodation. Our methodological approach follows a methodology applied by ONS (ONS, 2017) to model individual-level outcome variables using area-level predictors. In other words, we employ Census area-level data to predict the actual probability of being (dis)satisfied with the existing accommodation.

Once the model has been post-processed and evaluated, we took the final estimates for the coefficients in the model and then using external predictors available at national level, we generated synthetic values for England. These steps are discussed in more detail below.

4.3.3. Model specifications and evaluation

Based on literature review and experts' knowledge, we selected a series of potential variables that predict accommodation (dis)satisfaction in England. In the EHS, accommodation satisfaction is measured by a specific question ('How are you satisfied with your accommodation?') in which households can choose between 5 types of scaled answers, including a neutral response³. Given the small amount of data for each type of answers and type of methodology identified, we recoded the variable into a binary outcome ('Satisfied' or 'Dissatisfied'). In the context of the research which aims to identify areas of improvements in terms of housing satisfaction, we recoded neutral responses ('Neither being satisfied or dissatisfied') into 'Dissatisfied' responses.

Furthermore, in our model we have included only those LSOAs that had more than 1 response. This constraint has been applied to increase the robustness of the model, similarly to what has been done in other SAEs (e.g. Iparraguirre, 2016). We also used IMD 2015 domain scores to include area-level potential predictors such as income, crime or environmental conditions. Given that accommodation satisfaction might be generated by both specific conditions of a house and the broader environmental conditions, we included variables that measure relevant elements across these two contexts. For example, the age or health of the households are specific to the individual responses obtained, however, other factors such as pollution, crime or geographical barriers are important area-level indicators. The model evaluation looked at statistical significance of the predictors, multicollinearity, and distributions of the residuals. In terms of predictability performance, the AIC score and R score⁴ have been instrumental in assessing which final selection of the model.

The final model was obtained through a series of iterations and is shown in Supplementary Table 4.1 in Appendix 4. AiPC Supergroups classification was also added to the model to enhance the estimates. All the variables were statistically significant within 95% confidence interval and the key regression model assumptions such as no multicollinearity issues between

³ The answers to the question are structured in 5 different potential replies: 'Very satisfied', 'Fairly satisfied', 'Fairly dissatisfied', 'Very dissatisfied' and a neutral answer 'Neither satisfied or dissatisfied'.

⁴ The AIC score is the 'Akaike Information Criterion' that is used to assess which model performs better given the same dataset. The R score is calculated as the Pearson's correlation score between the observed share of people feeling lonely at LSOA level and the estimated share.

variables and residuals distribution were satisfactory. To generate the housing (dis)satisfaction estimates we nationally rescaled the results obtained to the observed values in the EHS survey, which was in line with previously SAE studies (ONS, 2017). We rescaled the results by multiplying each estimate by the ratio obtained from the observed mean and the estimated mean at national level. Following the rescaling, we get the final estimates for each LSOA in England.

4.4 Results and discussion

4.4.1. Accommodation Satisfaction in England

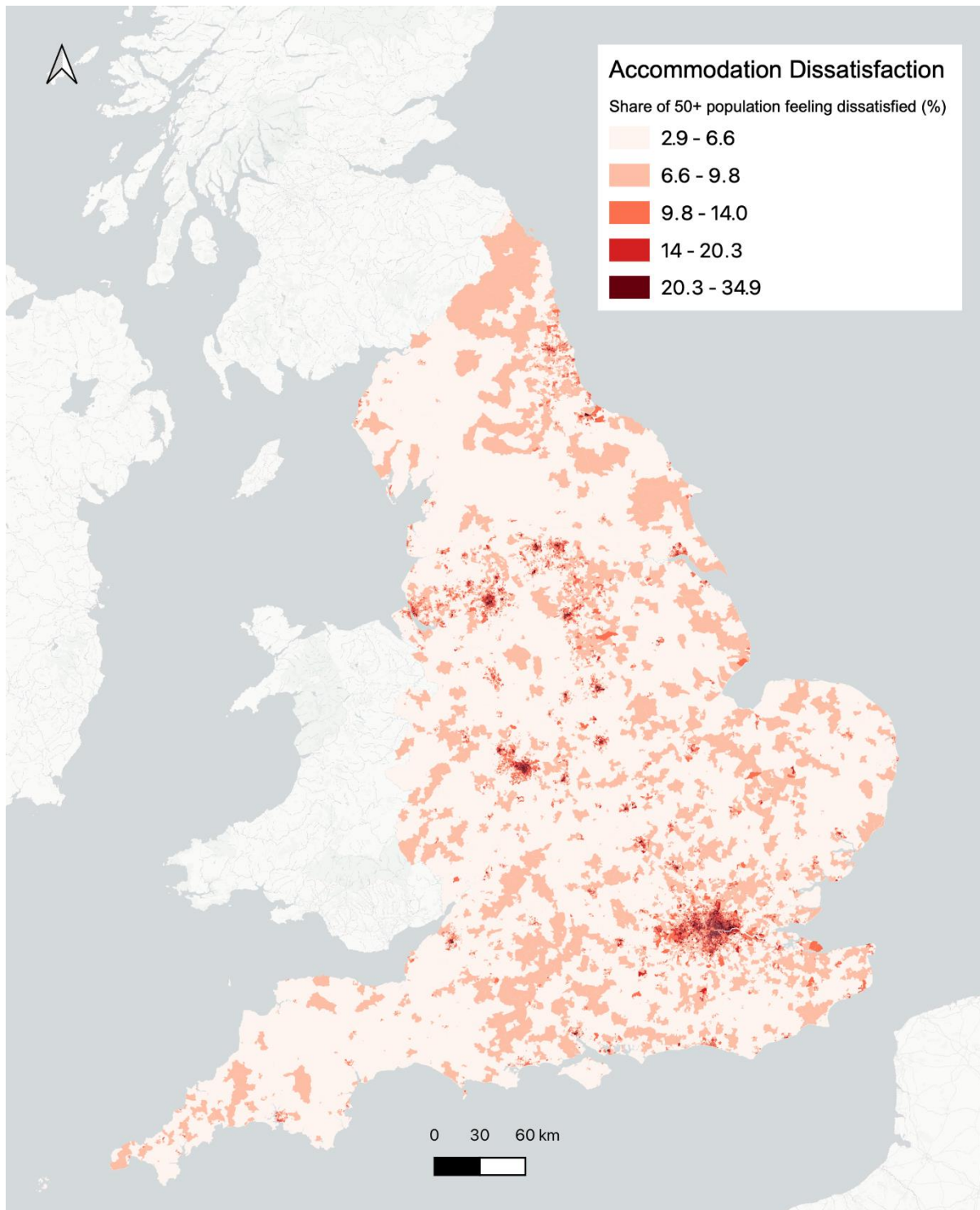
Our estimates show that older people in England are largely satisfied with their current housing. On average, only 7.69% of the older people households were dissatisfied with their accommodation. While this finding might sound reassuring, there is a significant spatial variation in housing dissatisfaction across England. Table 4.1 shows that the estimates for 50+ years old residents' range between 2.88% and 34.88%. The data are positively skewed revealing areas where the estimated dissatisfaction with accommodation is five times the average. Overall, accommodation dissatisfaction amongst the elderly tends to be concentrated in urban areas. On the contrary, rural, and urban-fringe areas display the highest housing satisfaction. However, this pattern is not binary. Multiple rural areas especially in the East of England, North West and South East England show higher than average share of people that are not satisfied with their accommodation.

Table 4.1 – Descriptive statistics of the share of 50+ population dissatisfied with their accommodation in England and Liverpool City Region (LCR)

	Min	Max	Weighted Mean	Weighted Median	SD	IQR
England	2.88%	34.88%	7.69%	6.21%	4.79%	5.09%
LCR	2.96%	28.12%	7.48%	6.47%	3.77%	5.40%

Source: authors' SAE for prevalence of accommodation satisfaction

Figure 4.1 – Accommodation dissatisfaction in the 50+ population in England – Natural Breaks classification scheme



Source: authors' SAE for accommodation satisfaction

4.4.2. Driving factors

Our model shows how multiple factors are driving the differential levels of accommodation satisfaction in England. These are the following:

- Share of people being homeowners (this includes households with an existing house mortgage)
- Share of people aged between 50 to 64 years old

- Share of people with limited long-term illness or disability
- IMD 2015 'Crime' domain score
- IMD 2015 'Barriers to Housing and Services' domain score

Housing ownership plays a substantial role in the identified patterns. On average, the higher the ownership rate, the higher the satisfaction and the reverse appears to be true: the higher the share of renters, the lower the satisfaction with their accommodation. Social renters are especially dissatisfied with their accommodation compared to both owners and private renters (DLUHC, 2021b).

The second strongest predictor in our model indicates that as the proportion of households aged between 50 to 64 years old increases, the probability of not being satisfied with their accommodation also increases. Broadly, household age is positively associated with levels of satisfaction - the satisfaction rates improve as age increases (Supplementary Figure 4.2. in Appendix 4). This insight can be linked to other relevant nodes in the discussion around age as a factor driving accommodation satisfaction. The lower rates of house ownership between people aged 50 to 64 years old might partially explain the substantially higher rate of dissatisfaction. The evidence shows that the share of households occupied by homeowners in the age group of 45-64 has been constantly declining since 2009/2010 (DLUHC, 2021a), while it was constant or increasing for the age groups of 65-74 and 75+ respectively. Households aged between 50 to 64 years old might also have dependent children living with them compared to more senior age groups, given that younger people tend to live with their parents longer nowadays (ONS, 2019).

Furthermore, a higher share of the 50+ population with long-term illnesses or disabilities is associated with higher levels of dissatisfaction. People with long-term illnesses might require certain housing standards or adaptations to meet their needs. These findings might also indicate a well-documented phenomenon of discriminatory design for people with physical or mental long-term illnesses in real estate (Satsangi et al., 2018) with rigid interior design plans which do not allow adaptations for people with such conditions. Given that nearly half of the 65+ population will not live disability-free in the next 20 years (ONS, 2018), it is important to underly how access to good accommodation for people with long-term illnesses and disabilities might be essential to create fair conditions among senior citizens.

While dissatisfaction is measured in the context of household accommodation, the perception is also influenced by various neighborhood characteristics. Our analysis shows that crime deprivation as measured by the IMD subdomain score plays a non-negligible role in influencing satisfaction. The lower the crime score, the higher is the satisfaction. Through a finer analysis, we can notice that particularly LSOAs with high IMD crime scores in inner cities area are the most dissatisfied in terms of accommodation satisfaction. On the other hand, the IMD Barriers to Housing and Services domain has almost no impact on determining accommodation satisfaction. However, the score is positively correlated (0.48) with the share of estimated dissatisfaction potentially revealing a link between higher barriers to housing and higher levels of dissatisfaction. This can be better understood by looking at the scores of the two subdomains (Supplementary Table 4.1. in Appendix 4): 'Geographical barriers' measuring proximity to local services and 'Wider barriers' measuring other issues such as housing affordability and homelessness. In relation to the previous exploration of the role of ownership,

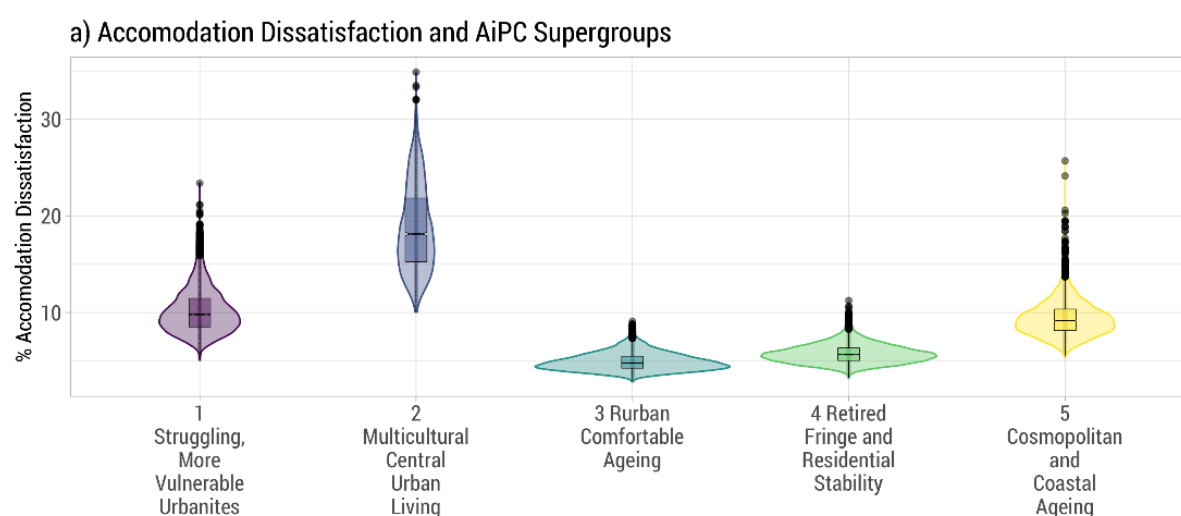
the lack of housing affordability appears to be strongly associated with higher level of housing dissatisfaction (r-correlation: 0.81) but negatively associated (-0.43) with proximity to services (the latter has been explored in detail in Chapter 2).

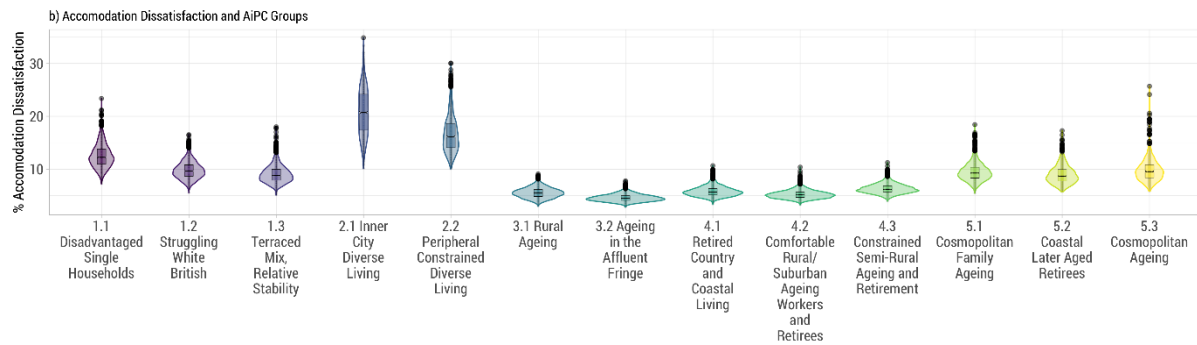
Cost of renting could be especially problematic in main urban centres. These areas are generally associated with higher cost of living and therefore can adversely impact housing satisfaction for ageing population that often relies on fixed income. Of the top 30 LSOAs by estimated housing dissatisfaction, 50% are in London, followed by a cluster of LSOAs in Birmingham gentrified neighborhood in the Westside and Sheffield city centre. Our estimates suggest that higher barriers to housing affordability are linked to higher levels of dissatisfaction. IMD Income score further supports this link between economic struggle and dissatisfaction.

4.4.3. AiPC and housing satisfaction in England

As a part of our research aims, we test whether the use of AiPC classification can enhance estimates of accommodation satisfaction in the population aged 50+. We argue that the AiPC classification might play an important role in helping policymakers to highlight those areas and population profiles that might require more policy interventions. As result, in addition to the predictors listed in section 4.4.2, our SAE model includes the AiPC clusters so we can assess the role played by each supergroup (SG). All the associations are statistically significant with 90% confidence intervals (CI) (see Supplementary Table 4.1 in Appendix 4). Supergroup 2 ‘Multicultural Central Urban Living’ is negatively associated with housing satisfaction with LSOAs classified within that supergroup having a higher proportion of the residents being not satisfied with the existing accommodation. Similarly, Supergroup 5 ‘Cosmopolitan Comfort Ageing’ shows similar patterns although the negative relationship is weaker. On the other hand, Supergroup 3 ‘Rurban Comfortable Ageing’ and Supergroup 4 ‘Retired Fringe and Residential Stability’ have a positive relationship with larger share of satisfied households.

Figure 4.2 - AiPC and Accommodation Dissatisfaction a) supergroup level; b) group level





Source: authors' calculation based on SAE for accommodation satisfaction and AiPC data

Our results show that the use of the AiPC in the model improves the predictability of the model measured its robustness and r squared scores shown in Supplementary Table 4.1, Appendix 4) It also offers new insights on how accommodation satisfaction changes across AiPC Supergroups and Groups. Spatially, AiPC SG 3 and 4 tend to be located mostly in rural areas while SG 2 and SG 5 tend to be close or in central urban areas. This link between higher dissatisfaction with more urban ageing population is clearly visible at the spatial level (Figure 4.1).

SG 2 tends to be the youngest cluster in terms of population age which is consistent with a lower rate of housing satisfaction compared to other older age groups. Furthermore, residents belonging to this group are the most ethnically diverse across the AiPC. Research has suggested that ethnic minorities are particularly affected by overcrowding accommodation which is a key factor in assessing housing satisfaction (Garrett et al., 2014). Indeed, SG 2 has the highest share of overcrowded accommodations among the other groups (Figure 4.2a) and it has the highest rates of social renting housing. Furthermore, ethnic minorities and foreign-born residents might be subject to some form of housing discrimination which reduces access to housing ownership and confines them to less affluent areas with poorer services and less safe neighborhoods (Gulliver, 2016). Figure 4.2b shows how residents living in the 'Inner City Diverse Living' group are the main reason why we see such a high level of dissatisfaction suggesting that a mix of different housing needs are not satisfied in this group.

SG 5 shares some similarities with previously discussed SG 2. Spatially, SG 5 is mostly located in the Southeast of England, especially in areas around and in London. SG 5 is characterized by the highest housing prices on average and the population in this group is still younger than other clusters with higher rate of people coming from non-White backgrounds. Closely followed by SG 2, they have the highest residential churn rate i.e., high residential mobility. This suggests that these areas are subject to stronger price changes in the private rental market. SG 5 shows more variability compared to SG 2. Group 5.3, which identifies mostly areas in city centres and has substantial variability among all the other groups but on average it has a higher-than-average level of dissatisfaction. On a similar note, Group 5.1 is mostly located in suburban areas around London, which negatively affects the level of satisfaction with the existing accommodation.

SG 1 classifies areas with substantial problems with accommodation satisfaction. These areas are mostly located in the outskirts of central urban areas with the lowest median house price and the highest crime levels. Residents of this SG are typically single households with a White

ethnicity background and low educational attainment. They also tend to be more deprived in terms of income compared to other AiPC groups. Figure 4.1b shows Group 1.1. has higher level of accommodation dissatisfaction, mostly concentrated in the Northwest large urban areas and Birmingham. Conversely, SG 3 and SG 4 are associated with a lower level of accommodation dissatisfaction. Both SGs have a higher median age, they are mostly homeowners and White when compared to the SG 2 and SG 5. They are largely married and living with couples with the lowest share of households living in overcrowding conditions. SG 3 residents have among the best health conditions with low share of people living with limiting long-term illnesses compared to other SGs including SG4. They also diverge in terms of broadband access and access to ICT services with the SG 3 having a far better score than SG 4.

Table 4.3 – AiPC Supergroups and SAE model covariates Accommodation Satisfaction in England (dis)satisfaction estimates in a major English urban area

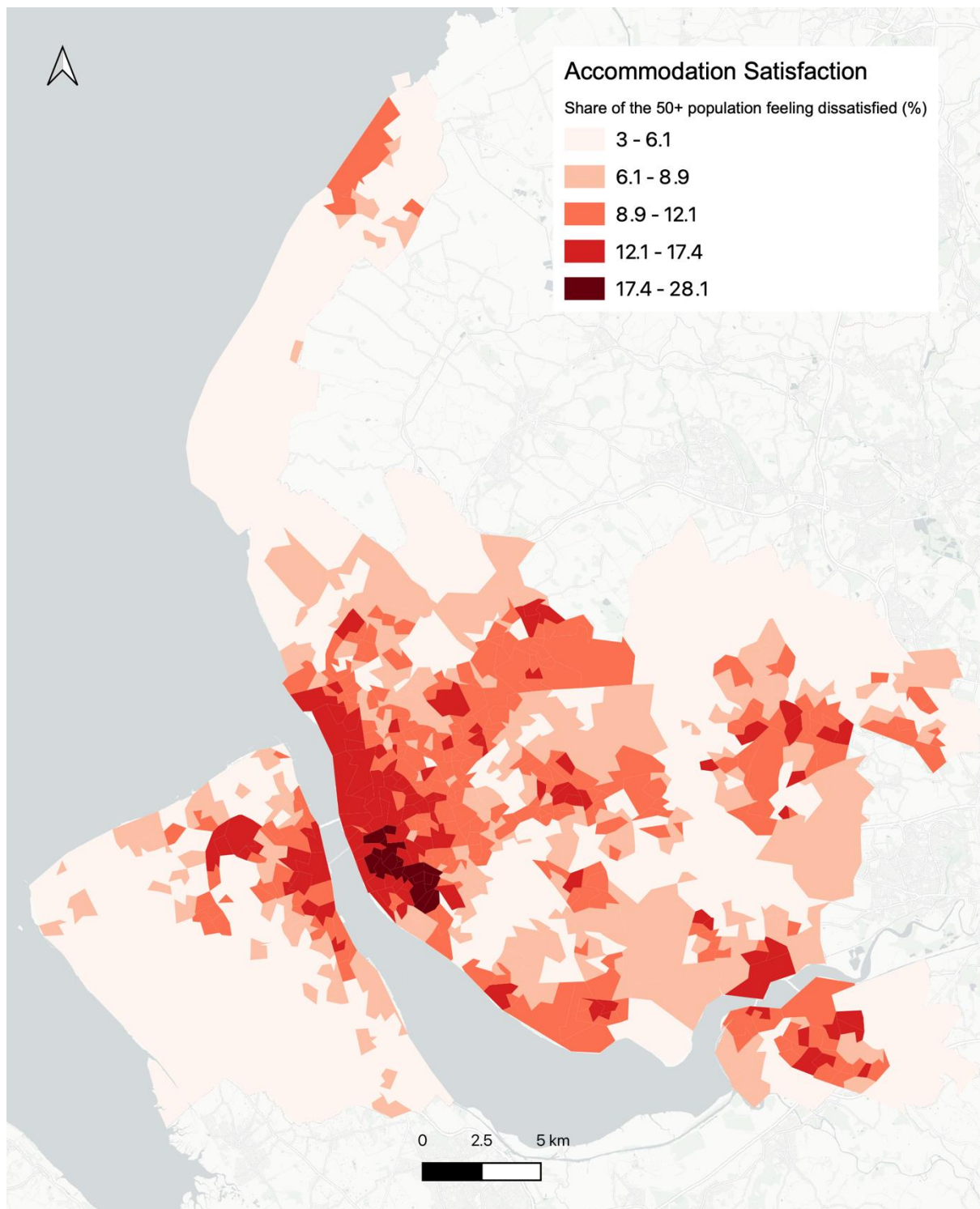
AiPC Supergroups	People Dissatisfied	Dissatisfaction	Ownership	Long-term illness	Age (50-64)	IMD Score	IMD Crime	IMD Barriers to Housing
1 Struggling, More Vulnerable Urbanites	369,388	10.0%	54.6%	48.1%	52.2%	39.7	0.5	19.9
2 Multicultural Central Urban Living	257,698	18.4%	49.1%	43.8%	58.7%	34.5	0.8	32.9
3 Rurban Comfortable Ageing	292,591	4.9%	89.1%	28.2%	52.4%	8.6	-0.7	23.5
4 Retired Fringe and Residential Stability	289,402	5.7%	82.1%	37.5%	50.2%	16.9	-0.2	16.5
5 Cosmopolitan and Coastal Ageing	192,436	9.2%	76.8%	31.4%	54.7%	14.5	0.1	20.8

Source: authors' calculation based on SAE for accommodation satisfaction, 2011 Census and AiPC data

4.4.4. Liverpool City Region and Accommodation satisfaction

Liverpool City Region (LCR) represents an interesting case study to investigate our housing (dis)satisfaction estimates in a major English urban area. Our research expertise and local knowledge of the city region and our established relationship with Cobalt Housing, a local housing association, make this area ideal to test practical applications of our estimates and the geodemographic classification. The proportion of LCR residents dissatisfied with their accommodation does not show a significant difference compared to the rest of England (Table 4.1). On average the share of dissatisfied residents in the LCR is slightly lower (7.48%) compared to the nationwide average (7.68%) while the median is slightly higher at 6.46% and 6.21% respectively.

Figure 4.3 - Housing dissatisfaction estimates in Liverpool City Region



Source: authors' SAE for accommodation satisfaction

Areas around LCR city centre show the highest share of the ageing population dissatisfied with their accommodation. Large part of the Georgian Quarter, Chinatown, Baltic Triangle, Toxteth, Ropewalks and Islington have on average almost a quarter of the total older population dissatisfied with the existing housing. Also, the more deprived neighborhoods outside the city

centre such as Vauxhall, Everton, Kirkdale and Bootle show concerning rates of housing dissatisfaction. Outside the city of Liverpool, central parts of Birkenhead, St. Helens and Widnes show similar patterns to Liverpool City Centre. The more affluent suburban and rural areas outside Liverpool City show a substantially higher than average rate of satisfaction. These include large parts of Sefton, southern and western Wirral and northern St. Helens. Areas with high housing satisfaction levels include other affluent suburban areas in Liverpool such as Allerton and Childwall.

4.4.5. AiPC and accommodation dissatisfaction in Liverpool City Region

The share of accommodation dissatisfaction across the AiPC Supergroups in LCR is consistent with the nationwide patterns. Above the average levels of dissatisfaction are in SG 2 (21.88%), SG 1 (10.14%), SG 5 (8.54%). Yet some differences between LCR and the national estimates emerge. For example, SG 2 has a higher share of dissatisfied residents compared to the national average, which may indicate that in Liverpool the housing stock for senior residents living in 'Multicultural Central Urban Living' areas might require more attention compared to other similar areas in England. This SG has substantially lower share of residents being homeowners (23.48% in LCR vs. 49.06% in England), larger proportion of the ageing population with long term illness (54.21% vs 43.78%) and higher IMD crime score (0.76 vs 1.06) respectively.

Geographically, the SG 2 is only distributed in Liverpool City Centre and adjacent areas (Figure 3.1b), particularly in the neighborhoods with the highest estimated housing dissatisfaction levels such as Georgian Quarter, Toxteth or Ropewalks (Figure 4.3). To an extent, these findings might be explained by the fact that these areas have recorded a significant increase in housing value and rent as a result of gentrification and redevelopment processes in the past years. The ownership rate (23.48%) is vastly inferior compared to the national level in the same supergroup (49.06%). With a large proportion of the ageing population being renters and potentially relying on fixed or low income generated by pensions, this could negatively affect perceptions on the accommodation where they live or create downwards pressure to move to less adequate, but more affordable accommodations. Furthermore, the potential change in the demographics in these areas might have badly impacted the existing formal and informal networks for older people. Another SG that represents a fairly large proportion of residents dissatisfied with their housing in LCR is SG 1 'Struggling, More Vulnerable Urbanities'. However, the average dissatisfaction rate is in line with the national estimates for this SG highlighting similar socio-economic and spatial patterns between areas in LCR and England. Spatially, SG 1 partially contains suburbs such as Bootle, Wavertree or Fairfield but also densely populated areas near the Liverpool City centre including Vauxhall and Everton areas as well as waterfront areas in Birkenhead and Runcorn.

Among the predictors driving housing (dis)satisfaction, the most notable difference between the nationwide statistics and LCR statistics for this SG is the higher IMD deprivation score. SG 5 shows a slightly lower share of dissatisfied 50+ residents which might be driven by a significant difference in the share of people with long-term illness and barriers to housing and services as captured by the IMD score. Lastly, SG 3 and SG 4 display proportions of dissatisfied residents that are in line with the national estimates and below the estimated national average.

Table 4.4. – AiPC Supergroups and SAE Accommodation Satisfaction model in LCR

AiPC Supergroups	People Dissatisfied	Dissatisfaction	Ownership	Long-term illness	Age (50-64)	IMD Score	IMD Crime	IMD Barriers to Housing
1 Struggling, More Vulnerable Urbanites	24,652	10.2%	53.6%	53.9%	54.1%	50.0	0.5	14.9
2 Multicultural Central Urban Living	1,226	21.9%	23.5%	54.2%	58.7%	46.3	1.1	23.4
3 Rurban Comfortable Ageing	4,469	4.2%	94.6%	31.6%	51.3%	8.5	-0.8	13.4
4 Retired Fringe and Residential Stability	9,443	5.3%	86.4%	40.0%	52.2%	18.9	-0.2	10.5
5 Cosmopolitan and Coastal Ageing	979	8.5%	74.7%	37.4%	53.1%	19.5	-0.1	13.7

Source: authors' calculation based on SAE for accommodation satisfaction, 2011 Census and AiPC data

4.5. Summary

In this chapter we introduce a practical application of the AiPC classification: estimating accommodation satisfaction in England in the population aged 50+. Housing needs vary across a person lifetime span and as result, the levels of satisfaction within the existing accommodation. However, existing surveys do not provide fine-grained data at small spatial scale assessing how accommodation satisfaction varies in the 50+ age group.

Leveraging small area estimation (SAE) methodology, we designed a model that both generates new synthetic estimates and allows us to understand the driving factors behind accommodation (dis)satisfaction. To our knowledge, our research not only produces first-of-its-kind estimates for accommodation satisfaction in England, but it also describes the relationship between several variables associated with different levels of satisfaction. The AiPC classification is used as a predictor in the SAE model generating the estimates.

After an iterative process to select the predictors, we found that home ownership is positively associated with satisfaction while having long-term illness or disability and being in the 50 – 64 age group is negatively associated with it. Using the two IMD score domains as predictors, we also found that higher crime rate is associated with lower satisfaction, while general barriers to housing does not show neither a negative nor positive impact. However, if we further analyse the latter, housing affordability appears to be strongly associated with higher level of satisfaction but negatively associated with proximity to services. Spatially, our results show a clear split between urban (lower satisfaction) and rural areas (higher satisfaction) with central areas in large urban centres (especially London) as concerning epicentres.

The AiPC Supergroup 2 'Multicultural Central Living' and Supergroup 5 'Cosmopolitan Comfort Ageing' areas are associated with lower satisfaction rate while the AiPC Supergroup 3 'Rurban Comfortable Ageing' and Supergroup 4 'Retired Fringe and Residential Stability' are with higher levels of satisfactions. Overall, Liverpool City Region shows similar patterns to the national ones with more central areas recording higher level of dissatisfaction compared to suburban and rural areas in the region. Specifically, neighbourhoods classified as part of the SG 2 show concerning rates of dissatisfaction, which might indicate that ethnically diverse ageing population is more likely to be disproportionately impacted.

5. Society - estimating loneliness in England

5.1 Introduction

Loneliness is a widespread social problem with vast and still underexplored implications. While some studies suggest that loneliness is more prevalent among young adults compared to other age groups (Department for Digital, Culture, Media & Sport, 2022), loneliness is also a major challenge for an ageing population. Indeed, loneliness has been defined as a ‘silent pandemic’ (Jeste et al., 2020) and feeling lonely is associated with higher mortality (Luo et al., 2012), depression (Gale et al., 2018) and heart attack (Thurston et al., 2009). Loneliness is not only a tragic social phenomenon, but it also adds a significant weight to UK public spending. Some estimates suggest that loneliness could cost £2.5 billion for UK employers (New Economics Foundation, 2017) and it could cost £6,000 per person among older people (McDaid et al., 2017). Some studies demonstrate how the COVID-19 pandemic and the shelter in place policies have further increased the number of people feeling lonely in England, especially among older people (Age UK, 2021). At the same time, investing in policies that fight loneliness generates an estimated 3x return for £1 pound spent (McDaid et al., 2017)

While loneliness is a national phenomenon, we lack a deeper geographical assessment of it. Especially, there is a need to explore geographies of loneliness, determine where it is more prevalent, but also identify factors driving loneliness in the ageing population. Furthermore, assessing loneliness using a multi-layered computational method might unveil untapped opportunities to design strategies to mitigate the phenomenon both across space and socio-economic profiles. Direct observations of loneliness levels underestimate the phenomena (Koropecj-Cox, 1998) and might raise concerns related to the privacy of the respondents.

As a result, we aim to generate synthetic and privacy-safe estimates of loneliness for 50+ years old in England at small area level using a small area estimation (SAE) techniques and ELSA Wave 6 data. We also test the utility of AiPC within that context to see whether the current estimates of loneliness can be enhanced by employing our bespoke classification. AiPC, as an excellent tool to flexibly identify different types of ageing population, their characteristics and profiles and therefore it can potentially leverage our understanding of this phenomenon.

5.2 Background

Loneliness is a cross-generational social issue, but it is especially important for older people who might lack the physical and mental resources to adapt and challenge the sense of feeling lonely. A series of multiple factors impact the ability to socialize and reduce the sense of loneliness. Research shows that loneliness appears to particularly affect women, people that are widowed, divorced or separated (Gale et al., 2018). Health conditions might adversely affect the ability to listen, speak, move and process information resulting in the ability to have a deeper connection with other human beings. It has been found that several socio-economic factors play an important role too. For instance, having a low income can reduce the opportunities to socialize which is highly relevant to many older people who rely on fixed income and live in unsafe neighborhoods. This, in turn, might increase fear and challenges for older people reducing their mobility and socializing. More affluent older people might

counterbalance the sense of being lonely with higher social and spatial mobility, they also might live in areas with better access to relevant services including community centres, associations or better broadband access (Matthews and Nazroo, 2015). The absence of services within walkable neighborhoods or adequate transport links might further reduce mobility and therefore create enhanced conditions for social isolation (Age UK, 2018). In the context of our research, it is worth noting that being lonely is different than being socially isolated. A person might feel lonely even if it has some or less frequent social connections, further complicating the full picture of loneliness among older people including its drivers and prevalence.

Existing national scale estimates on loneliness among people aged 65+ at small area level (LSOA) rely on data provided by Age UK. Age UK uses small area estimation (SAE) methods to generate estimates of the prevalence of loneliness in the population aged 65 years and older based on ELSA Wave 5 data (year 2010). However, this analysis excludes people aged between 50 and 64 years old and is based on an older version of the ELSA data.

It has been proved that application of geodemographic classifications can also further improve the quality of SAE models (Moon et al., 2019) and make it easier to interpret the variations of the estimates across space. The AiPC clusters can be used as a potential driving factor for predicting levels of observed loneliness and can help to avoid risky and unfair homogenization of the older population. By combining broader and multiple characteristics in distinguishable ageing population groups, we can study how loneliness varies spatially and across the AiPC profiles. Modelling loneliness is important since it defines the weights of the risk factors associated with loneliness. Indeed, qualitative research has mostly focused on identifying the different elements eroding social connections and creating the conditions for loneliness among senior people. However, we need to assess the impact of these core indicators to create actionable plans to mitigate the social phenomena. We also note that the measurement of loneliness is challenging and research shows that direct measurement of loneliness tends to underestimate the levels of the phenomenon (Koropecj-Cox, 1998).

5.3 Methodology

5.3.1 Data

The study employs ELSA (English Longitudinal Study of Ageing) Wave 6 (ELSA, 2012; <https://doi.org/10.5255/UKDA-SN-8434-1>) survey data to capture levels of loneliness across the population aged 50 years and older. ELSA is a longitudinal individual survey which measures multiple factors in a pool of respondents across the years and it is administered by University College London, Manchester University, Institute for Fiscal Studies, and National Centre for Social Research. ELSA survey track loneliness in England in the population aged 50 years old and older by asking a direct question (“How often do you feel lonely?”) which is answered by respondents according to a scale of frequency. Since we use logistic regression to model loneliness, the responses have been recoded into binary ‘feeling lonely/not feeling lonely’ responses⁵.

⁵ The responses are recoded into a ‘Yes/No’ value by aggregating ‘Hardly never’ and ‘Some time’ answers into a ‘No’ while ‘Often’ as ‘Yes’, consistent to Age UK methodology (Iparraguirre, 2016)

For the purpose of this research, we accessed sensitive data containing geographical information at LSOA level through UKDS secure data facilities. The data was pre-processed by including only valid responses and removing responses from Welsh LSOAs. We further pre-processed the dataset by selecting only LSOAs with at least more than 2 responses per LSOA. This reduces the bias, increases the robustness of the model and it is consistent with previous small area estimation (SAE) methods on loneliness using ELSA data (Iparraguirre, 2016).

The final dataset used to fit the SAE model contains 6507 responses across 2598 LSOAs in England i.e. 7.91% of the total 32,844 LSOAs in England. The results are distributed fairly randomly across the country (Supplementary Figure 5.1 in Appendix 5).

5.3.2 Estimation of loneliness prevalence

We generate synthetic values for loneliness prevalence in the aging population in England at LSOA level using SAE. Similarly, to the SAE on accommodation satisfaction (section 4.3 of this report), we use the same methodology to generate estimates of loneliness, since a full-scale sample at LSOA level for a national level does not exist. Furthermore, the sample size for each LSOA might be extremely small thus any takeaways might be biased by these small counts. To generate new estimates, we iteratively designed a model with area-level predictors to generate the share of population feeling lonely aged 50 years old and older. This approach is identical to the one used for the accommodation satisfaction estimates and it draws from the ONS approach (ONS, 2017).

The variables were selected following a multi-layered iterative approach. An initial set of variables were included looking at the existing literature review. We reduced the number of variables by using only variables available at LSOA level in Census 2011. Variables that were largely statistically not significant and showed multicollinearity were removed. The final model includes six predictors which are all statistically significant within a 95% CI. We tested a number of assumptions related to logistic regression model such as residuals distribution or independence of variables and we were satisfied with the results. Although, the level of significance of some AiPC Supergroups appears to be below conventional levels particularly in SG 4 and SG 5, the inclusion of them increased the performance of the model. Finally, to obtain the actual estimates across all the LSOAs in England, we rescale the estimates by the ‘national prevalence’ of loneliness captured in the ELSA survey., which is in line with other similar approaches.

5.4 Results and discussion

Our estimates imply that 6.94% of the 50+ population feels lonely in England. The share varies across LSOA from just 2.68% to 27.20% and it is slightly positively skewed.

Table 5.1 – Estimated Min, Max, Mean, Median, Standard Deviation (SD) and Interquartile range (IQR) of the share of 50+ population feeling lonely in England

Min	Max	Population Weighted Mean	Population Weighted Median	SD	IQR
2.68%	27.20%	6.94%	6.50%	3.25%	4.21%

Source: authors' SAE for prevalence of loneliness

These estimates are generated by a model that includes six predictors and the AiPC geodemographics (Table 5.1 in Appendix 5). The six statistically significant predictors include:

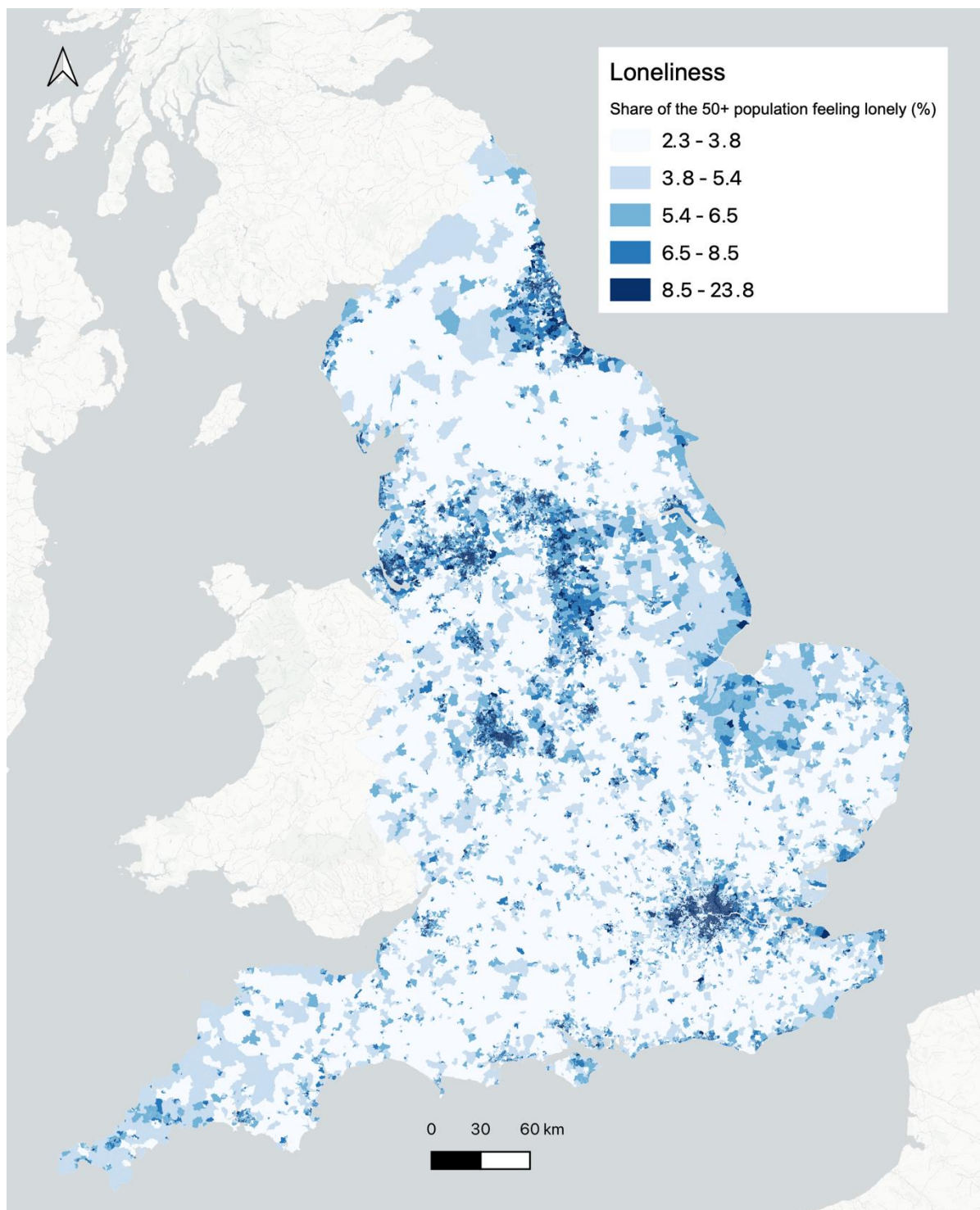
- Share of the 50+ population being divorced or separated
- Share of the 50+ population being widowed
- Share of the 50+ population being in poor health
- Share of the 50+ population being in fair health
- Share of the 50+ population having a limiting long-term illnesses or disability
- Share of the 50+ population aged between 75 and 84 years old

The proportion of residents being widowed is the strongest predictor driving the probability of being lonely at LSOA level. The presence of a partner can be a key element reducing loneliness with the sudden loss of a lifetime partner having a disproportional impact the feeling of being lonely. This can be explained by the required adjustments and an adverse impact on psychological well-being a widowed person might experience (Vedder et al., 2022).

Having poor or fair health can also substantially increase levels of loneliness in each area. For instance, difficulties in hearing or seeing reduces the ability to have meaningful social interactions or having mental health issues is especially relevant in this context. Poor health can impact the ability of individuals to move or access to services including digital services which might reduce the sense of being lonely. Furthermore, being divorced or separated is positively associated with higher levels of loneliness, however this predictor is not as strong as being widowed or having health difficulties.

Areas with higher proportion of residents aged between 75 to 84 years old show lower levels of loneliness. While the proportions of respondents feeling lonely tend to increase with age (Supplementary Figure 5.1. in Appendix 5), biological age per se does not seem to predict loneliness. Our findings are consistent with previous research drawing similar conclusions in relation to age (Iparraguirre, 2016). The addition of the AiPC to the model improves the predictability of the model by increasing the R-score from 27.77% to 28.44% (Supplementary Table 5.1 in Appendix). Compared to the Age UK estimates of loneliness among older people our model substantially improves the predictability by 58% (an increase in R Pearson from 17.93% to 28.44% respectively) and it extends the population group to 50+ people compared to only 65+ respondents in the Age UK SAE.

Figure 5.1 – Share of the 50+ population feeling lonely at LSOA level in England - estimated values



Source: authors' SAE for prevalence of loneliness

5.4.1 Spatial patterns of loneliness

Spatially, as Figure 5.1 shows, large urban centres are the areas where loneliness in the 50+ population is more prevalent while the opposite is true for more rural areas. On the one hand urban centres are exceptional nodes for human activities, with these areas on average having better access to services, offering easier opportunities to connect with other people thanks to the higher density of population and good walkable areas which should all foster a better

ageing in place process. Chapter 2 shows clearly that the central urban areas have better access to key services, reducing the burden of travelling which in turn, might be especially important as mobility might decrease as residents age. Also, higher density could enhance each resident's personal social network and social connectiveness while a good area walkability has positive physical and mental health outcomes. However, on the other hand access to services in more peripheral urban areas is limited compared to city centres. Furthermore, as loneliness might be associated with higher levels of deprivation (Victor and Pikhartova, 2020), less affluent urban areas can signal higher levels of loneliness.

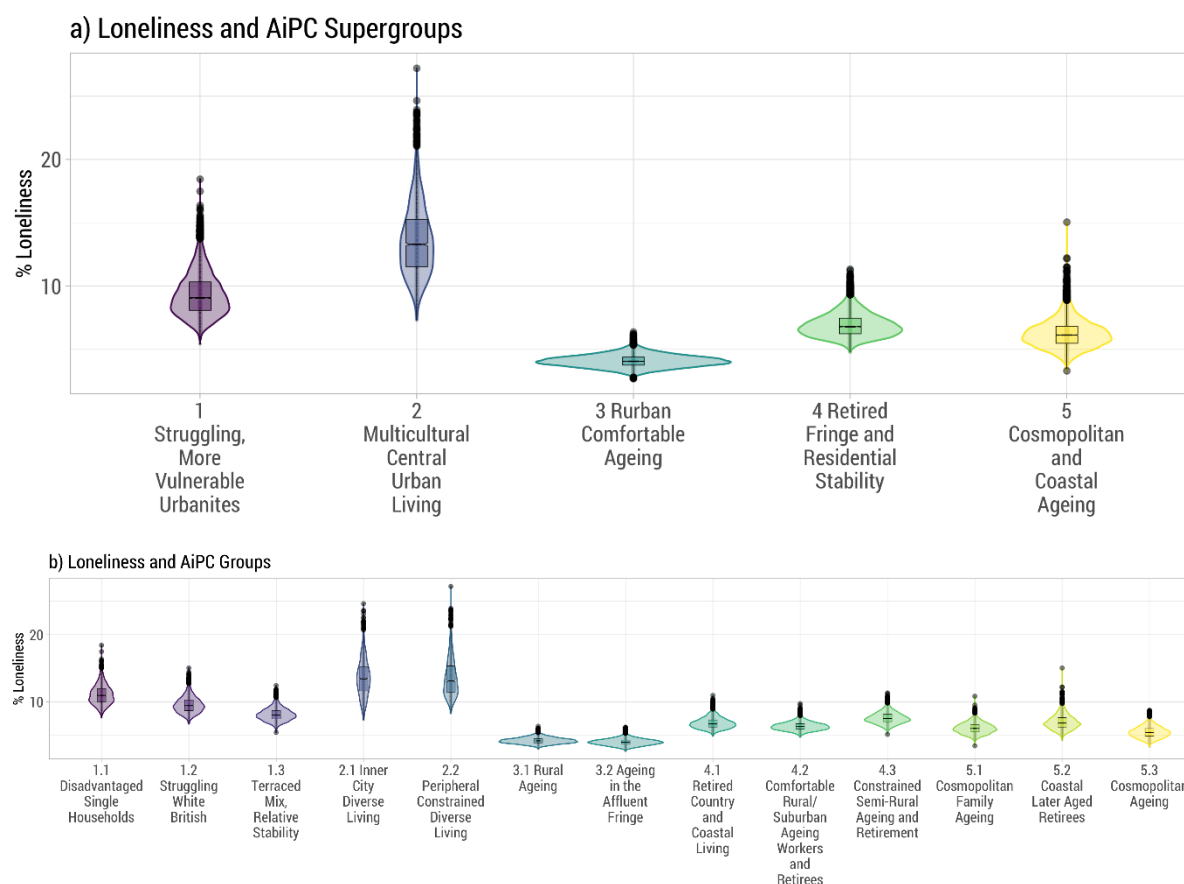
Our loneliness map (Figure 5.1 and Supplementary Figure 5.3. in Appendix 5) appears to display a donut-shape pattern of loneliness levels across the large urban settlements such as London, Manchester or Leeds: empty in the city centre but dense around it. Some small central areas show lower than average levels of loneliness but with quite sharp increase in the surrounding areas displaying substantially higher levels of loneliness. Our analysis unveils a high-level spatial inequality in terms of the proportion of older people feeling lonely. These numbers might suggest how loneliness levels can be associated with certain socio-economic inequalities. Indeed, loneliness SAE are extremely positively correlated with the IMD score (0.76): the higher the level of deprivation, the higher the prevalence of loneliness among 50+ population.

While urban areas show substantially high levels of loneliness in the ageing population, rural and rural/ urban fringe areas have the lowest level of estimated loneliness. These findings might be counterintuitive in the context of an over simplistic view of the problem that correlates higher levels of spatial isolation in rural areas with higher level of loneliness (Age UK, 2019). We suggest that these insights are the results of multiple dynamics in place. On average, the need for larger houses and lower housing costs might have progressively pushed older people at certain point in life to move to more suburban areas. Indeed, the substantially higher rate of ownership in those areas suggests that housing ownership might play a substantial role in the process. More rural areas and suburban areas have fewer single households and they attract more affluent senior individuals. Typically, the attractiveness of city centres appeals more to affluent and younger residents which in turn might drive out the senior people with often lower or fixed income. Cultural components also play a role. A historical well-established cultural phenomenon has placed a high value on living in less dense and decentralized areas with easy car parking and associated green spaces, especially among the 50+ age group (Smith Institute, 2009). It is worth noting though that not all non-urban areas are associated with low levels of loneliness. Some suburban and rural-fringe areas near cities such as London, Birmingham, Liverpool and Manchester have levels of loneliness that are at least 50% higher than the nationwide average.

5.4.2 AiPC and loneliness

The share of people feeling lonely vastly changes across the AiPC Supergroups (SG). SG 3 'Rurban Comfortable Ageing' has the smallest proportion of people feeling lonely (4.10%) while it is more than 3 times higher (13.57%) for the SG 2 'Multicultural Central Urban Living'. SG 4 'Retired Fringe and Residential Stability' (6.93%) and SG 5 'Cosmopolitan and Coastal Ageing' (6.31%) have slightly lower than average share of older residents feeling lonely. On the contrary, SG 1 'Struggling, More Vulnerable Urbanities' has a higher-than-average level of loneliness (9.36%).

Figure 5.2 – Boxplots of the prevalence of loneliness across AiPC Supergroups and Groups



Source: authors' calculation based on SAE for loneliness and AiPC data

The level of estimated loneliness across Supergroups can be better understood by looking at the characteristics of the Supergroups. Table 5.2. shows how the model predictors vary across the AiPC Supergroups. As the model highlights, the marital status affects the probability of feeling lonely. SG 1 has a substantially higher than average proportion of people being widowed, divorced and separated while SG 3 has the highest share of residents living in a couple or being married. SG 1 and SG 2 have the highest share of 50+ population living with poor and fair health conditions. Indeed, as these proportions decrease across SGs, the share of people not feeling lonely increases. This pattern is identical for the proportion of the population with long-term illnesses.

As seen in Chapter 1, the AiPC geodemographic is the result of multiple socio-economic characteristics grouped into a single profile. By leveraging the AiPC Supergroups, we can use these different ageing population profiles to explore the patterns between loneliness and other characteristics.

Access to the digital sphere is also almost proportionally correlated with lower level of loneliness across SGs. SG 3 and SG 5 have the best access to information, services, and social media showing the lowest levels of loneliness. SG 4 has worse digital engagement but still higher than SG 2 and especially SG 1 which they both show respectively the highest and the

second highest share of people feeling lonely across SGs. While we do not suggest that there is a direct link between lower level of loneliness and higher level of digital engagement, this hint might suggest enacting policies to boost access to digital opportunities especially when around one third of the 65+ population have never used internet (Age UK, 2016).

SG 3 and SG 4 which have lower than average estimated proportion of loneliness among ageing population, have the lowest levels of crime across the different AiPC supergroups while the opposite holds true for SG 1 and SG 2 which have higher than average estimated level of loneliness. High crime rate can affect the feeling of being lonely given the associated sense of insecurity which could affect mobility, reduce social interaction and general mental well-being (Victor and Pikhartova, 2020; Scharf et al., 2005). Similarly, income deprivation is lower in SG 3, SG 5 and SG 4 which they all have lower than average levels of loneliness. While these findings do not suggest a cause effect connection, they also suggest further areas of improvements and macro patterns across the estimates and AiPC Supergroups.

Table 5.2 – AiPC Supergroups and SAE loneliness model covariates

AiPC Supergroups	# People Feeling Lonely	Loneliness	Age Group 75 - 84	Widowed	Divorced and Separated	Fair Health	Poor Health	Long-term Illness
1 Struggling, More Vulnerable Urbanites	345,258	9.4%	16.7	19.4%	20.5%	32.8%	18.8%	48.1%
2 Multicultural Central Urban Living	190,425	13.6%	14.1	15.9%	20.8%	30.8%	18.4%	43.8%
3 Rural Comfortable Ageing	244,569	4.1%	15.61	13.0%	10.7%	21.7%	7.1%	28.2%
4 Retired Fringe and Residential Stability	353,137	6.9%	17.0	16.3%	13.4%	27.8%	11.5%	37.5%
5 Cosmopolitan and Coastal Ageing	132,493	6.3%	15.4	15.6%	17.3%	24.3%	9.6%	31.4%

Source: authors' calculation based on SAE for loneliness, 2011 Census and AiPC data

Finally, there are also some interesting spatial patterns that are worth noticing. In general, the AiPC Supergroups seem to confirm that there is an urban-rural divide in terms of prevalence of loneliness. SG 3 and SG 4 consist of largely rural or semi-rural areas and it has on average the lowest prevalence of loneliness, on the other hand SG 2 and SG 1 classifies largely as urban areas and they have the highest level of estimated loneliness. However, SG 5 represents an exception to this rule. SG 5 is mostly urban but it has the second lowest level of estimated loneliness per Supergroup. Specifically, AiPC Group '5.3. Cosmopolitan Ageing' has among the

lowest share of the population feeling lonely and it is mostly located in central areas (e.g. in Manchester, Oxford, London) and suburbs in Southwest London. Looking at the spatial distributions of the group, we can highlight the extent of the spatial inequalities in terms of loneliness in urban areas. AiPC 5.3. Group areas are adjacent to other neighborhoods with substantially higher than average levels of estimated loneliness showing how loneliness can vastly change in urban areas by few blocks.

5.5 Summary

In this chapter, we introduce and test how the AiPC classification can be used to generate estimates of the prevalence of loneliness in the population aged 50+ in England.

Loneliness is a major concern in the ageing population, and it has been defined a 'silent epidemic' with vast social, health and economic consequences. However, understanding its social and spatial patterns across England is challenging. Although representative, the existing surveys do not cover the whole England and therefore the prevalence at small area level has to be estimated. To overcome these data challenges, we adapt a similar approach to that from Chapter 4 and use small area estimation (SAE) technique to compute estimates of feeling lonely for population aged 50+ at small area scale in England. By doing that, we also identified the key factors driving loneliness in this age group. In this context, we tested whether the profiles identified by the AiPC could be helpful in assessing what population groups and areas struggle with higher-than-average levels of loneliness. As result, we tested the contribution of the AiPC to enhance SAE model for loneliness.

Age UK leverages SAE to create synthetic values of the prevalence of loneliness in 65+ population and it is considered the de-facto the most reliable model assessing the spatial patterns of loneliness in England, however our model which includes the AiPC considerably improves the model. Our results show how loneliness is more prevalent in urban areas rather than rural areas while this is not homogenous. On average rural areas show consistent lower share of people feeling lonely while suburban and rural-fringe areas near cities such as London, Birmingham and Liverpool have 50% higher than national average level of loneliness. Interestingly, some major urban centres such as Manchester, Leeds and London show a 'donut-shaped' pattern with low level of loneliness in more central areas surrounded by a dramatic increase in the surrounding areas.

We also identified key factors driving loneliness levels. The marital status is a key determinant with being divorced or separated and especially widowed increasing the levels of loneliness. Health issues are also relevant such as having a long-term illness or disability or living in poor or fair health conditions, which are also positively associated with higher prevalence of loneliness. AiPC Supergroup 1 and 2 show higher than average level of loneliness and this is consistent with the broader urban/rural split in the estimates since the two groups are mostly urban. At the same time, AiPC Supergroup 3 has the lowest level of estimated loneliness, and it is mostly rural followed by AiPC Supergroup 5 and AiPC Supergroup 4. Having explored the variation of the estimated loneliness across the underlying characteristics of the Supergroups, we also note interesting patterns. It appears that better access to the digital services is associated with lower levels of loneliness, while higher crime and income deprivation appear to have the opposite effect.

6. Conclusions

The population of England is ageing. Old age is typically equated with dependency and frailty and this demographic group is often viewed as a burden on the national fiscal system challenging stability and sustainability of the existing models of services, housing or and healthcare provisions. This demographic group has often been portrayed in the relevant debates as homogeneous, however, our experience of old age and of ageing is highly individualistic, itself determined by our wider socioeconomic characteristics and the places we live in. Policy and service planning needs to better capture the social and spatial heterogeneity of the ageing population if it is better meet the variable needs and potential opportunities an older and ageing population presents. To better support that, a more nuanced understanding of the geography of older people is needed, moving beyond simplistic evaluations of 'percentage aged 65+' and 'level of deprivation'.

Building on existing advances in the developments of geodemographics, we present a bespoke geodemographic classification of older people in England aged 50+ at small area level. The ageing in place classification (AiPC) employs both conventional and novel data sources and has been developed in consultation with an expert advisory panel including gerontologists, geriatricians, scholars, local authority policy makers and community workers. The AiPC classification containing 5 distinctive supergroups and 13 nested groups depicts distinctive features of the older population and their local environments and it is available as an open source data product to maximise its utility for end users. It is a multidimensional classification portraying differences and similarities between supergroups and groups across the nine key domains, distinguished by difference from the national average. The utility of the AiPC was then demonstrated by investigating a series of research questions relating to the three themes: neighbourhoods, housing and society. These included obtaining accessibility scores to relevant services for older people located within walking distance, housing (dis)satisfaction estimates at small area level and computing enhanced estimates of loneliness amongst ageing population.

The AiPC is, to the best of our knowledge, the first bespoke geodemographic classification of the older population in England and provides valuable new insights that can be used as an evidence base for policy makers. They can be implemented at both local and national contexts, in particular to improve service delivery and inform targeted policy interventions in relation to housing needs and loneliness of ageing population. The process of building the AiPC and demonstrating its utility was grounded within a stakeholder community to embed their expertise into designing the employed methodologies and optimise research outputs. It provides new and valuable insights that can be implemented at both local and national contexts, in particular to improve service delivery and inform targeted policy interventions. Our findings can also be used in emergency preparation and local community resilience arguably missing from the Covid-19 response. Our bespoke classification offers a more nuanced understanding of the likely needs of local older populations and can be applied to a wider regionally or nationally coordinated interventions and policy measures.

Though the methodology was rigorously designed, the adopted approach is not without limitations. First, we make use of Census data from 2011 as the basis of the classification which is already outdated, although at the time of creation this was still the gold-standard available data and the insights obtained remain of value. Second, surveys used to measure the digital

engagement, housing satisfaction or loneliness of the older population (e.g. British Population Survey, EHS or ELSA) were not representative at small area level, therefore synthetic values had to be computed. Though this may introduce some discrepancies, the methods employed to compute the estimates are rigorous and previously tested by other studies. Finally, we were unable to capture some key attributes identified by our expert panel due to a lack of reliable data. One particular example related to the (perceived) safety of older people in their local environments which was raised frequently as an important element, and is something to consider for future iterations. With the arrival of new Census data, it will be readily updateable as an open-source product, further maximising its continued use in the face of a rapidly ageing population. Future iterations must exploit the ever-growing availability of geo-referenced data to enhance the value of this classification, while end users should endeavour to illustrate where more age-disaggregated spatially referenced data is needed to further improve its performance.

References

- Abdi, A. M., Arewa, A. and Tyrer, M. 'Fuel Poverty and Health Implications of Elderly People Living in the UK'. *Energy and Sustainable Futures*. Cham: Springer International Publishing, 241-246.
- Age UK (2016) The Internet and Older People in the UK – Key Statistics (Accessed: 9/8/2022).
- Age UK (2018) All the lonely people: loneliness in later life: Age UK (Accessed: 18/8/2022).
- Age UK (2019) Later Life in the United Kingdom 2019 (Accessed: 17/8/2022).
- Age UK (2021) Impact of Covid-19 on older people's mental and physical health: one year on: London (Accessed: 9/8/2022).
- Atkins, M.T., 2018. "On the move, or staying put?" An analysis of intrametropolitan residential mobility and ageing in place. *Population, Space and Place*, 24(3), p.e2096.
- Balsas, C.J., 2004. Measuring the livability of an urban centre: an exploratory study of key performance indicators. *Planning, Practice & Research*, 19(1), pp.101-110.
- Bartlett, H. & Carrol, M. (2011) Ageing in Place Down Under. *IFA Global Ageing*, 7(2): 5-34.
- Buffel, T., Phillipson, C. and scharf, T. (2012) 'Ageing in urban environments: Developing 'age-friendly' cities', *Critical Social Policy*, 32(4), pp. 597-617.
- Calafiore, A., Dunning, R., Nurse, A. and Singleton, A., 2022. The 20-minute city: An equity analysis of Liverpool City Region. *Transportation Research Part D: Transport and Environment*, 102, p.103111.
- Campbell, F.K., 2010. Crippin' the flâneur: Cosmopolitanism and landscapes of tolerance. *Journal of Social Inclusion*, 1(1), pp.75-89.
- Caselli, B., Carra, M., Rossetti, S. and Zazzi, M., 2022. Exploring the 15-minute neighbourhoods. An evaluation based on the walkability performance to public facilities. *Transportation Research Procedia*, 60, pp.346-353.
- Cockings, S., Martin, D., & Harfoot, A. (2020, 2020/12/01). Developing a National Geodemographic Classification of Workplace Zones. *Applied Spatial Analysis and Policy*, 13(4), 959-983. <https://doi.org/10.1007/s12061-020-09337-4>
- Comber, A., Brunsdon, C., Charlton, M., & Cromby, J. (2021). The changing geography of clinical misery in England: lessons in spatio-temporal data analysis. In *Big Data Applications in Geography and Planning*. Edward Elgar Publishing.
- Da Silva, D.C., King, D.A. and Lemar, S., 2019. Accessibility in practice: 20-minute city as a sustainability planning goal. *Sustainability*, 12(1), pp.1-20.
- Dargay, J. M. (2001). The effect of income on car ownership: evidence of asymmetry. *Transportation Research Part A: Policy and Practice*, 35(9), 807-821.
- Darlington-Pollock, F., Dolega, L. and Dunning, R. (2021) Ageism, overlapping vulnerabilities and equity in the COVID-19 pandemic. *Town Planning Review: Volume 92, Issue 2*, 92(2), pp.203-207.
- Department for Digital, C., Media & Sport (2022) Investigating factors associated with loneliness in adults in England. Available at: <https://www.gov.uk/government/publications/factors-associated-with-loneliness-in-adults-in-england/investigating-factors-associated-with-loneliness-in-adults-in-england> (Accessed: 17/08/22).
- Department for Levelling Up Housing and Communities (2021) 'Table FA5212 (S707): Satisfaction with area by characteristics of the household, 2020-21.'. Available at: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data

ata/file/1088627/FA5212_satisfaction_with_area_by_characteristics_of_the_household.ods (Accessed).

Department for Levelling Up Housing and Communities (DLUHC) (2016) English housing survey: Housing for older people report, 2014–15: Department for Levelling Up Housing and Communities (DLUHC).

Department for Levelling Up Housing and Communities (DLUHC) (2021) 'Table FC2101 (S370): Percentage of each age group that are owner occupiers, 2020-21'. Available at: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/1088718/FC2101_Percentage_of_each_age_group_that_are_owner-occupiers.xlsx (Accessed).

Dobner, S., Musterd, S. and Droogleever Fortuijn, J., 2016. 'Ageing in place': experiences of older adults in Amsterdam and Portland. *GeoJournal*, 81(2), pp.197-209.

Duim, E., Lebrão, M.L. and Antunes, J.L.F., 2017. Walking speed of older people and pedestrian crossing time. *Journal of Transport & Health*, 5, pp.70-76.

Dunning, R. and Nurse, A., 2020. The surprising availability of cycling and walking infrastructure through COVID-19. *Town planning review*, 91(1), pp.1-7.

Dunning, R., Calafiore, A., Nurse, A., 2021. 20-minute neighbourhood or 15-minute city? *Journal of the Town and Country Planning Association*, 90, 5/6, 157-159.

EHS (2008-14) 'English Housing Survey, 2008-2014'. Department for Communities and Local Government. UK Data Service. <https://doi.org/10.5255/UKDA-SN-6923-6>

ELSA (2012) 'English Longitudinal Study of Ageing: Waves 6-8, 2012-2017'. NatCen Social Research. UK Data Service. <https://doi.org/10.5255/UKDA-SN-8434-1>

Elsinga, M. and Hoekstra, J. (2005) 'Homeownership and housing satisfaction', *Journal of Housing and the Built Environment*, 20(4), pp. 401-424.

Fernández-Portero, C., Alarcón, D. and Barrios Padura, Á. (2017) 'Dwelling conditions and life satisfaction of older people through residential satisfaction', *Journal of Environmental Psychology*, 49, pp. 1-7.

Fitzpatrick, K., Brewer, M.A. and Turner, S., 2006. Another look at pedestrian walking speed. *Transportation research record*, 1982(1), pp.21-29.

Gale, C. G., Singleton, A., Bates, A. G., & Longley, P. A. (2016). Creating the 2011 area classification for output areas (2011 OAC). *Journal of Spatial Information Science*, 12, 1-27.

Gale, C. R., Westbury, L. and Cooper, C. (2018) 'Social isolation and loneliness as risk factors for the progression of frailty: the English Longitudinal Study of Ageing', *Age Ageing*, 47(3), pp. 392-397.

Garrett, H., Piddington, J. and Nicol, S. (2014) 'The housing conditions of minority ethnic households in England', Better Housing briefing paper, 24.

Gibb, K. (2015) 'The multiple policy failures of the UK bedroom tax', *International Journal of Housing Policy*, 15(2), pp. 148-166.

Gonzalez, M.C., Hidalgo, C.A. and Barabasi, A.L., 2008. Understanding individual human mobility patterns. *nature*, 453(7196), pp.779-782.

Gower, A. and Grodach, C., 2022. Planning Innovation or City Branding? Exploring How Cities Operationalise the 20-Minute Neighbourhood Concept. *Urban Policy and Research*, pp.1-17.

Grant, T.L., Edwards, N., Sveistrup, H., Andrew, C. and Egan, M. (2010) Neighborhood walkability: older people's perspectives from four neighborhoods in Ottawa, Canada. *Journal of aging and physical activity*, 18(3), pp.293-312.

- Gray, J., Buckner, L., & Comber, A. (2021). Extending Geodemographics Using Data Primitives: A Review and a Methodological Proposal. *ISPRS International Journal of Geo-Information*, 10(6), 386.
- Griffith, M. (2011) Hoarding of Housing: The intergenerational crisis in the housing market: Intergenerational Foundation.
- Gulliver, K. (2016) Forty years of Struggle: A window on Race and Housing, Disadvantage and Exclusion: Human City Institute.
- Guralnik, J.M., Ferrucci, L., Balfour, J.L., Volpato, S. and Di Iorio, A., 2001. Progressive versus catastrophic loss of the ability to walk: implications for the prevention of mobility loss. *Journal of the American Geriatrics Society*, 49(11), pp.1463-1470.
- Guzman, L.A., Arellana, J., Oviedo, D. and Aristizábal, C.A.M., 2021. COVID-19, activity and mobility patterns in Bogotá. Are we ready for a '15-minute city'? *Travel Behaviour and Society*, 24, pp.245-256.
- Hillnhütter, H., 2021. Stimulating urban walking environments—Can we measure the effect? *Environment and Planning B: Urban Analytics and City Science*, p.23998083211002839.
- Holt-Lunstad, J., Smith, T. B., Baker, M., Harris, T. and Stephenson, D. (2015) 'Loneliness and Social Isolation as Risk Factors for Mortality: A Meta-Analytic Review', *Perspectives on Psychological Science*, 10(2), pp. 227-237.
- House of Commons (2018) Housing for older people: Second report of session 2017–19.
- Hunter, N. (2016). Geodemographic and life course perspectives of population ageing in Australia: informing the policy response to population ageing.
- Ilmarinen, J. (2006) The ageing workforce—challenges for occupational health. *Occupational Medicine*: 363-363.
- Im, H.N. and Choi, C.G., 2020. Measuring pedestrian volume by land use mix: Presenting a new entropy-based index by weighting walking generation units. *Environment and Planning B: Urban Analytics and City Science*, 47(7), pp.1219-1236.
- Iparraguirre, J. (2016) 'Predicting the prevalence of loneliness at older ages', *Age UK*, 18.
- Jeste, D. V., Lee, E. E. and Cacioppo, S. (2020) 'Battling the Modern Behavioral Epidemic of Loneliness: Suggestions for Research and Interventions', *JAMA Psychiatry*, 77(6), pp. 553-554.
- Kissfazekas, K., 2022. Circle of paradigms? Or '15-minute' neighbourhoods from the 1950s. *Cities*, 123, p.103587.
- Koropecj-Cox, T. (1998) 'Loneliness and Depression in Middle and Old Age: Are the Childless More Vulnerable?', *The Journals of Gerontology: Series B*, 53B(6), pp. S303-S312.
- Leventhal, B. (2016). *Geodemographics for marketers: Using location analysis for research and marketing*. Kogan Page Publishers.
- Lewis, C. and Buffel, T. (2020) 'Aging in place and the places of aging: A longitudinal study', *J Aging Stud*, 54, pp. 100870.
- Liu, Y., Singleton, A., & Arribas-Bel, D. (2019). A principal component analysis (PCA)-based framework for automated variable selection in geodemographic classification. *Geo-spatial Information Science*, 22(4), 251-264.
- Lord, A., Batey, P., Buck, M., Darlington-Pollock, F., Dembski, S., Dunning, R., Moore, T., Singleton, A. and Sturzaker, J. (2019) 'An Evidence Base to support Cobalt Housing's Growth Strategy'.
- Luo, Y., Hawkey, L. C., Waite, L. J. and Cacioppo, J. T. (2012) 'Loneliness, health, and mortality in old age: a national longitudinal study', *Soc Sci Med*, 74(6), pp. 907-14.

Manifesty, O.R. and Park, J.Y., 2022. A Case Study of a 15-Minute City Concept in Singapore's 2040 Land Transport Master Plan: 20-Minute Towns and a 45-Minute City. *International Journal of Sustainable Transportation*, 5(1), pp.1-11.

Matthews, K. and Nazroo, J. (2015) 'Understanding digital engagement in later life', Developer Documentation: Government of UK.

McDaid, D., Bauer, A. and Park, A.-L. (2017) 'Making the economic case for investing in actions to prevent and/or tackle loneliness: a systematic review', London: London School of Economics and Political Science.

Moon, G., Twigg, L., Jones, K., Aitken, G. and Taylor, J. (2019) 'The utility of geodemographic indicators in small area estimates of limiting long-term illness', *Social Science & Medicine*, 227, pp. 47-55.

Moreno, C., Zaheer, A., Didier, C., Gall, C., Pratlong, F. et al. (2021) Introducing the "15-Minute City". Sustainability, resilience and place identity in future post-pandemic cities, *Smart Cities*, 4 (1) (2021), pp. 93-111

Morgan, M., Young, M., Lovelace, R., & Hama, L. (2019). OpenTripPlanner for R. *Journal of Open Source Software*, 4(44), 1926.

New Economics Foundation (2017) The Cost of Loneliness to UK Employers: The impact of loneliness upon business across the UK (Accessed: 15/08/2022).

Nurse, A. and Dunning, R. (2021) Is COVID-19 a turning point for active travel in cities?. *Cities & health*, 5(sup1), pp.S174-S176.

ONS (2017) Model-Based Estimates of households in poverty for Middle Layer Super Output Areas, 2013/14 Technical Report.

ONS (2018) Health state life expectancies, UK: 2015 to 2017. Available at: <https://www.ons.gov.uk/peoplepopulationandcommunity/healthandsocialcare/healthandlifeexpectancies/bulletins/healthstatelifeexpectanciesuk/2015to2017#:~:text=In%20the%20UK%20in%202015,months%20over%20the%20same%20period>. (Accessed: 17/08/22).

ONS (2018) *Overview of the UK Population: November 2018*. Office for National Statistics, Available at: <https://www.ons.gov.uk/peoplepopulationandcommunity/populationandmigration/populationestimates/articles/overviewoftheukpopulation/november2018>

ONS (2019) Milestones: journeying into adulthood. Available at: <https://www.ons.gov.uk/peoplepopulationandcommunity/populationandmigration/populationestimates/articles/milestonesjourneyingintoadulthood/2019-02-18#parents> (Accessed: 10/08/2022).

Pannell, J., Aldridge, H. and Kenway, P. (2012) 'Market assessment of housing options for older people', New Policy Institute: London, UK.

Pozoukidou, G. and Chatziyiannaki, Z., 2021. 15-Minute City: Decomposing the new urban planning eutopia. *Sustainability*, 13(2), p.928.

Rose, M., 2017. Women walking Manchester: desire lines through the original modern city (Doctoral dissertation, University of Sheffield).

Rowley, S. and Ong, R. (2012) Housing affordability, housing stress and household wellbeing in Australia [FR], Melbourne: Australian Housing and Urban Research Institute Limited. Available at: <https://www.ahuri.edu.au/research/final-reports/192>.

RTPi (2004) Planning for an ageing population. Available at: <https://tinyurl.com/yy6ecufb>

Satsangi, M., Theakstone, D., Matthews, P., Lawrence, J., Rummery, K., Mackintosh, S. and Boniface, G. (2018) 'The housing experiences of disabled people in Britain', Manchester: Equality and Human Rights Commission.

Scharf, T., Phillipson, C. and Smith, A. E. (2005) 'Social exclusion of older people in deprived urban communities of England', *Eur J Ageing*, 2(2), pp. 76-87.

Schimpl, M., Moore, C., Lederer, C., Neuhaus, A., Sambrook, J., Danesh, J., Ouwehand, W. and Daumer, M., 2011. Association between walking speed and age in healthy, free-living individuals using mobile accelerometry—a cross-sectional study. *PloS one*, 6(8), p.e23299.

Schonlau, M. (2002, 2002/12/01). The Clustergram: A Graph for Visualizing Hierarchical and Nonhierarchical Cluster Analyses. *The Stata Journal*, 2(4), 391-402.
<https://doi.org/10.1177/1536867X0200200405>

Schwanen, T. and Ziegler, F., 2011. Wellbeing, independence and mobility: an introduction. *Ageing & Society*, 31(5), pp.719-733.

Singleton, A. D., & Spielman, S. E. (2014). The past, present, and future of geodemographic research in the United States and United Kingdom. *The Professional Geographer*, 66(4), 558-567.

Singleton, A., Alexiou, A., & Savani, R. (2020, 2020/07/01/). Mapping the geodemographics of digital inequality in Great Britain: An integration of machine learning into small area estimation. *Computers, Environment and Urban Systems*, 82, 101486.
<https://doi.org/https://doi.org/10.1016/j.compenvurbsys.2020.101486>

Skinner, M.W., Cloutier, D. & Andrews, G.J. (2014) Geographies of Ageing. Progress and possibilities after two decades of change. *Progress in Human Geography*, 39(6):776-799.

Smith Institute (2009) 'Housing and Growth in Suburbia'.

Stephan, Y., Sutin, A.R. and Terracciano, A., 2015. "Feeling younger, walking faster": subjective age and walking speed in older adults. *Age*, 37(5), pp.1-12.

Strohmeier, F., 2016. Barriers and their influence on the mobility behavior of elder pedestrians in urban areas: challenges and best practice for walkability in the city of Vienna. *Transportation Research Procedia*, 14, pp.1134-1143.

Sustrans, 2020. *What is a 20-minute neighbourhood?*, Accessed at: <https://www.sustrans.org.uk/our-blog/get-active/2020/in-your-community/what-is-a-20-minute-neighbourhood>.

Thurston, R. C. and Kubzansky, L. D. (2009) 'Women, loneliness, and incident coronary heart disease', *Psychosom Med*, 71(8), pp. 836-42.

Van Hoof, J., Kazak, J.K., Perek-Białas, J.M. and Peek, S., 2018. The challenges of urban ageing: Making cities age-friendly in Europe. *International Journal of Environmental Research and Public Health*, 15(11), p.2473.

Vasara, P., 2015. Not ageing in place: Negotiating meanings of residency in age-related housing. *Journal of aging studies*, 35, pp.55-64.

Vedder, A., Boerner, K., Stokes, J. E., Schut, H. A. W., Boelen, P. A. and Stroebe, M. S. (2022) 'A systematic review of loneliness in bereavement: Current research and future directions', *Current Opinion in Psychology*, 43, pp. 48-64.

Victor, C. R. and Pikhartova, J. (2020) 'Lonely places or lonely people? Investigating the relationship between loneliness and place of residence', *BMC Public Health*, 20(1), pp. 778.

Weng, M., Ding, N., Li, J., Jin, X., Xiao, H., He, Z. and 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, pp.259-273.

World Health Organization. (2007). Global age-friendly cities: a guide. World Health Organization. <https://apps.who.int/iris/handle/10665/43755>

World Health, O. 2007. Global age-friendly cities: a guide. Geneva: World Health Organization.

- Wu, Y.T., Kingston, A., Houlden, V. and Franklin, R., 2022. The longitudinal associations between proximity to local grocery shops and functional ability in the very old living with and without multimorbidity: results from the Newcastle 85+ study. *Archives of Gerontology and Geriatrics*, p.104703.
- Xiang, L., Stillwell, J., Burns, L., Heppenstall, A., & Norman, P. (2018). A geodemographic classification of sub-districts to identify education inequality in Central Beijing. *Computers, Environment and Urban Systems*, 70, 59-70.
- Yang, Y., Dolega, L., Pollock-Darlington, F (2022). Aged in Place Classification. Creating a geodemographic classification for ageing population in England. *Applied Spatial Analysis and Policy*. Forthcoming
- Yang, Y., Dolega, L., Pollock-Darlington, F (2022). Aged in Place Classification. Creating a geodemographic classification for ageing population in England. *Applied Spatial Analysis and Policy*. Accepted for publication on 24/10/2022.
- Zhang, F., Zhang, C. and Hudson, J., 2018. Housing conditions and life satisfaction in urban China. *Cities*, 81, pp.35-44.
- Atkins, M.T., 2018. "On the move, or staying put?" An analysis of intrametropolitan residential mobility and ageing in place. *Population, Space and Place*, 24(3), p.e2096.
- Zhang, W., Zhao, Y., Cao, X. J., Lu, D., & Chai, Y. (2020). Nonlinear effect of accessibility on car ownership in Beijing: Pedestrian-scale neighborhood planning. *Transportation research part D: transport and environment*, 86, 102445.
- Ziegler, F., 2012. "You have to engage with life, or life will go away": An intersectional life course analysis of older women's social participation in a disadvantaged urban area. *Geoforum*, 43(6), pp.1296-1305.

Appendix 1

Supplementary Table 1.1 - Domains and variables for AiPC

N o	Domain	Name	Description	Denominator
1	People	Age: 50-64 (%)	% of persons: aged 50 to 64	older people (age over 50)
2		Age: 65-74 (%)	% of persons: aged 65 to 74	older people (age over 50)
3		Age: 75-84 (%)	% of persons: aged 75 to 84	older people (age over 50)
4		Age: 85 and over (%)	% of persons: aged 85 and over	older people (age over 50)
5		Older Person Ratio	Population aged 65 and over, relative to population 18-64	people age 18-64
6		Median age	Median age (of all people)	all people
7		Female (%)	% of persons: female	older people (age over 50)
8		Marital status (%)	% of persons: married or in a registered civil partnership	older people (age over 50)
9		Single person household (%)	% of persons: living in single person household	older people (age over 50)
10		Coupled household (%)	% of persons: living in a couple	older people (age over 50)
11		Living with dependent children (%)	% of persons: living with dependent children	older people (age over 50)
12		Living with non-dependent children (%)	% of persons: living with non-dependent children	older people (age over 50)
13		Household	% of persons: living in household (rather than communal establishment)	older people (age over 50)

		resident s (%)		
1 4		White British (%)	% of persons: White British	older people (age over 50)
1 5		Asian (%)	% of persons: Asian/Asian British: Indian, Pakistani, Bangladeshi,Chinese and other Asian	older people (age over 50)
1 6		Black, mix and others (%)	% of persons: Black/African/Caribbean/Black British, Mixed or Other (including other white) ethnic groups	older people (age over 50)
1 7		Low English proficie ncy (%)	% of persons : cannot speak English or cannot speak English well	older people (age over 50)
1 8		Born oversea s (%)	% of persons: non-UK born	older people (age over 50)
1 9		Religion (%)	% of persons: identified with a religion	older people (age over 50)
2 0		Owned outright (%)	% of persons: own the property outright	older people (age over 50)
2 1		with mortga ge or shared owners hip	% of persons: own the property with a mortgage, loan or shared ownership	older people (age over 50)
2 2		Socially rented (%)	% of persons: social renting	older people (age over 50)
2 3	Housing	Privatel y rented (%)	% of persons: private renting (includes living rent free)	older people (age over 50)
2 4		Detache d, semi or bungalo w housing (%)	% of persons (of all age): live in a detached or semi- detached house or bungalow	all households
2 5		Terrace d housing (%)	% of persons (of all age): live in a terrace or end- terrace house	all households
2 6		Flats (%)	% of persons (of all age): live in a flat	all households

27		Spare rooms (%)	% of persons: household with 1 or more spare rooms	older people (age over 50)
28		Crowded (%)	% of persons: household with not enough rooms	older people (age over 50)
29		No central heating (%)	% of persons: household without central heating	older people (age over 50)
30		Poor quality housing (%)	% of social and private homes that fail to meet the decent home standard (related to hazards in the home, state of disrepair, modernisation, and thermal comfort)	all households
31		Median house price	Median house price	all households
32		Education: low (%)	% of persons: Other or No qualifications	older people (age over 50)
33	Work and Education	Education: medium (%)	% of persons: Level 1, 2 or Apprenticeship	older people (age over 50)
34		Education: high (%)	% of persons: Level 3, 4, or higher	older people (age over 50)
35		FT employed (%)	% of persons: full-time employed	older people (age over 50)
36		PT employed (%)	% of persons: part-time employed	older people (age over 50)
37		Self-employed (%)	% of persons: self-employed	older people (age over 50)
38		Unemployed (%)	% of persons: unemployed or economically inactive to look after home or family	older people (age over 50)
39		Retired (%)	% of persons: retired	older people (age over 50)
40		Care: 0 hour (%)	% of persons: provide more than 20 hours unpaid care a week	older people (age over 50)
41		Care: 1-19 Hours(%)	% of persons: provide more than 20 hours unpaid care a week	older people (age over 50)
41				

4 2		Care: more than 20 hours (%)	% of persons: provide more than 20 hours unpaid care a week	older people (age over 50)
4 3		Travel to work: 10k+ (%)	% of persons: travel 10km or more for work	Economiclly active older (Age over 50) people
4 4	Mobility	Mobility (%)	% of households that have changed between the end of 2016 and the start of 2011, providing estimate of “churn” of the residential population	all households
4 5		Car access (%)	% of persons: car or van in household	older people (age over 50)
4 6	Financial Security	Income deprivat ion (%)	% of persons who living in a income deprived household (Income deprivation affecting older people index)	older people (age over 60)
4 7		Fuel poverty (%)	% of households in fuel poverty	all households
4 8	Health	LLTI: lot	Age Standardised Illness Ratio: Day-to-day activities limited a lot	older people (age over 50)
4 9		LLTI: little	Age Standardised Illness Ratio: Day-to-day activities limited a little	
5 0		General health: bad	Age Standardised Illness Ratio: Geaneral health of bad	older people (age over 50)
5 1		General health: fair	Age Standardised Illness Ratio: Geaneral health of fair	
5 2		Antide mentia (A)	Prescribing rate of Acetylcholinesterase inhibitors (Antidementia) to each LSOA per person (50+) per year	older people (age over 50)
5 3		Antide mentia (M)	Prescribing rate of Memantine (Antidementia) to each LSOA per person (50+) per year	older people (age over 50)
5 4		GP access	Average travel time to nearest GP by Public Transport and walking	all households
5 5		Hospital access	Average travel time to nearest Hospital by Public Transport and walking	all households
5 6		Pharma cy access	Average travel time to nearest Pharmacy by car	all households
5 7		Digital		
		Broadba nd access (%)	% of persons: broadband access at home	older people (age over 50)

58		ICT use: information (%)	% of persons (internet users aged 50+): use internet for information (hobbies, interests, services and products)	older people (age over 50) who use internet
59		ICT use: online shopping and banking (%)	% of persons (internet users aged 50+): use internet for online shopping and banking	older people (age over 50) who use internet
60		ICT use: social (%)	% of persons (internet users aged 50+): use internet for social networks and voice/video calls.	older people (age over 50) who use internet
61		Broadband speed	Average broadband download speed	older people (age over 50)
62	Outdoor space and living environment	Grocery	Average travel time to nearest Food Store by Public Transport and walking	all households
63		Town centre	Average travel time to nearest Town Centre by Public Transport and walking	all households
64		Leisure centre	Average road distance to nearest Leisure Centre	all households
65		Green space (active)	Average road distance to nearest green space	all households
66		Green space (passive)	Proportion of greenspace within a 900 m buffer (~15 minutes) from where people live	all households
67		Air Quality: NO2	Level of NO2	all households
68		Air Quality: PM10	Level of PM10	all households
69		Air Quality: SO2	Level of Sulphur Dioxide (SO2)	all households
70		Crime Index	composite index of crime rate (derived from IMD) in LSOA	all people
71	Civic Participation	Civic density	Number of civic assets within 1 km buffer of LSOA, divided by the number of people (of all age groups) in the LSOA	all people

Source: Yang, Dolega and Pollock-Darlington (2022)

Supplementary Table 1.2 - List of secondary datasets (except Census) and the corresponding variables

Dataset	Variable	Description
British Population Survey	Broadband access (%)	% of persons: broadband access at home
	ICT use: information (%)	% of persons (internet users aged 50+): use internet for information (hobbies, interests, services and products)
	ICT use: online shopping and banking (%)	% of persons (internet users aged 50+): use internet for online shopping and banking
	ICT use: social (%)	% of persons (internet users aged 50+): use internet for social networks and voice/video calls.
CDRC Broadband Speed Data	Broadband speed	Average broadband download speed
Journey time statistics	Grocery	Average travel time to nearest Food Store by Public Transport and walking
	Town centre	Average travel time to nearest Town Centre by Public Transport and walking
	GP access	Average travel time to nearest GP by Public Transport and walking
	Hospital access	Average travel time to nearest Hospital by Public Transport and walking
	Pharmacy access	Average travel time to nearest Pharmacy by car
Access to Healthy Assets & Hazards Data	Leisure centre	Average road distance to nearest Leisure Centre
	Green space (active)	Average road distance to nearest green space
	Green space (passive)	Proportion of greenspace within a 900 m buffer (~15 minutes) from where people live
	Air Quality: NO2	Level of NO2
	Air Quality: PM10	Level of PM10
	Air Quality: SO2	Level of Sulphur Dioxide (SO2)
English Indices of multiple deprivation (2019)	Crime Index	composite index of crime rate (derived from IMD) in LSOA
	Income deprivation (%)	% of persons who living in a income deprived household (Income deprivation affecting older people index)
	Poor quality housing (%)	% of social and private homes that fail to meet the decent home standard (related to hazards in the home, state of disrepair, modernisation, and thermal comfort)
Ordinance Survey Point of Interests data	Civic density	Number of civic assets within 1 km buffer of LSOA, divided by the number of people (of all age groups) in the LSOA
NHS English Prescribing data and registered patients data	Antidementia (A)	Prescribing rate of Acetylcholinesterase inhibitors (Antidementia) to each LSOA per person (50+) per year
	Antidementia (M)	Prescribing rate of Memantine (Antidementia) to each LSOA per person (50+) per year
Low Income Low Energy	Fuel poverty (%)	% of households in fuel poverty

Efficiency (LILEE) data in England		
CDRC Residential Mobility Index	Mobility (%)	% of households that have changed between the end of 2016 and the start of 2011, providing estimate of “churn” of the residential population
Median house prices by lower layer super output area: HPSSA dataset 46	Median house price	Median house price

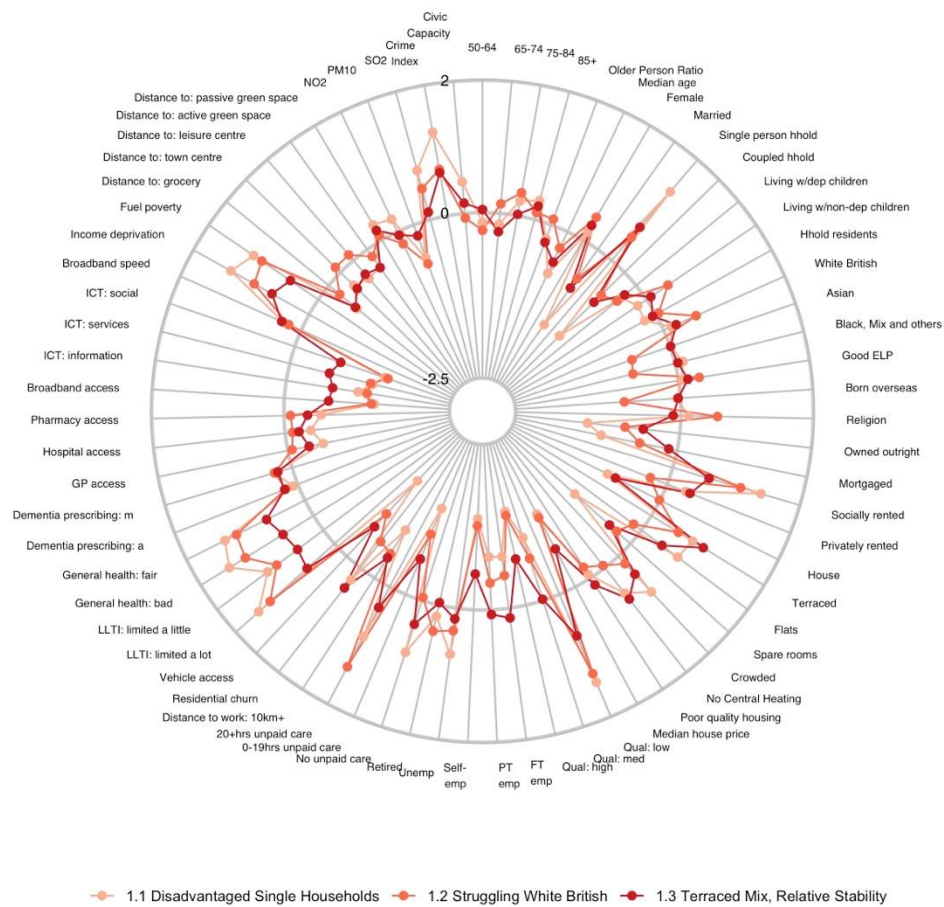
Source: Yang, Dolega and Pollock-Darlington (2022)

Appendix 2

Radar plots for AiPC groups

1. Supergroup 1 “Struggling, More Vulnerable Urbanites”
 - 1.1 Disadvantaged Single Households
 - 1.2 Struggling White British
 - 1.3 Terraced Mix, Relative Stability

Supplementary Figure 2.1. Radar plot of groups in supergroup “Struggling, More Vulnerable Urbanites”



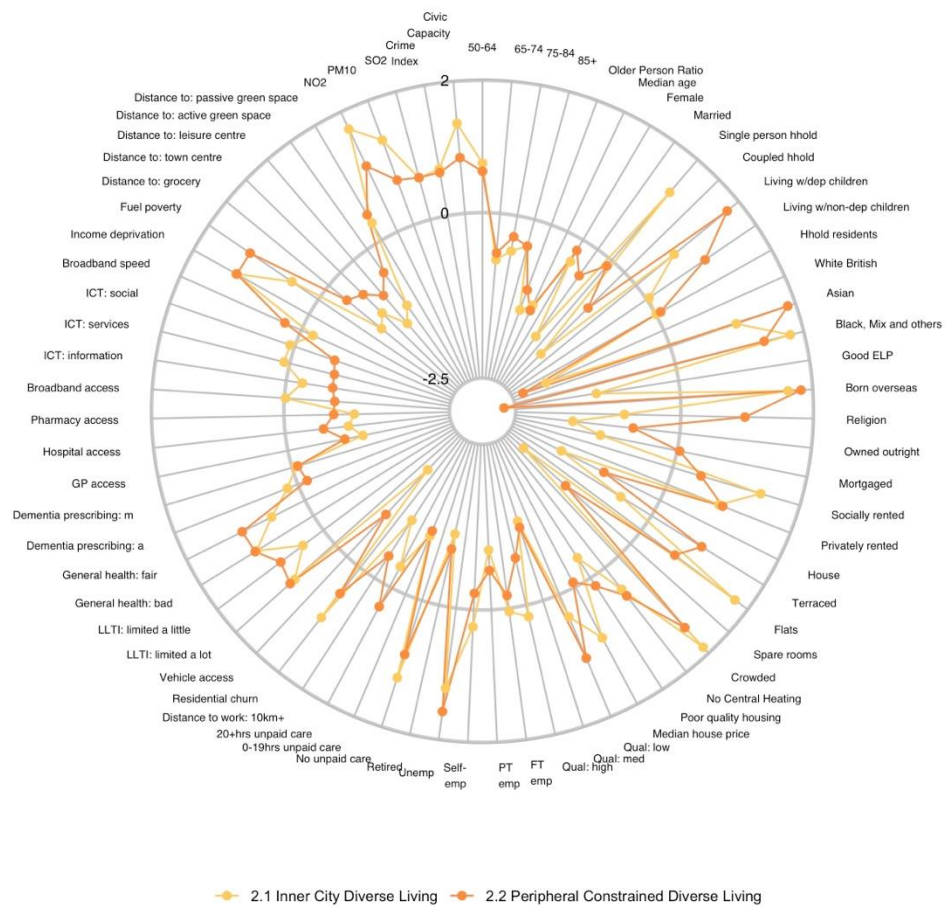
Source: Yang, Dolega and Pollock-Darlington (2022)

2. Groups in Supergroup “Multicultural Central Urban Living”

2.1 Inner City Diverse Living (Parent Supergroup: Multicultural Central Urban Living)

2.2 Peripheral Constrained Diverse Living (Parent Supergroup: Multicultural Central Urban Living)

Supplementary Figure 2.2. Radar plot of groups in supergroup “Multicultural Central Urban Living”



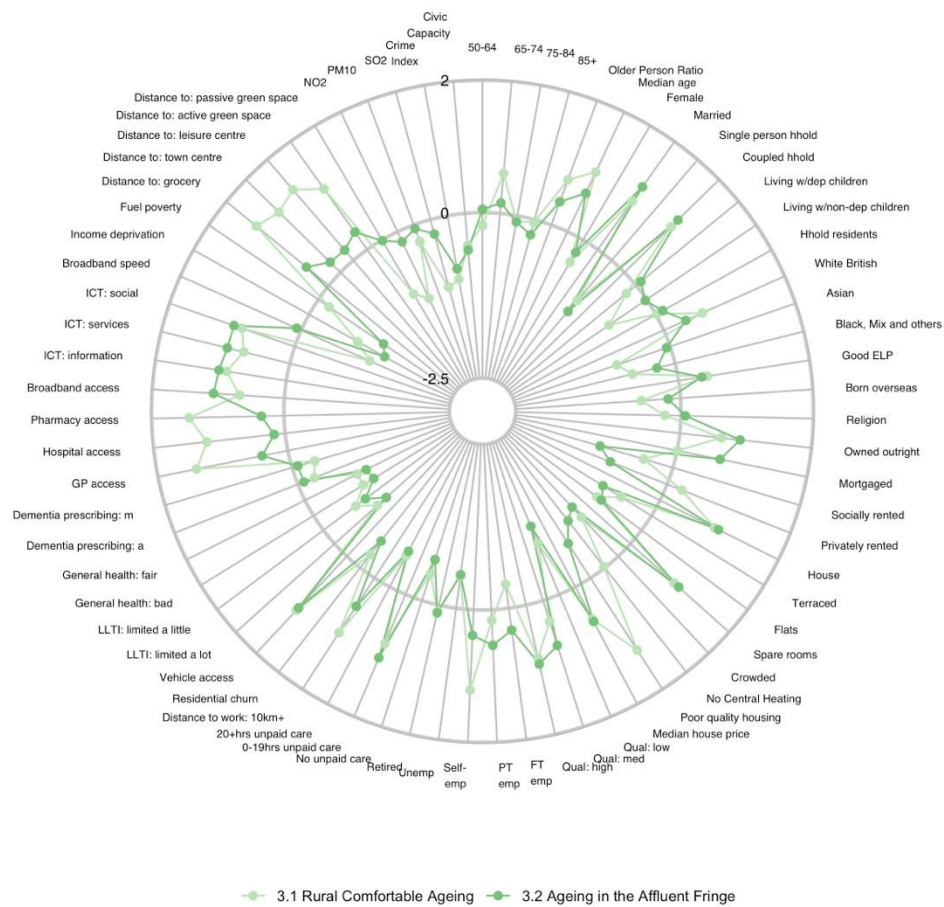
Source: Yang, Dolega and Pollock-Darlington (2022)

3. Groups in Supergroup “Rurban Comfortable Ageing”

3.1 Rural Comfortable Ageing

3.2 Ageing in the Affluent Fringe

Supplementary Figure 2.3. Radar plot of groups in supergroup “Rurban Comfortable Ageing”

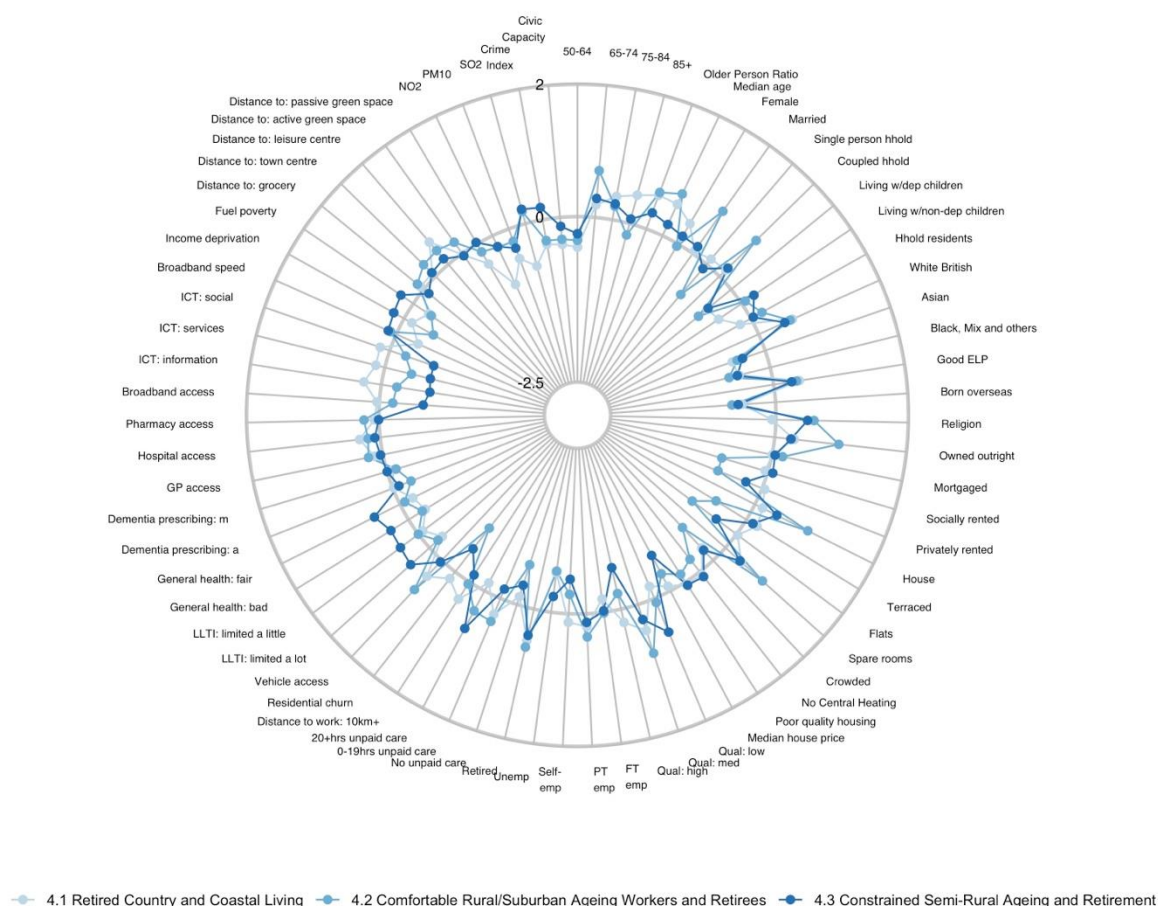


Source: Yang, Dolega and Pollock-Darlington (2022)

4. Groups in Supergroup “Retired Fringe and Residential Stability”

- 4.1 Retired Country and Coastal Living
- 4.2 Comfortable Rural/Suburban Ageing Workers and Retirees
- 4.3 Constrained Semi-Rural Ageing and Retirement

Supplementary Figure 2.4. Radar plot of groups in supergroup “Retired Fringe and Residential Stability”

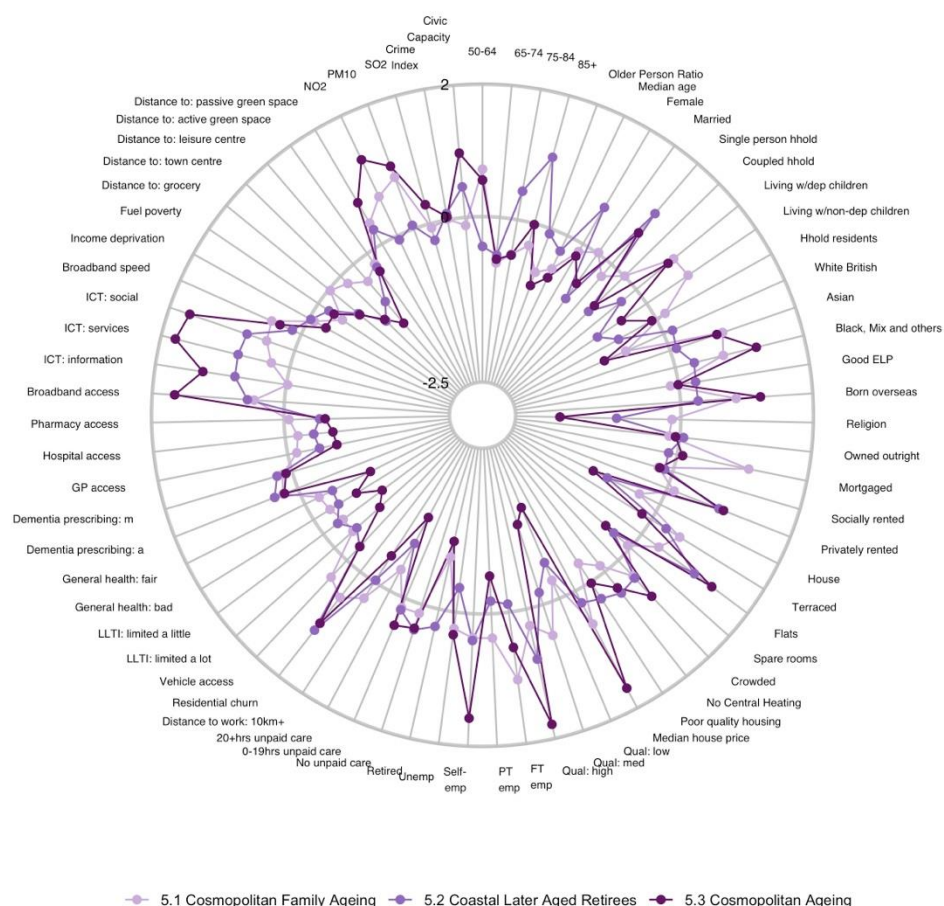


Source: Yang, Dolega and Pollock-Darlington (2022)

5. Groups in Supergroup “Cosmopolitan Comfort Ageing”

- 5.1 Cosmopolitan Family Ageing
- 5.2 Coastal Later Aged Retirees
- 5.3 Cosmopolitan Ageing

Supplementary Figure 2.5. Radar plot of groups in supergroup “Retired Fringe and Residential Stability”



Source: Yang, Dolega and Pollock-Darlington (2022)

Appendix 3

Table 3.1. 20 Minute City for the ageing population: Service Categories

Service Domain (Level 1)	Service Category (Level 2)	Service Type (Level 3)
Late parenting	Schools & Education	First, primary and infant schools Nursery schools and pre- and after-school care Parenting and childcare services
Stock up	Specialised Food	Organic, health, gourmet and kosher foods Herbs and spices Green and new age goods Grocers, farm shops and pick your own Markets Delicatessens Bakeries Butchers Fishmongers
	Essential food	Supermarket chains (Corporate convenience store i.e. Tesco, Sainsburys, Morrison, Coop) Food Banks

Enjoy the outdoors	Recreational space Outdoor Attractions	Commons Country and national parks Picnic areas Municipal Parks and Gardens Public Parks Ponds Lakes and waters Reservoirs Tams, pools and meres Bird reserves, collections and sanctuaries Farm-based attractions Horticultural attractions
Be engaged in your community	Community Facilities Community Organizations	Places of worship Halls and community centres Libraries Animal welfare organisations Charitable organisations Community networks and projects Conservation Organisations Political parties and related organisations Religious organisations Sports clubs and associations
Take good care of your health	Health - Primary Care Health – Secondary Care Health - Specialists and alternatives Personal Care Sport Facilities	Doctors surgeries Chemists and pharmacies Hospices Hospitals Accident and emergency hospitals Physical therapy Walk-in centres Clinics and health centres Day and Care Centres Mental health centres and practitioners Nursing and residential care homes Foot related services Dental surgeries Dieticians and nutritionists Optometrists and opticians Surgeons and cosmetic surgeries Spas Slimming clubs and services Hair and beauty services Athletics facilities Bowling facilities Golf ranges, courses, clubs and professionals Gymnasiums, sports halls and leisure centres Squash courts Swimming pools Tennis facilities
Get around	Transit	Railway Stations, Junctions and Halts Bus Stops

		Hail and ride zones
Stay mentally active	Culture	Historic buildings including castles, forts and abbeys Art galleries Museums
	Entertainment	U3A Cinemas Social clubs Theatres and concert halls Bingo halls Racecourses and greyhound tracks Snooker and pool halls
Retail and Leisure	Non-food shops	Department stores Discount stores Pets, supplies and services Books and maps General household goods Clothing Footwear Garden Centres and Nurseries Charity shops (included in Charitable Organisations)
	Financial services	Retail centres Banks and building societies Cash Machines
	Leisure Services	Post Offices Restaurants Pubs, Bars and Inns Cafes, Snack Bars and Tea Rooms Fish and Chip Shops

Source: Dunning et al. (2022)

Appendix 4

Supplementary Table 4.1. – Model to estimate accommodation satisfaction with and without AiPC Supergroups in England

<i>Predictors</i>	Model			With AiPC		
	<i>Odds Ratios</i>	<i>CI</i>	<i>p</i>	<i>Odds Ratios</i>	<i>CI</i>	<i>p</i>
(Intercept)	22.96	18.32 – 28.85	<0.001	21.16	16.65 – 26.96	<0.001
Age Group (50-64)	0.43	0.36 – 0.52	<0.001	0.44	0.37 – 0.52	<0.001
Tenure Ownership	2.54	2.14 – 3.03	<0.001	2.32	1.92 – 2.80	<0.001
Long-term Illness	0.54	0.45 – 0.64	<0.001	0.53	0.44 – 0.63	<0.001
IMD ‘Crime’ Score	0.75	0.69 – 0.81	<0.001	0.84	0.76 – 0.93	0.001
IMD ‘Barriers to Housing’ Score	0.99	0.98 – 0.99	<0.001	0.99	0.99 – 1.00	0.011
AiPC SG [2 Multicultural Central Urban Living]				0.63	0.52 – 0.77	<0.001
AiPC SG [3 Rural/Rural-Urban Fringe, Comfortable Ageing]				1.22	0.97 – 1.54	0.094
AiPC SG [4 Retired Rural and Coastal Stability]				1.18	0.98 – 1.42	0.077
AiPC SG [5 Ageing Suburban Comfort]				0.81	0.65 – 1.01	0.053
Observations	17105			17105		
AIC	8734.3			8706.8		
R	26.89%			28.30%		

Source: Department for Communities and Local Government. (2017). *English Housing Survey, 2008-2014: Secure Access*. [data collection]. 6th Edition. UK Data Service. SN: 6923,

<http://doi.org/10.5255/UKDA-SN-6923-6>

Department for Communities and Local Government. (2018). *English Housing Survey, 2014-2016: Secure Access*. [data collection]. 3rd Edition. UK Data Service. SN: 8121,

<http://doi.org/10.5255/UKDA-SN-8121-3>

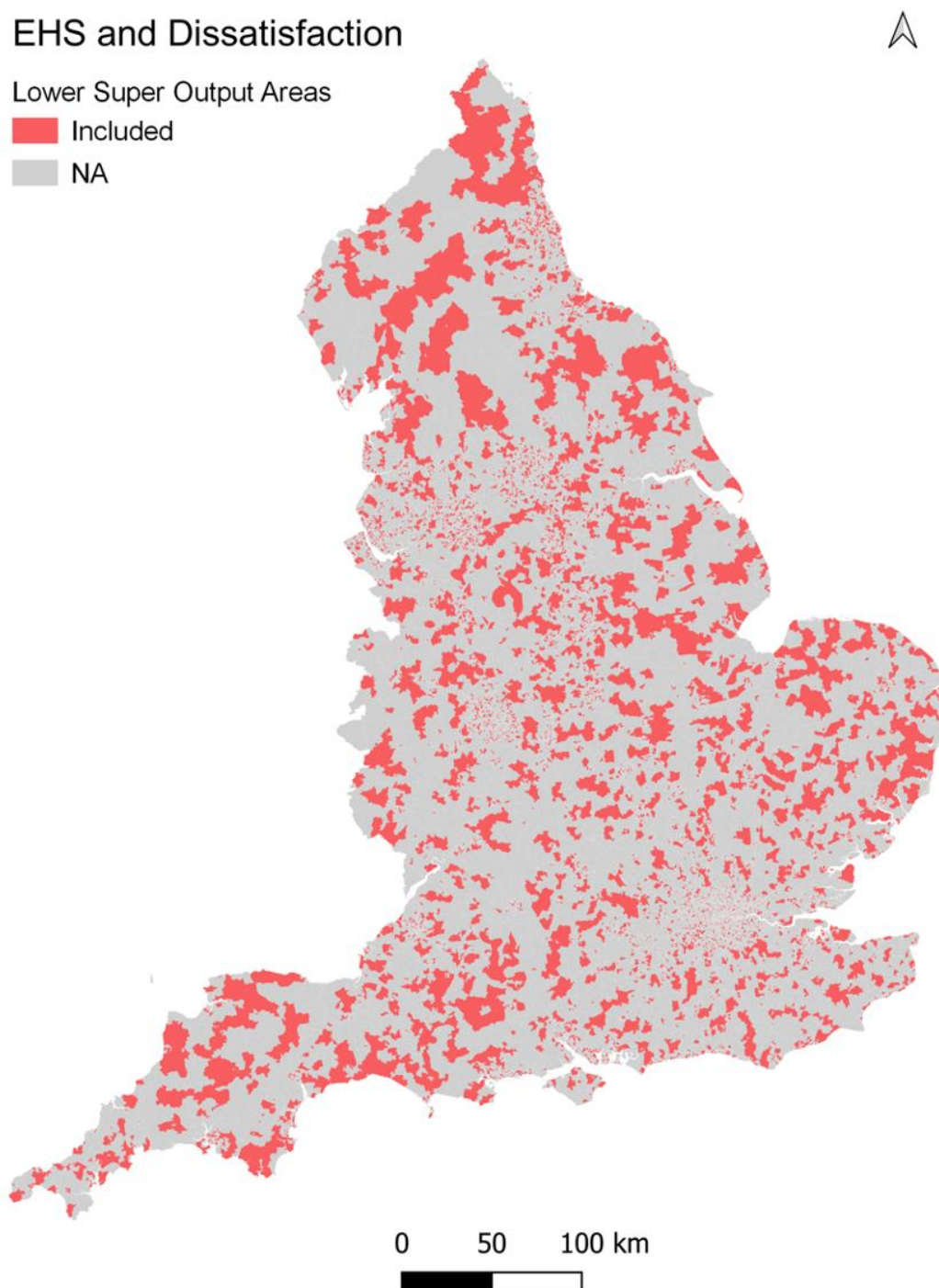
Supplementary Table 4.2. – Extended model to estimate accommodation satisfaction with and without the AiPC Supergroups in England

<i>Predictors</i>	Model			With AiPC Supergroup		
	<i>Odds Ratios</i>	<i>CI</i>	<i>p</i>	<i>Odds Ratios</i>	<i>CI</i>	<i>p</i>
(Intercept)	11.11	5.50 – 23.18	<0.001	11.04	5.31 – 23.66	<0.001
Overcrowding	0.36	0.20 – 0.65	0.001	0.41	0.23 – 0.75	0.003
Age Group (50 – 64)	0.43	0.36 – 0.52	<0.001	0.44	0.37 – 0.53	<0.001
Ownership	2.63	2.15 – 3.22	<0.001	2.50	2.04 – 3.08	<0.001
Long-term illness	0.58	0.48 – 0.70	<0.001	0.57	0.47 – 0.68	<0.001
EPC: AB	1.57	0.48 – 5.52	0.469	1.72	0.52 – 6.05	0.385
EPC: C	2.19	1.12 – 4.10	0.018	2.33	1.20 – 4.37	0.010
EPC: D	1.86	0.96 – 3.46	0.055	1.91	0.99 – 3.54	0.046
EPC: E	1.87	0.95 – 3.52	0.060	1.95	1.00 – 3.66	0.045
EPC: F	1.48	0.70 – 3.02	0.292	1.56	0.74 – 3.17	0.232
IMD Income	0.45	0.24 – 0.83	0.011	0.36	0.16 – 0.80	0.013
IMD Environment	0.99	0.98 – 1.00	0.269	1.00	0.99 – 1.01	0.696
IMD Geographical Barriers	1.05	0.95 – 1.15	0.378	1.00	0.90 – 1.12	0.933
IMD Indoors Spaces	1.02	0.85 – 1.23	0.822	0.98	0.81 – 1.18	0.841
IMD Outdoors Spaces	0.86	0.76 – 0.96	0.006	0.93	0.83 – 1.04	0.220
AiPC Supergroup [2 Multicultural Central Urban Living]				0.63	0.51 – 0.78	<0.001
AiPC Supergroup [3 Rural/Rural-Urban Fringe, Comfortable Ageing]				1.06	0.79 – 1.43	0.688
AiPC Supergroup [4 Retired Rural and Coastal Stability]				1.08	0.87 – 1.34	0.512
AiPC Supergroup [5 Ageing Suburban Comfort]				0.73	0.56 – 0.95	0.017
Observations	15983			15983		
AIC	8321.5			8305.4		
R	27.93%			28.92%		

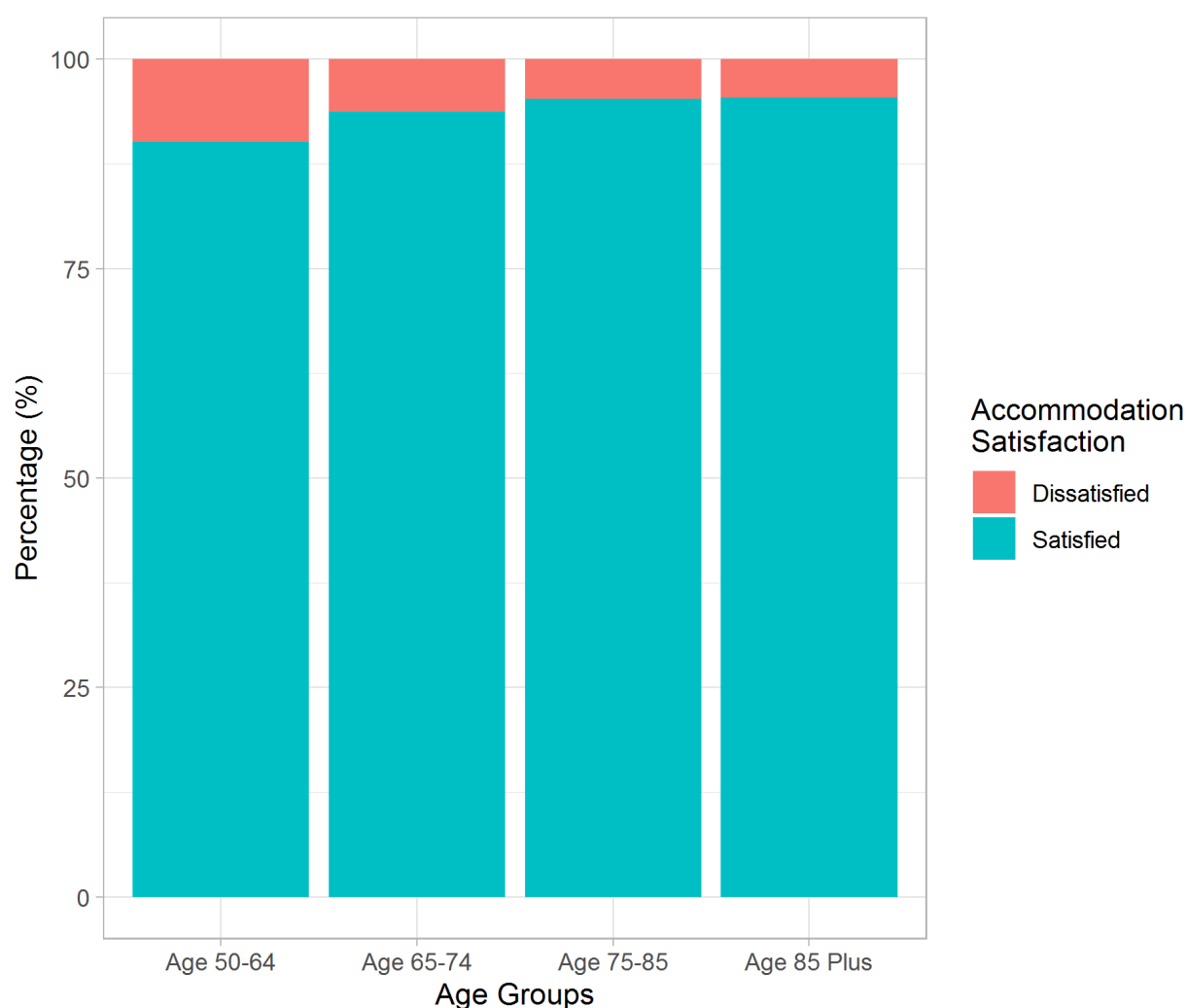
Source: Department for Communities and Local Government. (2017). English Housing Survey, 2008-2014: Secure Access. [data collection]. 6th Edition. UK Data Service. SN: 6923, <http://doi.org/10.5255/UKDA-SN-6923-6>

Department for Communities and Local Government. (2018). English Housing Survey, 2014-2016: Secure Access. [data collection]. 3rd Edition. UK Data Service. SN: 8121, <http://doi.org/10.5255/UKDA-SN-8121-3>

Supplementary Figure 4.1. – Map of the LSOAs in England with at least 2 valid responses for accommodation satisfaction status in the EHS survey (2009 – 2015)



Supplementary Figure 4.2. – Accommodation satisfaction across age groups in the EHS survey



Number of observations = 27300

Source: Department for Communities and Local Government. (2017). English Housing Survey, 2008-2014: Secure Access. [data collection]. 6th Edition. UK Data Service. SN: 6923, <http://doi.org/10.5255/UKDA-SN-6923-6>
 Department for Communities and Local Government. (2018). English Housing Survey, 2014-2016: Secure Access. [data collection]. 3rd Edition. UK Data Service. SN: 8121, <http://doi.org/10.5255/UKDA-SN-8121-3>

Appendix 5

Supplementary Table 5.1 – Model to estimate probability of not feeling lonely with and without the AiPC in England

<i>Predictors</i>	Model			With AiPC		
	<i>Odds Ratios</i>	<i>CI</i>	<i>p</i>	<i>Odds Ratios</i>	<i>CI</i>	<i>p</i>
(Intercept)	51.03	39.36 – 67.08	<0.001	48.75	33.22 – 72.85	<0.001
Divorced/Separated	0.31	0.20 – 0.49	<0.001	0.33	0.21 – 0.52	<0.001
Poor Health	0.15	0.09 – 0.24	<0.001	0.17	0.10 – 0.28	<0.001
Fair Health	0.34	0.23 – 0.52	<0.001	0.36	0.24 – 0.55	<0.001
Long-term Illness	0.58	0.39 – 0.86	0.007	0.58	0.39 – 0.86	0.007
Age Group (75-85)	1.64	1.07 – 2.56	0.026	1.59	1.04 – 2.49	0.036
Widowed	0.15	0.10 – 0.23	<0.001	0.15	0.10 – 0.23	<0.001
AiPC SG [2 Multicultural Central Urban Living]				0.58	0.34 – 1.02	0.052
AiPC SG [3 Rural/Rural-Urban Fringe, Comfortable Ageing]				1.19	0.84 – 1.68	0.326
AiPC SG [4 Retired Rural and Coastal Stability]				0.92	0.66 – 1.29	0.646
AiPC SG [5 Ageing Suburban Comfort]				1.06	0.66 – 1.75	0.802
Observations	6507			6507		
AIC	2372.7			2372.7		
R	27.77%			28.44%		

Source: NatCen Social Research. (2019). English Longitudinal Study of Ageing: Waves 6-8, 2012-2017: Census 2011 Lower Layer Super Output Areas: Secure Access. [data collection]. UK Data Service. SN: 8434, <http://doi.org/10.5255/UKDA-SN-8434-1>

Supplementary Figure 5.1. – Map of the LSOAs in England with at least 2 valid responses for loneliness status in the ELSA survey Wave 6

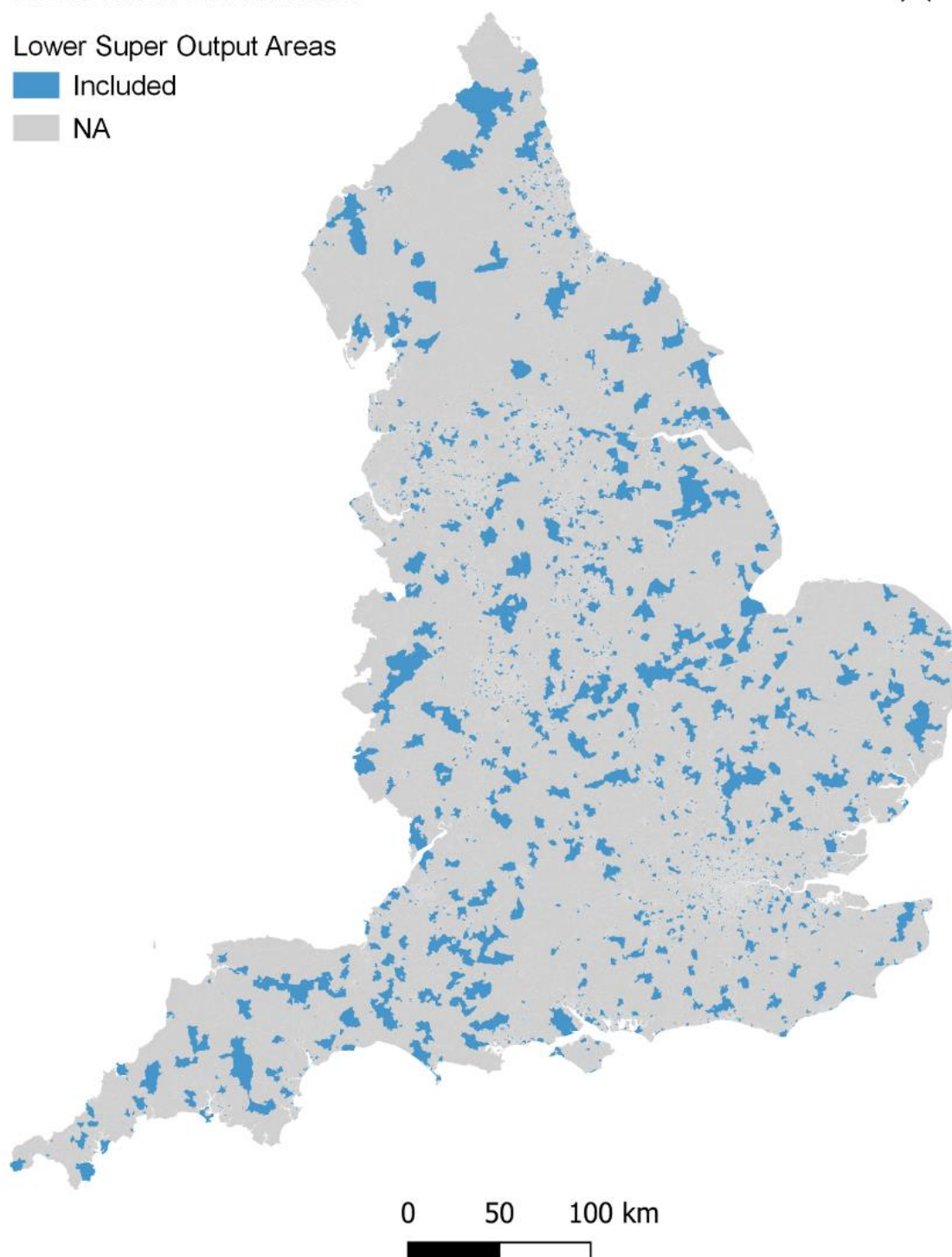
ELSA and Loneliness



Lower Super Output Areas

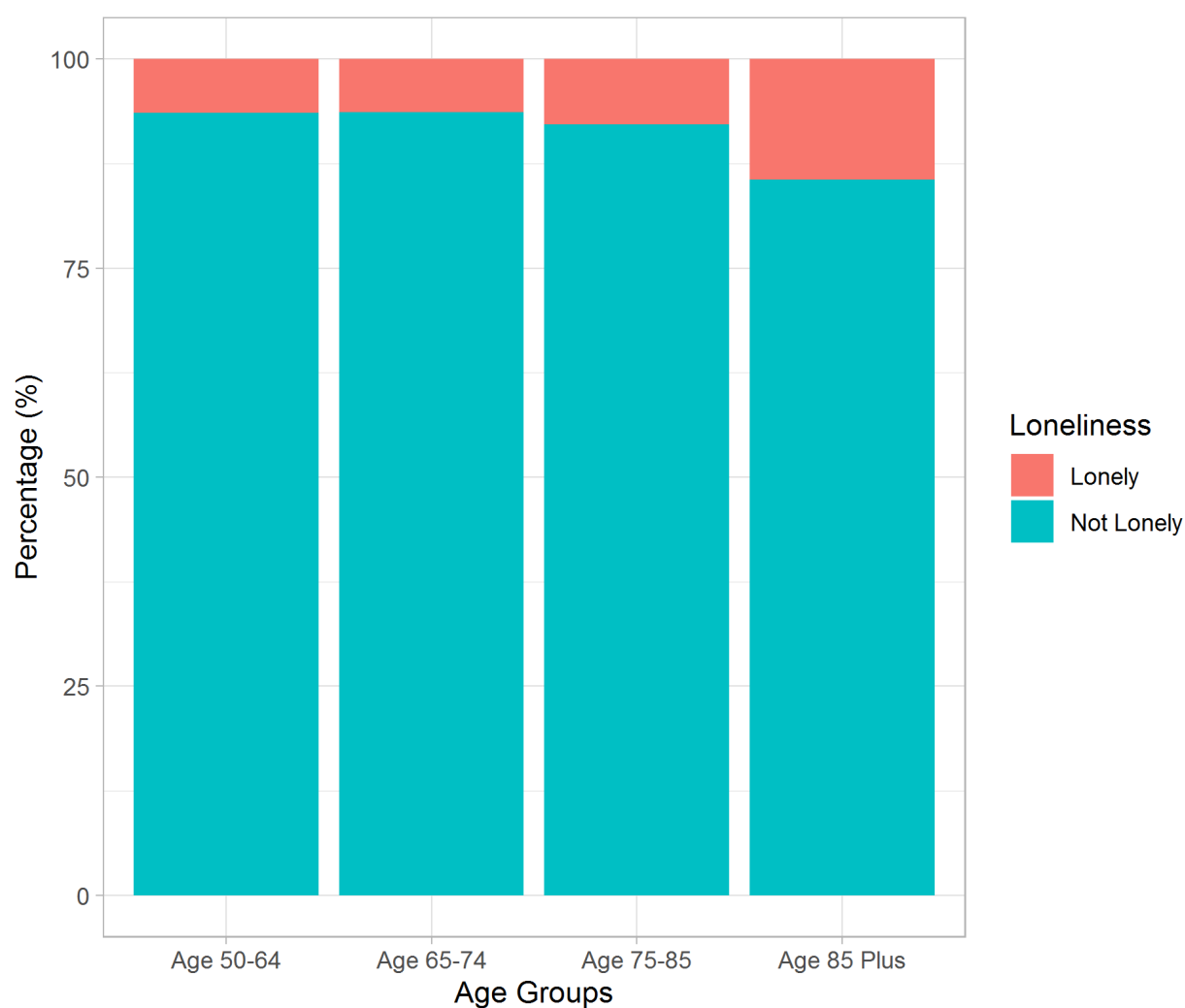
■ Included

■ NA



Source: NatCen Social Research. (2019). *English Longitudinal Study of Ageing: Waves 6-8, 2012-2017: Census 2011 Lower Layer Super Output Areas: Secure Access*. [data collection]. UK Data Service. SN: 8434, <http://doi.org/10.5255/UKDA-SN-8434-1>

Supplementary Figure 5.2. – Loneliness across age groups in the ELSA Wave 6 survey



Number of observations = 8510

Source: NatCen Social Research. (2019). *English Longitudinal Study of Ageing: Waves 6-8, 2012-2017: Census 2011 Lower Layer Super Output Areas: Secure Access*. [data collection]. UK Data Service. SN: 8434, <http://doi.org/10.5255/UKDA-SN-8434-1>

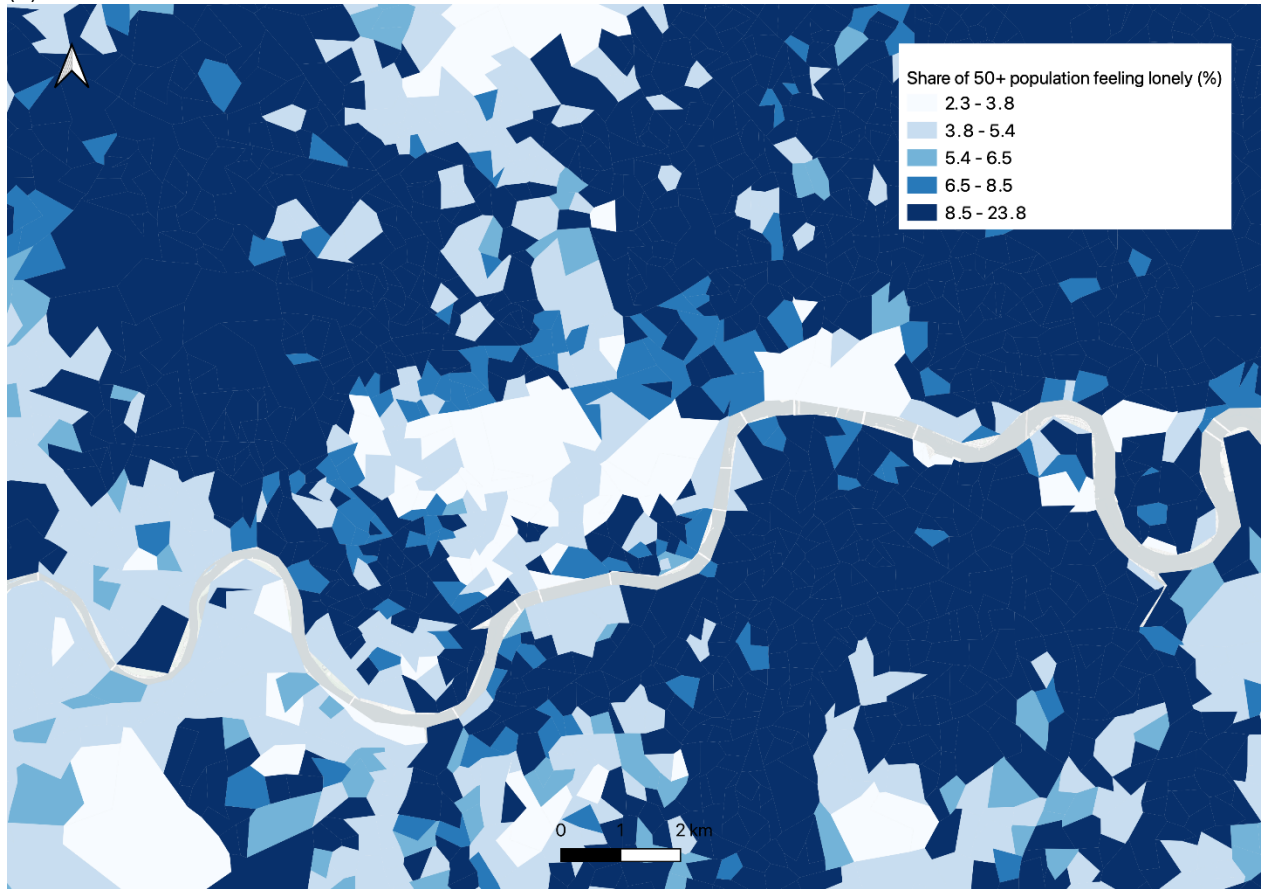
Supplementary Table 5.2 – Extended model to estimate probability of not feeling lonely with and without the AiPC Supergroups in England

<i>Predictors</i>	Model			With AiPC Supergroup		
	<i>Odds Ratios</i>	<i>CI</i>	<i>p</i>	<i>Odds Ratios</i>	<i>CI</i>	<i>p</i>
(Intercept)	60.15	40.26 – 91.00	<0.001	59.74	30.37 – 119.91	<0.001
Divorced/Separated	0.38	0.23 – 0.64	<0.001	0.39	0.24 – 0.66	<0.001
Poor Health	0.15	0.09 – 0.26	<0.001	0.15	0.09 – 0.27	<0.001
Fair Health	0.37	0.24 – 0.58	<0.001	0.37	0.24 – 0.58	<0.001
Long-term Illness	0.59	0.39 – 0.89	0.012	0.58	0.38 – 0.88	0.010
Age Group (75 – 84)	1.63	1.05 – 2.60	0.033	1.60	1.03 – 2.54	0.042
Age Group (85+)	0.91	0.36 – 2.60	0.857	0.88	0.34 – 2.52	0.796
IMD Income	0.26	0.06 – 1.31	0.098	0.32	0.03 – 3.06	0.314
IMD Crime	1.00	0.82 – 1.21	0.989	1.02	0.84 – 1.25	0.834
IMD Barriers to Housing	1.00	0.98 – 1.02	0.808	1.01	0.99 – 1.03	0.372
IMD Geographical Barriers	1.00	0.99 – 1.01	0.967	0.99	0.98 – 1.00	0.190
Widowed	0.13	0.08 – 0.21	<0.001	0.13	0.08 – 0.21	<0.001
AiPC Supergroup [2 Multicultural Central Urban Living]				0.49	0.26 – 0.95	0.031
AiPC Supergroup [3 Rural/Rural-Urban Fringe, Comfortable Ageing]				1.21	0.65 – 2.22	0.546
AiPC Supergroup [4 Retired Rural and Coastal Stability]				0.88	0.55 – 1.41	0.607
AiPC Supergroup [5 Ageing Suburban Comfort]				0.79	0.44 – 1.45	0.449
Observations	6097			6097		
AIC	2210.6			2211.4		
R	29.74%			30.52%		

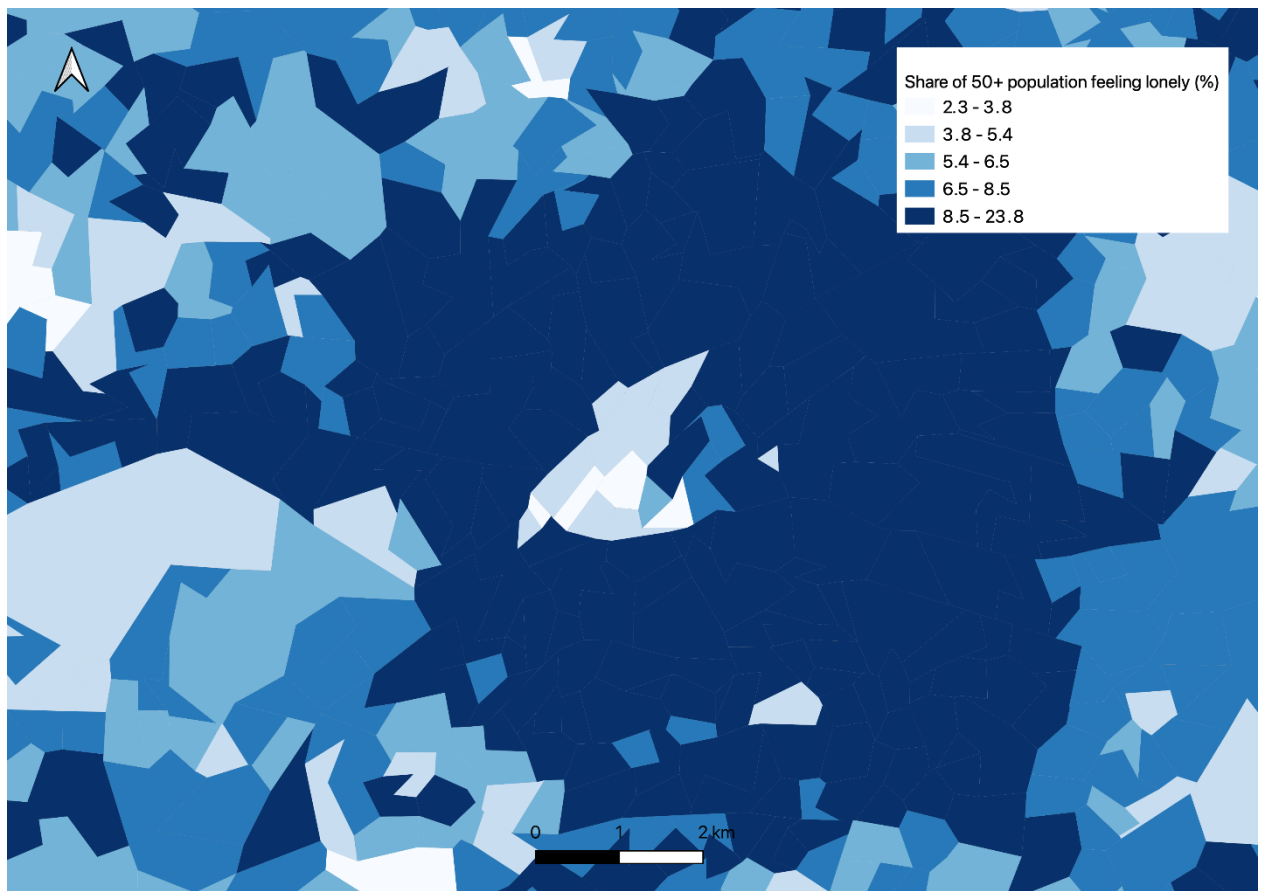
Source: NatCen Social Research. (2019). *English Longitudinal Study of Ageing: Waves 6-8, 2012-2017: Census 2011 Lower Layer Super Output Areas: Secure Access*. [data collection]. UK Data Service. SN: 8434, <http://doi.org/10.5255/UKDA-SN-8434-1>

Supplementary Figure 5.3 – Maps of share of 50+ people feeling lonely in London (a), Manchester (b), Leeds (c), Liverpool (d)

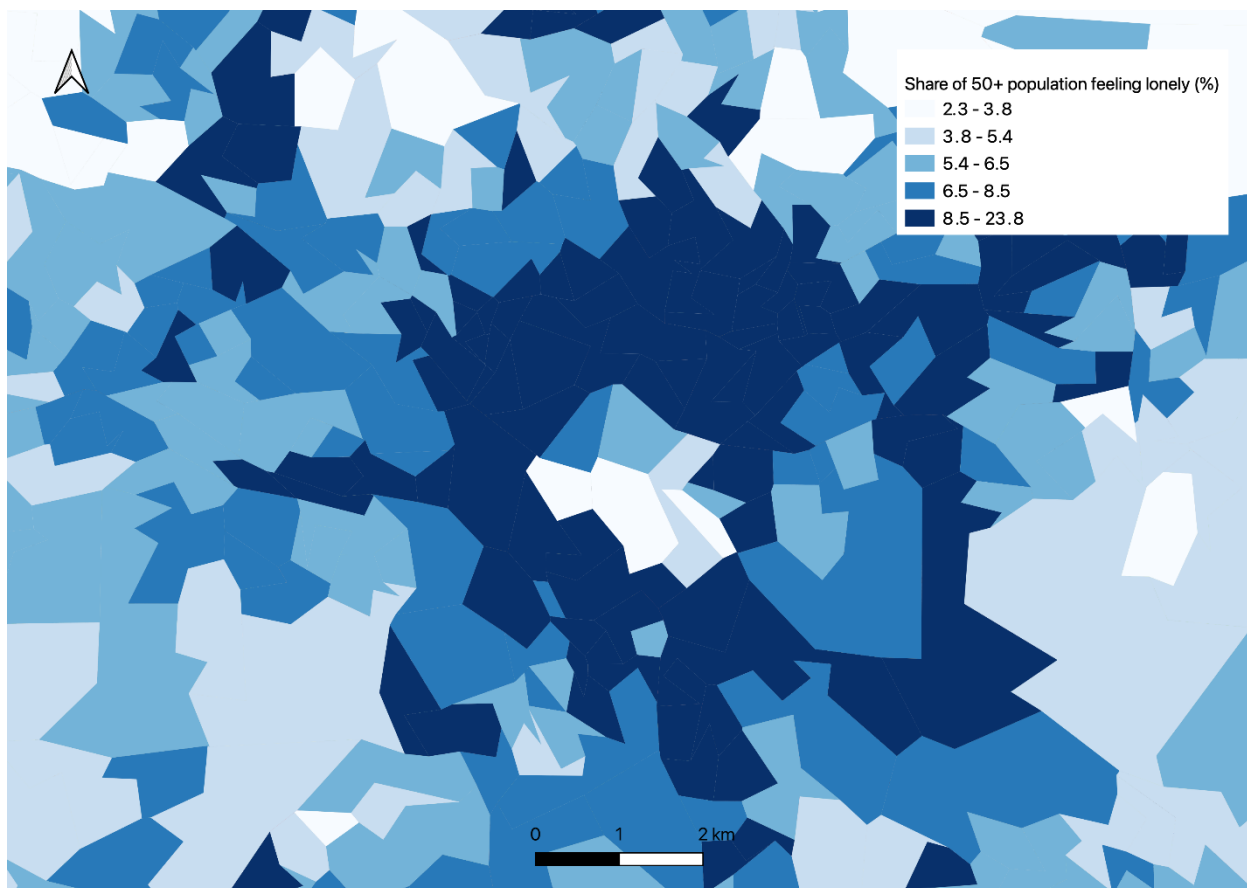
(a) London



b) Manchester



c) Leeds



d) Liverpool

