Constructing a composite index to measure loneliness amongst older populations

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The candidate confirms that the work submitted is his own and that appropriate credit has been given where reference has been made to the work of others.

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Abstract

Loneliness is a social phenomenon that is gaining increased recognition in the UK. Studies have found it to be as damaging to an individual's health as obesity and smoking. The British Government, and several charities, including The Campaign to End Loneliness, Age UK and the British Red Cross have highlighted a lack of tools for appropriately measuring and analysing loneliness in older populations. Thus, authorities do not know who is affected by loneliness most severely, or where they reside. Presently, measures of loneliness depend on surveys asking individuals whether they are lonely. These measures have many conceptual and practical drawbacks, importantly, small sample sizes mean they are not directly applicable at the neighbourhood level. A new composite index that measures loneliness in older populations at the area level is presented here. Its construction takes two primary methodological steps clearly described in this thesis. Firstly, it analyses the primary characteristics that are associated with loneliness in old age through national survey data, the wider literature, and consultation with stakeholders. Secondly, relevant indicators are selected, normalised, weighted and aggregated into a reproducible composite index that identifies neighbourhoods at highest risk of loneliness in older populations. The key characteristics associated with loneliness in older populations are widowhood, living alone, poor health and low income. Four other peripheral characteristics are also identified, these include national language ability, rates of hate crime in the local area, smoking status and provision of informal care. The index reveals that the spatial distribution of loneliness in older populations in England is clustered in coastal areas and former industrial Northern cities. The neighbourhood at highest risk of loneliness in England is in Christchurch, Dorset. Loneliness amongst older populations is found to be more common in rural areas and is not found to have a strong relationship with multiple deprivation.

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Glossary

Abbreviation	Description
ADL	Activities of Daily Living
AUC	Area Under Curve
AUKI	Age UK Index
BBC	British Broadcasting Company
CI	Confidence Intervals
dJG	de Jong Gierveld
ECCI	Essex County Council Index
ELSA	English Longitudinal Study of Ageing
GP	General Practice
HDI	Human Development Index
IMD	Index of Multiple Deprivation
LBI	Lucy and Burns Index
LSOA	Lower layer Super Output Area
MAUP	Modifiable Area Unit Problem
MSOA	Middle layer Super Output Area
NHS	National Health Service
OECD	Organisation for Economic Cooperation and Development
ONS	Office for National Statistics
OR	Odds Ratio
ROC	Receiver Operating Characteristic
UCLA	University of California, Los Angeles
UK	United Kingdom
UN	United Nations
WHO	World Health Organisation

Chapter 1. Introduction

Recognition that loneliness is a key social issue in the United Kingdom (UK) has increased in recent years. Media coverage of the issue has proliferated, especially within the context of the COVID-19 pandemic (Campbell, 2020). Even before the pandemic, however, news outlets highlighted a loneliness "epidemic" (Easton, 2018). Acknowledgement of the phenomena has impacted policy, with the 2018 UK Government releasing a report entitled "A Strategy for Tackling Loneliness", and subsequently becoming the first government in the world to appoint a Minister for Loneliness (Department for Digital, Culture, Media and Sport, 2018). This chapter will introduce the topic of loneliness and provide the context and rationale for the creation of a new tool to measure loneliness in older populations, next, it will outline the primary aims of this thesis. The final section in this chapter will outline the structure of this thesis.

1.1. Providing the context

Most academic research regarding loneliness has focussed on older populations (Flood, 2005). This is largely because it is older populations who are most likely to live alone and suffer from issues such as reduced mobility and ailing health that can impact their ability to achieve desired social outcomes (Courtin and Knapp, 2017). The issue of loneliness amongst older populations is becoming more severe as the UK deals with an ageing population (Gentleman, 2016). By 2039, around one in four people in the UK will be aged 65 or over (ONS, 2021), whist 24% of older adults suffer from loneliness at least some of the time, with 7% suffering from chronic loneliness (Age UK, 2018). Technological advances are further compounding the issue, with apparently innocuous technologies such as self-checkouts at supermarkets further removing human interaction from day-to-day life (Hosie, 2017).

This thesis will focus exclusively on loneliness amongst older populations; however, it is important to note that loneliness is not a condition uniquely suffered by this age group, with some studies suggesting that younger people are commonly affected by loneliness too (Barreto et al, 2021). Loneliness is defined in this research as a perceived discrepancy between achieved and desired social outcomes, with a more specific and detailed definition of the term loneliness, including the theoretical basis for the chosen definition, described in Chapter 2. It is important to note here that there is a theoretical distinction between social isolation and loneliness in the literature (Victor et al, 2000). Individuals who have few family or friends and have limited contact with people are socially isolated (Shankar et al, 2011). Loneliness, however, is the cognitive and emotional counterpart to social isolation, where one evaluates the quantity and quality of social contact as lacking (de Jong Gierveld and Havens, 2004). To re-phrase, this means that an individual can be socially isolated (have very few friends or family), but be perfectly content with their social activity, and thus not be lonely. Others may have many social contacts, but not be satisfied with their social activity, and thus feel lonely.

Loneliness can affect individuals in numerous ways. It can negatively impact an individual's wellbeing and is a key risk factor for depression and suicide (Hawkley and Cacciopo, 2010; O'Luanaigh and Lawlor, 2008). It is known to increase the risk of heart disease and high blood pressure (O'Luanaigh and Lawlor, 2008), dementia and cognitive decline (Wilson et al, 2007), and considerably increase the chances of early mortality (Patterson and Veenstra, 2010). Loneliness has been found to be as great a risk factor to health as obesity, smoking, poverty and poor housing (Holt-Lunstad et al, 2010; Green 2015). Some individual's circumstances are particularly emotive, with reports in the media of older people visiting Accident and Emergency or booking appointments at their General Practice (GP) just to have someone to talk to. One particular case involved a Scottish man who sat on the bus all day and rode around the city, simply because he had nothing else to do and it was free with his bus pass (Green, 2015). In addition to the health risks of loneliness for the individual, these risks subsequently have negative economic impacts through increased strain on social and health care services (Christiansen et al, 2020). It is estimated that the effects of loneliness are costing the taxpayer £6,000 for each decade of an older individual's life (Coughlan, 2017). The National Health Service's (NHS) director of acute care says the increasing costs of caring for isolated elderly patients, if not urgently addressed, could "ultimately cripple" the NHS (Gentleman, 2016).

Whilst increased recognition and appreciation of the scale and severity of the loneliness epidemic has acted as a catalyst for policy change, there is still considerable progress to be achieved. Reports have highlighted that in 2018, 74 of the 152 Local Authorities in England spent nothing on services to directly combat loneliness, with average spending falling compared to the previous year (Buchan, 2017). Furthermore, the British Government tasked the Office for National Statistics (ONS) to devise a loneliness measure to aid analysis of the phenomena (BBC, 2018), and nothing has yet materialised.

Considering the substantial risks of loneliness to both the individual and society, it is important that we understand exactly who is at risk of loneliness so that intervention strategies can be implemented. Current methods of measurement involve the use of social surveys that ask respondents if they suffer from loneliness or derivatives of loneliness. These methods have multiple conceptual and practical flaws which are highlighted in Chapter 2, but importantly, they are not well suited to identifying lonely neighbourhoods as they are not applied widely enough for the collection of data at the small area level. Consequently, the British charity, The Campaign to End Loneliness, has emphasised the difficulty in identifying where loneliness exists, and has characterised current intervention strategies coordinated by local authorities as "hit and miss" (Goodman et al, 2015, p. 26). The same charity has called for the creation of loneliness maps that allow local authorities to ascertain which neighbourhoods are at greatest risk of loneliness (Goodman et al, 2015). Similarly, the British Red Cross has also recognised a need for a loneliness measure that can gauge the impact of preventative strategies implemented by authorities at the local level (Red Cross, 2019). This thesis, therefore, outlines the creation of a loneliness index that is applicable at the neighbourhood level and easily accessible for local authorities and charities. The primary aims of this thesis are:

- To identify the primary characteristics associated with loneliness amongst older populations.

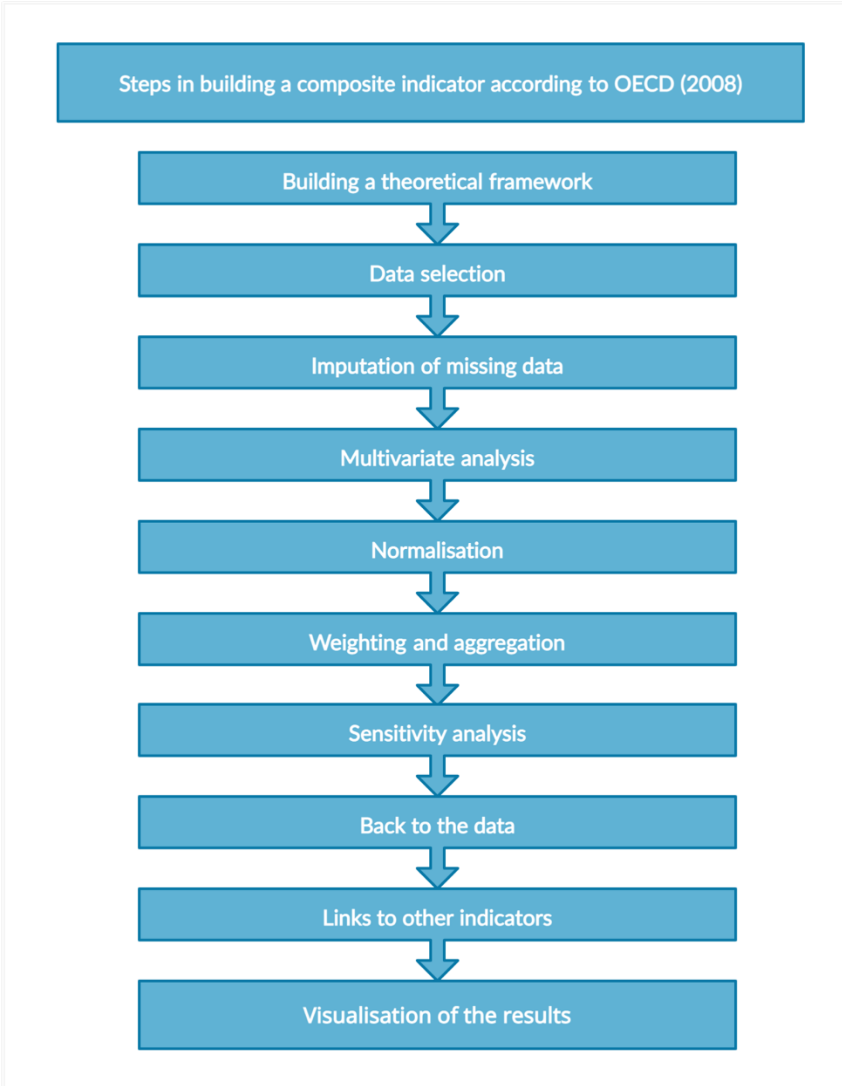
- To develop an index that allows for the analysis of the spatial variations in loneliness amongst older populations and the identification of neighbourhoods at highest risk.

By completing these two aims this thesis contributes to the ability of charities and local authorities to alleviate loneliness in the community. Stakeholders will have an increased understanding of the characteristics which are associated with loneliness in older populations, and they will have a new tool that can be used to measure the risk of loneliness by neighbourhood for the whole of England. Therefore, the index can help to inform policy and intervention strategies by identification of areas at highest risk, and the ability to benchmark across different locations and different time frames.

1.2. Thesis Structure

As outlined in the previous section, the primary output of this thesis is the development of a framework to measure and analyse loneliness in older populations at the small area level. The structure of this thesis is informed by the Organisation for Economic Co-operation and Development (OECD, 2008) *Handbook on Constructing Composite Indicators* and the ten key steps that comprise best practice for building a composite indicator. These steps ensure indicators are valid, robust and transparent, and therefore meaningful for real world application. The ten steps are summarised in the flowchart shown in Figure 1 and are used to structure this thesis. Structuring the index in such a way will ensure that it is transparent and accessible to third parties, such as local government or charitable bodies, who may wish to reproduce the index to inform policy or coordinate intervention strategies aimed at reducing loneliness within the community. To aid the reader, a version of the flowchart presented in Figure 1 will be repeated at the beginning of each chapter, with the relevant steps addressed in the chapter clearly highlighted.

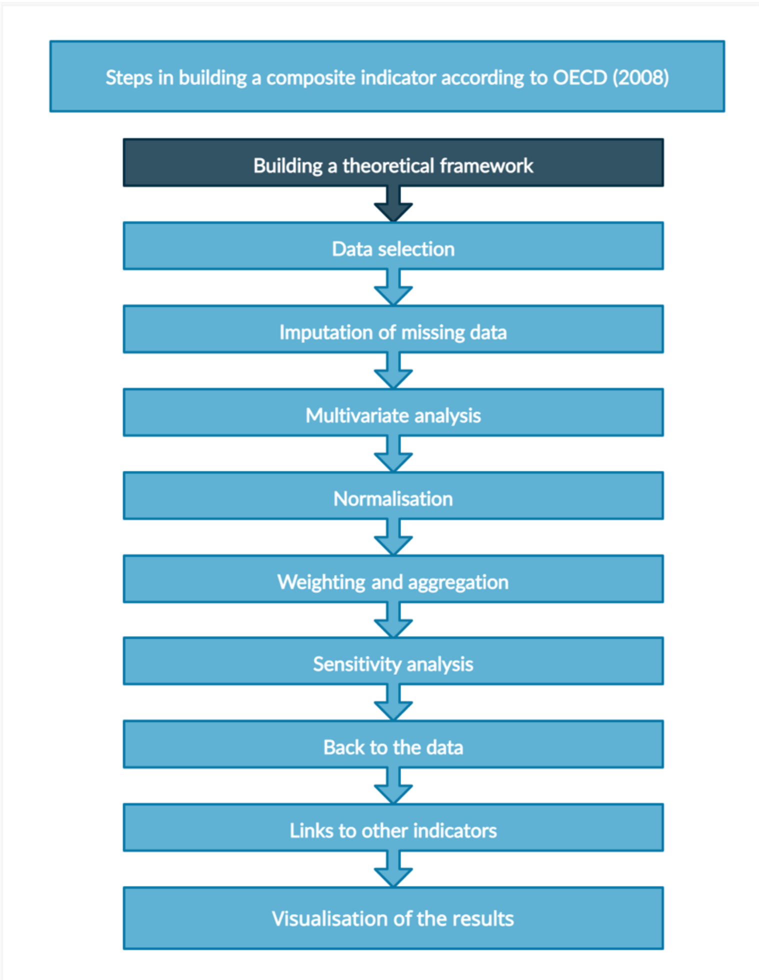
Figure 1: Flowchart outlining the steps in the construction of a composite indicator (OECD, 2008, p. 20-21)



Chapter 2. Theoretical Perspectives and Measurement of Loneliness

The purpose of this chapter is to construct a sound theoretical framework that will aid the construction of the composite index. This chapter focuses on the theoretical foundations of existing loneliness research, exploring what it means to be lonely, and the causes of loneliness (Section 2.1). Next, building on the identified theoretical approaches, it offers a working definition of loneliness (Section 2.2). Finally, this chapter will evaluate the current tools that are used to measure loneliness, analysing their benefits and drawbacks (Sections 2.3 and 2.4). The outcome of this chapter is a clear definition of the concept being measured and an understanding of the criteria that a new loneliness measure needs to fulfil in order to improve the current tools being used to measure loneliness (Section 2.5). This will satisfy the first step in the construction of a composite indicator "building a theoretical framework" (OECD, 2008), as highlighted in Figure 2.

Figure 2: Flowchart outlining the steps that will be addressed in Chapter 2.



2.1. Theoretical Foundations

This section explores the four main theoretical foundations of loneliness research and uses these to select a working definition of loneliness. Eight theoretical conceptualisations of loneliness have been identified in the literature, with most of the work pertaining to the fields of psychology and sociology (Peplau and Perlman, 1982). Of these, only four are commonly used and therefore only these will be addressed in this chapter. The four commonly employed conceptualisations are known as the psychodynamic approach; the existentialist approach; the cognitive approach; and the interactionalist approach (Donaldson and Watson, 1996). The other four approaches include the phenomenological approach, sociological explanations, the privacy approach and the general systems theory, for a summary of these approaches see Peplau and Perlman (1982). Victor et al (2000) point out that none of the theoretical approaches pertain to loneliness in older populations specifically, with theoretical foundations in gerontological research often completely absent or merely implicit. This chapter will now summarise the four main theoretical foundations of loneliness.

2.1.1. The Psychodynamic Approach

The psychodynamic approach is built on the Freudian tradition of psychology (Donaldson and Watson, 1996). The first theorisation of loneliness traced the origins of the concept back to childhood, where a child learns the joys of being loved and cared for, which then translates into a narcissistic orientation in adulthood as similar desires persist (Zilboorg, 1938). Subsequent scholars, including Sullivan (1953) and Fromm-Riechmann (1959), also trace the origins of loneliness to childhood. The former cites the need for human intimacy that begins with an infant's desire for human contact, and the latter suggests that loneliness can begin with premature weaning from the mother. Both suggest that dysfunctional parent-child relationships can create a personality base that is latterly conducive to loneliness.

The psychodynamic conceptualisation is formed with a clinical perspective and is solely concerned with a pathological understanding of loneliness (Peplau and Perlman, 1982). This is a considerable drawback of the approach as it fails to take into account any aspects of the social world, such as bereavement, that may contribute to one's feelings of loneliness (Donaldson and Watson, 1996).

2.1.2. The Existentialist Approach

Existentialists argue that loneliness is intrinsic to human experience as we are all ultimately individuals (Peplau and Perlman, 1982). The leading theorist in the existentialist paradigm is Moustakas (1972), who distinguishes between "loneliness anxiety" and "true loneliness".

Loneliness anxiety is a series of response mechanisms that prevent people from dealing with their reality and encourages them to seek companionship. True loneliness is the loss of such anxieties that comes with the acceptance that humans are ultimately alone (Tzouvara et al, 2015). According to Moustakas (1972), true loneliness can be a positive and creative force where one has an honest encounter with themselves. Existentialists thus encourage people to overcome their loneliness anxiety (Peplau and Perlman, 1982).

Moustakas' (1972) theories also come from working in a clinical setting. Due to their understanding of loneliness as an unavoidable human experience, existentialists do not seek the causal roots of loneliness (Peplau and Perlman, 1982). A key limitation of this conceptualisation is the lack of distinction between social isolation and loneliness, this is especially limiting for research into loneliness in older populations (Donaldson and Watson, 1996).

2.1.3. The Cognitive Approach

The cognitive approach is a more contemporary conceptualisation, it is developed from observations of the general population, rather than clinical settings (Peplau and Perlman, 1982). The cognitive framework argues that loneliness occurs when people perceive their social relations to be lacking relative to a societal standard (Weeks, 1992). In other words, the cognitive approach finds the cause of loneliness to be the deficit between desired and achieved social outcomes. Therefore, unlike the psychodynamic and existentialist approaches, it focuses on individual circumstances as the cause of loneliness (Peplau and Perlman, 1982).

Donaldson and Watson (1996) claim that understanding loneliness as a cognitive evaluation allows society to work towards a reduction of loneliness. They cite empirical examples where this has been achieved through increasing an individual's self-esteem (See: Andersson, 1986; Moore and Schultz, 1989), thus offering credence to the cognitive approach. Criticisms of this framework argue that the theory ignores the value of social networks in ameliorating loneliness (Wenger et al, 1993).

2.1.4. The Interactionalist Approach

Similar to the cognitive approach, the interactionalist approach focuses on loneliness in general populations. First theorised by Weiss (1973), the approach conceptualises loneliness as having two primary dimensions, emotional loneliness and social loneliness. Weiss (1973) believes that these two dimensions of loneliness have different causes and effects. Emotional loneliness relates to the absence of an attachment figure, such as a spouse, and an emotionally lonely person tends to feel emptiness and restlessness. A socially lonely person lacks meaningful friendship and a sense of community and thus has a propensity to feel both bored and socially marginalised. When an individual's social and emotional requirements are unfilled, they experience loneliness.

The interactionalist approach relates to the cognitive approach through defining loneliness as a deficit in social relations (Donaldson and Watson, 1996), albeit focussing on absolute deficits rather than perceived deficits. Rook (1984) argues that understanding loneliness as having both social and emotional components is important. This view is supported by de Jong Gierveld (1987) who believes that loneliness is multidimensional, and the quality and quantity of social relations must be considered. Criticisms of this theory include the argument that the proposed social dimension of loneliness is an objective state and does not take into account one's feelings towards the lack of social interaction, i.e. an individual may enjoy their solitude (Larsen et al, 1985; Wenger et al 1993).

2.2. Using Theory to Define Loneliness

To measure loneliness, it is important to define exactly what is meant by the term. This section identifies a working definition for loneliness after considering the theoretical approaches outlined in Section 2.1. The four key paradigms in loneliness research are not mutually exclusive (Peplau and Perlman, 1982), nor is proceeding with a single theoretical perspective necessarily desirable (Donaldson and Watson, 1996). As Victor et al (2000) highlighted, most research into gerontological loneliness has been atheoretical. However, contemporary studies that have investigated the causal factors of loneliness (e.g. those reviewed in the data selection phase in Chapter 3) have typically used an understanding that loneliness is subjective. Moreover, they have measured a range of variables that pertain to the social and emotional dimensions of loneliness such as frequency of social contact as well as marital status. Consequently, they have implicitly worked within either a cognitive or interactionalist framework, or a combination of the two (See: Cohen-Mansfield et al, 2009; Cornwell and Waite, 2009; Dahlberg and Mckee, 2014; Luhmann and Hawkley, 2016).

Donaldson and Watson (1996) explicitly advocate for this approach. They propose that combining the interactionalist and cognitive approaches allows a researcher to consider both the feelings of older individuals and their social and emotional circumstances. The existentialist and psychodynamic approaches may have a robust theoretical basis but they offer little in the gerontological field because they do not consider current conditions as having an influence on feelings of loneliness.

For this study, it is important to provide a clear definition of loneliness. This should consider the various theoretical foundations outlined in Section 2.1, as well as recommendations from scholars in the gerontological field. This thesis uses the definition of loneliness provided by de Jong Gierveld (1998). It incorporates both the cognitive and interactionalist perspectives, thus understanding loneliness to be both multidimensional and the result of a cognitive evaluation:

> *"Loneliness is a situation experienced by the individual as one where there is an unpleasant or inadmissible lack of (quality of) certain relationships. This includes situations in which the number of existing relationships is smaller than is considered desirable or admissible, as well as situations where the intimacy one wishes for has not been realised. Thus, loneliness is seen to involve the manner in which the person perceives, experiences, and evaluates his or her isolation and lack of communication with other people."* (de Jong Gierveld, 1998, pp. 73-74).

2.3. Measuring Loneliness

The challenges in defining and theorising loneliness compound the problems in trying to measure it. Two main approaches have been used to measure loneliness in academia: the use of self-reported measures; and the development of multi-item scales. Both are individual-level measurements (Wenger, 1983). It is these two methods that are used in the studies that investigate variables associated with loneliness amongst older populations (Chapter 3). Descriptions of these specific tools and their benefits and drawbacks are now considered.

2.3.1. The Self-Reported Measure

A self-reported measure is a simple direct question where a respondent evaluates how often they experience loneliness on an ordinal scale usually ranging from "never" to "always" (Victor et al, 2001). The method is known as direct because the question will explicitly use the words "lonely" or "loneliness" (Shiovitz-Ezra & Ayalon, 2012). This measure only considers the frequency with which one experiences loneliness and does not produce information on the nature, causes or consequences of loneliness (Fees et al, 1999). Thus, researchers who use the self-reported measure tend to work within the cognitive approach (Victor et al, 2005). Furthermore, it assumes a common understanding of loneliness by study participants, when in reality it often varies across different cultures (Jylha, 2004). Whilst the stigma associated with the concept of loneliness may lead to respondents giving answers they perceive to be publicly acceptable, rather than a true representation of their feelings (Victor et al, 2005). This is specifically understood to be a problem amongst men (Borys and Perlman, 1985). As such, the use of multi-item scales that assess loneliness indirectly is often advocated rather than a single question.

2.3.2. Multi-Item Scales

Multi-item scales measure derivatives of loneliness to infer perceived or actual relationship deficits rather than measuring feelings of loneliness per se (Maragoni and Ickes, 1989). The two most used multi-item scales of loneliness are the University of California, Los Angeles (UCLA) scale and the de Jong Gierveld (dJG) scale. Both are reliable and valid measures (Penning et al, 2014). They deliberately avoid the use of the words “lonely” or “loneliness” and as such are indirect measures (Shiovitz-Ezra and Ayalon, 2012). Figures 3 and 4 show the individual items included in the dJG and UCLA scales respectively, with shortened versions of the scales for use in larger surveys also identified. The two separate multi-item scales are reviewed in Sections 2.3.3 and 2.3.4.

Figure 3: Survey items used in the different variations of the de Jong Gierveld scale. Taken from de Jong Gierveld and Van Tillburg (2006).

Items of the 11-Item (original) and 6-Item (short) De Jong Gierveld Loneliness Scales

Statement	Original Emotional Subscale	Original Social Subscale	Short Emotional Subscale	Short Social Subscale
1. There is always someone I can talk to about my day-to-day problems[a]		X		
2. I miss having a really close friend	X			
3. I experience a general sense of emptiness	X		X	
4. There are plenty of people I can rely on when I have problems[a]		X		X
5. I miss the pleasure of the company of others	X			
6. I find my circle of friends and acquaintances too limited	X			
7. There are many people I can trust completely[a]		X		X
8. There are enough people I feel close to[a]		X		X
9. I miss having people around	X		X	
10. I often feel rejected	X		X	
11. I can call on my friends whenever I need them[a]		X		

Figure 4: Survey items in the UCLA scale and the three-item shortened version. Taken from Hughes et al (2004).

Items in Revised UCLA Loneliness Scale (R-UCLA)[a] and Three-Item Loneliness Scale

R-UCLA Loneliness Scale

Directions: Indicate how often you feel the way described in each of the following statements. Circle one number for each.

Statement	*Never*	*Rarely*	*Sometimes*	*Often*
1. I feel in tune with the people around me.[b]	1	2	3	4
2. I lack companionship.	1	2	3	4
3. There is no one I can turn to.	1	2	3	4
4. I do not feel alone.[b]	1	2	3	4
5. I feel part of a group of friends.[b]	1	2	3	4
6. I have a lot in common with the people around me.[b]	1	2	3	4
7. I am no longer close to anyone.	1	2	3	4
8. My interests and ideas are not shared by those around me.	1	2	3	4
9. I am an outgoing person.[b]	1	2	3	4
10. There are people I feel close to.[b]	1	2	3	4
11. I feel left out.	1	2	3	4
12. My social relationships are superficial.	1	2	3	4
13. No one really knows me well.	1	2	3	4
14. I feel isolated from others.	1	2	3	4
15. I can find companionship when I want it.[b]	1	2	3	4
16. There are people who really understand me.[b]	1	2	3	4
17. I am unhappy being so withdrawn.	1	2	3	4
18. People are around me but not with me.	1	2	3	4
19. There are people I can talk to.[b]	1	2	3	4
20. There are people I can turn to.[b]	1	2	3	4

Three-Item Loneliness Scale

Lead-in and questions are read to respondent.

The next questions are about how you feel about different aspects of your life. For each one, tell me how often you feel that way.

Question	*Hardly Ever*	*Some of the Time*	*Often*
First, how often do you feel that you lack companionship: Hardly ever, some of the time, or often?	1	2	3
How often do you feel left out: Hardly ever, some of the time, or often?	1	2	3
How often do you feel isolated from others? (Is it hardly ever, some of the time, or often?)	1	2	3

NOTE: For both scales, the score is the sum of all items.
a. Russell, Peplau, and Cutrona (1980).
b. Item should be reversed before scoring.

2.3.3. UCLA Loneliness Scale

First developed by Russell et al (1978), the 20-item UCLA scale has since been revised (Russell et al, 1980; Russell, 1996), and a shortened 3-item version was also developed for use in large surveys by Hughes et al (2004) (Figure 4). According to Allen and Oshagan (1995), it is the most psychometrically sound measure of loneliness. The Department for Digital, Culture, Media and Sport (2018) recommends the 3-item version for use in their surveys and general research into loneliness by other parties.

The UCLA scale was created within a theoretical perspective of loneliness that understands it as a unidimensional construct that is an emotional response to the discrepancy between desired and achieved levels of social contact (Robinson et al, 1991). As such, it understands loneliness as an affective state, rather than a cognitive one (Penning et al, 2014). Its theorisation of loneliness as unidimensional considers all incidents of loneliness to be experienced in the same way, whether emotional or social in cause. It has been criticised for its unidimensional construct, with other definitions and measures preferring to consider loneliness to be multidimensional in nature (Cramer and Barry, 1999).

2.3.4. De Jong Gierveld Scale

By contrast, the dJG Scale (de Jong Gierveld and Kamphuis, 1985) is an 11-item loneliness scale that uses an interactionalist perspective to consider both social and emotional dimensions. This enables it to be used as a comprehensive measure of loneliness or as two separate social and emotional loneliness subscales (de Jong Gierveld and van Tilburg, 2006). A shorter 6-item version has also been created (de Jong Gierveld and van Tilburg, 1999) (Figure 3). De Jong Gierveld (1987) notes that the scale also uses a cognitive approach with loneliness being understood as the manner in which respondents evaluate their isolation or lack of social contact. Criticisms of the scale include the lack of specificity in some of the items, which may lead to other facets of wellbeing or mental health being accounted for that do not necessarily relate to loneliness (Shaver and Brennan, 1991).

2.3.5. Are the Multi-Item Scales Reliable?

Both the UCLA and dJG scales have been criticised, with several studies suggesting that it is sometimes unclear what exactly they are measuring, whether it be loneliness, a particular dimension of loneliness, or some other emotional or cognitive factor (Penning et al, 2014). Criticisms have also arisen over the effects of the methods used on the results of the scales, for example, whether the items are worded in a positive or negative direction and how this influences responses (Penning et al, 2014). Furthermore, certain key issues associated with the self-reported measure persist in the multi-item scales. For example, Nicolaisen and Thorsen (2014) assert that some of the items will also elicit socially acceptable responses that mask true feelings, such as those asking respondents to evaluate their number of close relationships. In addition, these scales are also culturally specific, and they often make theoretical assumptions between certain social activities, such as social engagement, and feelings of loneliness (Victor et al, 2005).

Moreover, an understanding of the correlation between the self-reported measure of loneliness and the multi-item scales is lacking. Few studies have investigated whether the results of the two methods demonstrate consistency. Shiovitz-Ezra and Ayalon (2012) compare the use of the self-reported measure with the shortened version of the UCLA scale developed by Hughes et al (2004) (Figure 4). Inconsistent with the theory that the self-reported measure may encourage respondents to misrepresent their true feelings due to the stigma associated with loneliness, the authors found the prevalence of loneliness to be higher when using the self-reported measure than the multi-item scale. The authors also reported that the relationship between loneliness and its associated characteristics differed using the two techniques, with younger people and highly educated people being less likely to be identified as lonely using the self-reported measure than with the multi-item scales. Similarly, Nicolaisen and Thorsen (2014), used the 6-item dJG scale and the self-reported measure to compare the difference in results they produce. Contradicting Shiovitz-Ezra and Ayalon (2012), they found that it was older respondents and men who were less likely to self-report as lonely, although the overall prevalence of loneliness was consistent with the two techniques. These studies demonstrate that the tools used to understand loneliness are imperfect as they produce inconsistent results.

Methods of administration and issues intrinsic to the collection of survey data can also introduce biases, for example, self-completed surveys may be perceived to protect confidentiality compared to those conducted with an interviewer present (de Leeuw, 1992). Others have highlighted issues of nonresponse and declining participation that threatens the integrity of surveys (Krueter, 2013). Whilst insufficient sample sizes mean that the data are rarely granular enough to produce estimates of certain characteristics, such as loneliness, at the small area level (Datta and Ghosh, 2012). In summary, both the multi-item scales and the self-reported measures demonstrate a lack of specificity that has led to inconsistent results across methods (Shiovitz-Ezra and Ayalon, 2012; Nicolaisen and Thorsen, 2014). Such issues, coupled with the challenges inherent in conducting surveys, may make intervention strategies aimed at alleviating loneliness difficult to implement as there is a poor understanding of who exactly is lonely and where these populations reside.

2.4. Moving Beyond Surveys

This section will review other methods that have been used to measure loneliness. Specifically, it will focus on the application of composite indices in loneliness research, and as such explores area-based measures as opposed to the individual-based approaches outlined in Section 2.3. Following the shortcomings of the existing measures, some researchers and organisations have tried to move beyond the survey-based approaches. The charity, Age UK, highlighted the challenge in locating lonely older individuals and argued that this is impeding their attempts to alleviate loneliness in the community (Davidson and Rossall, 2015). Targeted efforts so far have been simplistic and have included strategies such as handing out leaflets to the recently bereft (Goodman et al, 2015). According to 'The Campaign to End Loneliness', methods such as leafletting are insufficient as they fail to consider how a range of circumstances can lead to loneliness and simply focus on one subsection of the lonely, in this case, the bereft. Especially important is finding individuals experiencing multiple risk factors as these are the most at-risk (Goodman et al, 2015). Consequently, such charities have called for the mapping of loneliness to identify the local areas that have a higher concentration of older people that need assistance (Goodman et al, 2015). Articulated more explicitly by Lucy and Burns (2017, p. 2):

> *"…by indexing and spatially visualising where loneliness in the elderly population is most likely to occur, policies can be put in place, and in specific locations, to effect the greatest change".*

Thus, there is a need to explore the potential application of such area-based composite indices in studies of loneliness in older populations.

2.4.1. Area-Based Composite Indices in Social Science

Area-based composite indices have been applied to a wide variety of social domains, such as deprivation (McLennan et al, 2019), environmental health (Saib et al, 2015), sustainable commuting (Reikkinen and Burns, 2018), neighbourhoods vulnerable to crime (Chainey, 2008), childhood wellbeing (Bradshaw et al, 2009), and "thriving places" (Townsely et al, 2018). Composite indices are particularly useful when seeking to quantify and locate phenomena that are both difficult to define and lacking with regards to data, consequently such an approach is well suited to the concept of loneliness. There have been several attempts to create area-based composite indices for loneliness amongst older populations, and these are reviewed below.

According to the OECD (2008), when developed with the use of robust statistical techniques and in a clear and transparent way, composite indices can be used to: summarise social phenomena that cannot be represented by a single indicator; allow for easy interpretation of complex and multidimensional issues; be used for benchmarking of progress between different regions; place issues of performance at the centre of public policy; and facilitate communication with the public (OECD, 2008).

2.4.2. Age UK's Loneliness Index

Age UK is the only organisation to create an index of loneliness that is applicable to the whole of England. The study investigates characteristics that were deemed to be associated with those who self-reported as "often" lonely, using data from the *English Longitudinal Study of Ageing* (ELSA) (Iparraguirre, 2016). As the ELSA does not have data available at lower geography level, once the characteristics associated with loneliness had been identified, corresponding indicators were found from the 2011 census and used to create the index (Iparraguirre, 2016). The analysis conducted by Iparraguirre (2016), using the ELSA, highlighted five factors as being correlated with loneliness: self-reported health status, marital status, household size, housing tenure, and having difficulties completing activities of daily living (ADLs). Being limited to census data, the only variables used in the final index were marital status, household size, self-reported health status and age (Age UK, 2020).

Although Iparraguirre (2016) provides a good starting point for indexing and mapping loneliness amongst older populations, there are a number of statistical flaws and inaccuracies. There is inclusion of statistically insignificant results, omission of statistically significant results in error, and misinterpretation of the multilevel logistic regression model as presented in Table 2 of their report (Iparraguirre, 2016, p. 8). If such inaccuracies were not present in the final index then this is not clear, and therefore the methods used to create the index are not fully clear and transparent, which could lead to wider misinterpretation by users. The sole use of census data and only four variables limit the index and assumes a somewhat narrow view of the causes of loneliness. As Matz et al (2017) explain, complex psychological phenomena are unlikely to be fully explained by just a few strong indicators, this advice is echoed by Buecker et al (2020) in the context of loneliness amongst older populations.

2.4.3. Lucy and Burns (2017) Loneliness Index

Building on the initial work completed by Age UK, Lucy and Burns (2017) created an index of loneliness amongst older populations for the London Borough of Southwark. The selection of variables for the index was informed by a literature review, and they included the following characteristics: single person households, poor self-reported health, lack of education, poor access to public transport and a neighbourhood level measure of deprivation.

Lucy and Burns' (2017) research offers a more comprehensive attempt to index loneliness amongst older populations with the inclusion of a wider variety of variables compared to Age UK. However, selection of indicators and the construction process were not informed by statistical analysis. Moreover, common techniques used in the creation of a composite indicator, such as sensitivity analysis, or the application of weights to ensure reliability, were not employed. This means that the methods used in the creation of the index do not satisfy basic requirements outlined by the OECD (2008) for the creation of a meaningful and robust index. Furthermore, the Index of Multiple Deprivation (IMD) is included as a variable of socioeconomic deprivation in the index. Use of a different composite indicator within the index is not good practice as the IMD includes a myriad of other variables relating to issues including employment, crime and living environment that refer to all ages (not just older populations) and no research was presented by Lucy and Burns (2017) linking such factors to loneliness. Thus, the IMD, and by extension, Lucy and Burns' (2017) loneliness index, measures circumstances that may not have an influence on loneliness in older populations. Furthermore, this may also lead to double counting of some domains as indicators relating to health and education are included in the IMD as well as directly in the index. Finally, due to a lack of available data, this index is not reproducible on the national scale as it uses a variable of Public Transport Accessibility Level that is only available for Greater London. This means the index is not well suited to benchmarking across regions or for analysis of the phenomena on the national scale.

2.4.4. Essex County Council Loneliness Index

The Essex County Council Loneliness index provides the most comprehensive attempt to quantify loneliness and incorporates around fifteen different variables into the index (Essex County Council, 2013). Variable selection was informed by the literature and combines both the IMD and commercial data from the Mosaic household dataset. The latter provides household-level data for a variety of different characteristics such as widowhood, financial stability and measures of ill health (Essex County Council, 2013).

Although this index garnered attention from other local authorities such as Gloucestershire County Council who have replicated it (BBC, 2015), there are notable concerns about the validity of its construction and practical drawbacks of the outputs. Firstly, it again employs the use of the IMD, which, as previously addressed, is conceptually flawed with relation to measuring loneliness (see Section 2.4.3). Secondly, it is not clear exactly how variables were selected for inclusion, with the report indicating they were simply chosen following a literature review without further analysis. With such a high quantity of variables included, it is likely that some domains are being double counted in the index. For example, there are six variables relating to an individual's heath included in the index, with a health domain also being included in the IMD.

With no further analysis having taken place, it is highly likely that double counting is taking place and giving too much influence to the health domain within the index. Thirdly, it is not clear what defines each variable, for example, one variable is simply described as "struggling financially" (Essex County Council, 2013), with no clear definition of exactly how this is being measured or what comprises the variable. Fourth, information outlining how the variables were normalised and aggregated to create the index is not described. Finally, the index makes use of costly commercial data from Experian, making it less accessible to other local authorities or charities who may wish to reproduce the index.

2.5. Identifying a new approach

Seemingly, the existing survey measures outlined in Section 2.3 are insufficient to geographically locate those older individuals suffering most severely from loneliness. The development of a composite index may be better suited to identifying where lonely people are *most likely* to live. Although there have been initial attempts to create an area-based index for loneliness (as discussed in Section 2.4), these indices are underdeveloped. They have seldom been based on robust statistical analysis or involved any serious attempt at validation, nor ensured transparency in the construction phase.

In summary, this chapter has identified a theoretical framework for the creation of a new composite index that aims to measure loneliness amongst older populations in England. The key tenets of this new framework are clearly outlined below:

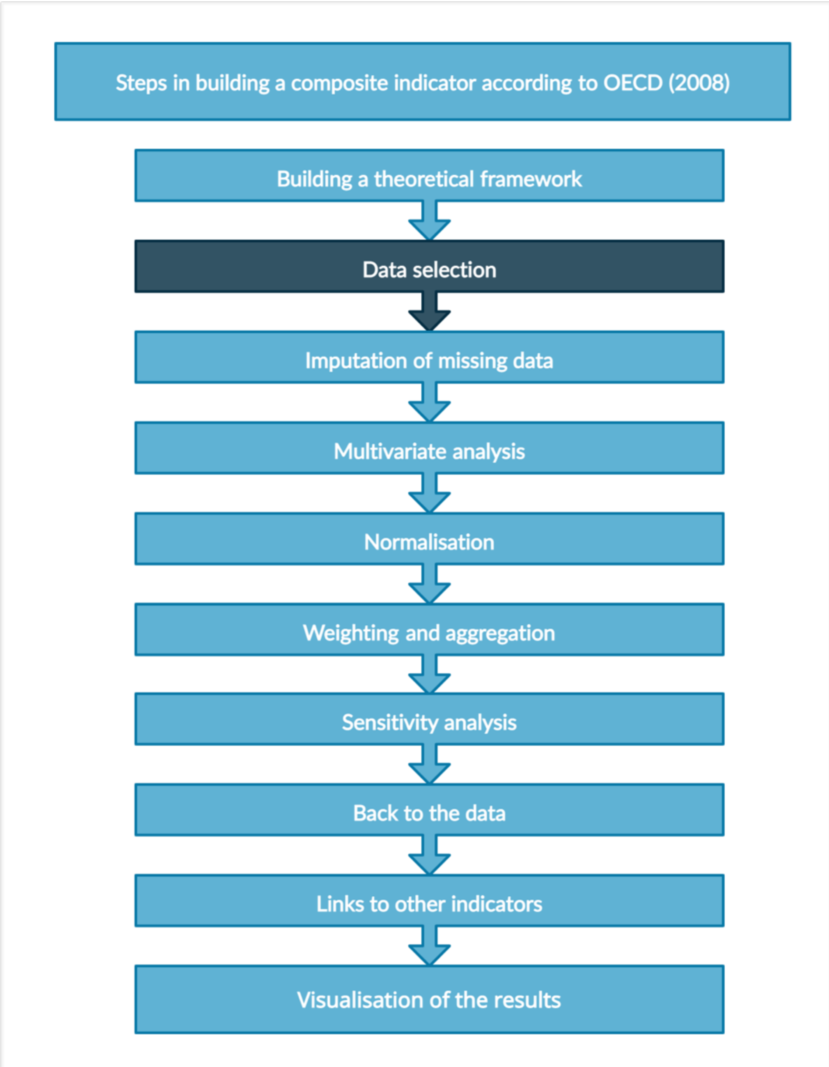
- Loneliness is defined as a perceived deficit between desired and achieved social outcomes that incorporates both social and emotional facets of loneliness.
- A broad variety of indicators should be included to capture loneliness as comprehensively as possible.
- Index construction must be clear and transparent and incorporate robust statistical analysis where possible.
- The index must be applicable at the small-area level so that it can aid local authorities and charities in the identification of areas at risk of loneliness.
- The index should be reproducible so that it can be used for benchmarking and analysing loneliness spatially and temporally.
- Finally, attempts must be made to validate the index to ensure its accuracy.

Consideration will now turn in Chapter 3 to the data selection process that is integral to the construction of the index. This chapter will focus on identifying characteristics associated with loneliness amongst older populations that have previously been identified by studies in the literature. Chapter 4 will then empirically investigate the characteristics identified by the literature through secondary data. This will help determine and evaluate their importance. These findings will then be used to inform the application of appropriate construction methods (normalisation, weighting and aggregation) in the final composite index (Chapters 5).

Chapter 3. Empirical Investigation of Loneliness and Associated Characteristics

In Chapter 2, a theoretical framework for the measurement of loneliness was developed. According to the OECD (2008), the next step in the construction of the index is to identify possible variables that can be used as indicators (Figure 5). This chapter provides a thorough review of the empirical studies that have investigated characteristics that are associated with feelings of loneliness in older populations.

Figure 5: Flowchart outlining the steps that will be addressed in Chapter 3.



The theoretical framework advised that the selection of variables should be informed by statistical analysis where possible. Consequently, this section will outline all the possible characteristics that could be incorporated into the index. These variables will then undergo a more rigorous selection process in Chapter 4, which conducts the multivariate analysis step, as advised by the OECD (2008), using a secondary data source (Section 4.1). This chapter is split into ten different sections, each will review a different set of characteristics, as summarised in Table 1.

Table 1: Outline of the sections and structure of Chapter

Section	*Characteristic investigated*
3.1	Oldest age
3.2	Gender
3.3	Ethnicity and migration
3.4	Marital status and living arrangements
3.5	Health indicators
3.6	Income, education and employment
3.7	Internet usage
3.8	Variables of social activity
3.9	Neighbourhood variables
3.10	Conclusion

3.1. Loneliness and Oldest Age

Table 2: Summary table of the literature referring to the relationship between loneliness and oldest age.

Characteristic	*Summary of Characteristic*	*Study*	*Correlation with Loneliness*	*Additional Notes*
Oldest Age	Usually defined as being 75 or 80 years old and over.	Dykstra, 2009	Positive	Conclusion after a thorough review of the empirical literature.
		Jylha, 2004	Positive	Loneliness increases for the oldest old because it is at this age that the other debilitating factors are most severe, e.g. decreased mobility and social interaction.
		Flood, 2005	Positive	
		Dykstra et al, 2005	Positive	
		Ferreira-Alves et al, 2014	Positive	
		Aylaz et al, 2012	Positive	
		Park et al, 2020	Positive	
		Cornwell and Waite, 2009	Positive	
		Heylen, 2010	No	A study of social loneliness in particular. The author suggests the finding is due to oldest age groups placing more value in the emotional dimension of loneliness.

Dykstra (2009) concludes that the literature overwhelmingly suggests that loneliness increases in the oldest age groups, an association found in a range of studies (Jylha, 2004; Flood, 2005; Dykstra et al, 2005; Ferreira-Alves et al, 2014; Aylaz et al 2012; Park et al, 2020; Cornwell and Waite, 2009). These scholars distinguish between the "young-old" and the "oldest-old", although the age at which studies assert that oldest age begins varies between either 75 (e.g. Cornwell and Waite, 2009) or 80 years of age (e.g. Dykstra et al, 2005). Regarding the studies in Table 2, not all refer to the concept of young-old and oldest-old explicitly, instead, Aylaz et al (2012) and Park et al (2020) simply note that there is a strong positive correlation between loneliness and age, thus they also find the association between oldest age and loneliness.

Whilst the academic consensus on the association between oldest age and loneliness appears strong, the reason for this observation is less conclusive. Jylha (2004) finds that the oldest-old are at higher risk because of debilitating factors that are associated with both loneliness and oldest age, such as decreasing mobility and decreasing social interaction. Conversely, Cornwell and Waite (2009) find that even though loneliness increases in oldest age, objective social isolation does not change, thus the increase in loneliness is largely due to an increase in desired social outcomes. However, Cornwell and Waite's (2009) study investigates few confounding variables, such as deteriorating health. Therefore, Jylha (2004) offers more robust results as they control for a wider variety of confounding variables, such as marital status and health.

Inconsistent with the wider literature, Heylen (2010) did not find an increase in loneliness in oldest age. The study used the dJG social subscale, and as such, it measured social loneliness specifically, as opposed to emotional loneliness. Citing a commonly reported phenomenon, Heylen (2010) suggest that the oldest-old were not found to be socially lonelier than the young-old because the oldest-old value the quality rather than the quantity of their social relations. Therefore, they are more affected by the emotional dimension of loneliness than the social dimension. In summary, the academic consensus is that the likelihood of an individual feeling lonely increases as they pass the ages of 75 or 80, although this is unlikely to be a direct relationship.

3.2. Loneliness and Gender

Table 3: Summary table of the literature referring to the relationship between loneliness and gender.

Characteristic	***Summary of Characteristic***	***Study***	***Correlation with Loneliness***	***Additional Notes***
Gender	Being female.	Luhmann and Hawkley, 2016	Positive	This research uses the 3-item UCLA scale as a measure of loneliness.
		Victor and Yang, 2012	Positive	This research uses the self-reported measure of loneliness.
		Jylha, 2004	Positive	Association only found at bivariate level.
		Cohen-Mansfield et al, 2009	Positive	Women lonelier as they are more likely to experience other factors associated with loneliness such as widowhood and poor health.
		Ferreira-Alves et al, 2014	Positive	Women lonelier as they are more likely to experience other factors associated with loneliness such as widowhood.
		Buecker et al, 2020	Positive	This research uses the 3-item UCLA scale as a measure of loneliness.
		Nicolaisen and Thorsen, 2014	Positive and Non	Finds a positive association using a self-reported measure of loneliness and no association using a multi-item scale.
		Flood, 2005	Negative	Women are more avid social capitalists than men.
		Dahlberg and Mckee, 2014	Negative	Men have smaller social networks than women.
		Menec et al, 2019	Negative	Loss of a spouse is four times more damaging to men's self-reported loneliness than for women.

Gender is perhaps the most widely debated demographic characteristic in relation to loneliness (Table 3). Debates persist around which gender has a higher propensity to loneliness and which measures accurately capture the extent of loneliness in both genders (see Section 2.3). The common assumption is that loneliness is more prevalent amongst women (Victor et al, 2009). Indeed, a variety of studies, that use both the self-reported measure of loneliness and the 3-item UCLA multi-item scale find this to be true (Victor et al, 2009; Victor and Yang, 2012; Luhmann and Hawkley 2016; Buecker et al, 2020).

Nicolaisen and Thorsen (2014) measured loneliness prevalence using both the self-reported technique and the shortened six-item dJG scale. They found that in older populations, women were more likely to self-report as lonely, but when using the multi-item scale, there were no differences. This finding is consistent with the theory previously cited that men are less likely to directly admit to loneliness (Section 2.3), but contradicts the above studies that used the 3-item UCLA scale (above) and still found women to be lonelier than men. It lends further evidence to the argument that different methodologies capture loneliness in different populations.

A variety of studies assert that women are often lonelier than men because women are more likely than men to suffer from widowhood, live alone or suffer from poor health, and it is these factors that make them lonely (Jylha 2004; Cohen-Mansfield et al, 2009; Ferreira-Alves et a, 2014). A smaller collection of studies find men to be lonelier than women (Flood, 2005; Dahlberg and Mckee, 2014; Menec et al, 2019). These suggest that the primary reason for their findings is that men have smaller social networks than women. There is no academic consensus on the relationship between gender and loneliness. Variations persist in reported prevalence, methodologies, and influence of confounding factors. The prevailing discourse is that gender is unlikely to be directly related to loneliness.

3.3. Loneliness, Ethnicity and Migration

Table 4: Summary table of the literature referring to the relationship between loneliness, ethnicity and migration.

Characteristic	***Summary of Characteristic***	***Study***	***Correlation with Loneliness***	***Additional Notes***
Ethnicity	Being an ethnic minority	Wu and Penning, 2015	Positive	
		De Jong Gierveld et al, 2015	Positive	Especially for those who do not speak the national language.
		Menec et al, 2015	No	Used neighbourhood-level indicator of language.
		Victor et al, 2012	Positive	UK based study. All ethnicities found to increase risk of loneliness except those of Indian heritage.
Migration	Migrating to a new area	Buecker et al, 2020	Positive	
		Van den Berg et al, 2015	Positive	
		Wenger and Burholt, 2004	Positive	

Belonging to an ethnic minority or migrating (internally or externally) is frequently hypothesised as being linked to loneliness (Table 4). In the UK, Victor et al (2012) found that most ethnic minorities, such as those who identified as Pakistani, Bangladeshi, Afro-Caribbean, and Chinese were found to be considerably lonelier than those who declared themselves British, except for the Indian population. Researchers have not been able to explain this key finding but propose that it may be a result of differing settlement patterns of the Indian communities. Language is often used to indicate ethnicity, with multiple Canadian studies finding that those who do not speak the national language are especially vulnerable to loneliness (Wu and Penning, 2015; de Jong Gierveld et al, 2015). Menec et al (2019), did not find poor language proficiency to be an indicator of loneliness. However, unlike Wu and Penning (2015) and de Jong Gierveld et al (2015), they used aggregate-level data, and an ecological fallacy may be present, such that certain areas with relatively high numbers of non-native speakers have low rates of loneliness but may still contain individuals who experience loneliness induced by language barriers. Thus, the study does not offer the same level of detail as Wu and Penning (2015) and de Jong Gierveld et al (2015).

Rather than focussing on ethnicity, Van den Berg et al (2015), Wenger and Burholt (2004) and Buecker et al (2020) found that those who had migrated in their life, whether internally or externally, were found to be lonelier than those who did not have a history of migration. The literature, therefore, suggests that the language you speak, your ethnic origin and whether or not you had migrated in your life, all influenced an individual's propensity to be lonely.

3.4. Loneliness, Marital Status and Living Arrangements

Table 5: Summary table of the literature referring to the relationship between loneliness, marital status and living arrangements.

Characteristic	**Summary of Characteristic**	**Study**	**Correlation with Loneliness**	**Additional Notes**
Single Marital Status	Whether an individual is never married, divorced, widowed.	Menec et al, 2019	Positive	Especially for those who are widowed or male.
		Savikko et al, 2005	Positive	Especially in those widowed within the last 6 years.
		Routasalo et al, 2006	Positive	
		Wenger and Burholt, 2004	Positive	Especially for those who are widowed, the effect continues to deteriorate with time.
		Victor et al, 2005	Positive	Especially for those who are widowed.
		Aartsen and Jylha, 2011	Positive	
		Victor and Bowling, 2012	Positive	Suggests a “coming to terms” (p. 327) effect with the passing of time.
		Scharf and de Jong Gierveld, 2008	Positive	
		Theeke, 2009	Positive	Included the category of “Married - spouse absent from home”, which was found to be the most powerful predictor of loneliness of all the marital categories.
		Cornwell and Waite, 2009	Positive	
		Cohen-Mansfield et al, 2009	Positive	
		Dahlerg and Mckee, 2014	Positive	
		Ferreira-Alves et al, 2014	Positive	
		Flood, 2005	Positive	

		Jylha, 2004	Positive	Only at bivariate level, association is confounded with living arrangements.
		Luhmann and Hawkley, 2016	Positive	
		Nicolaisen and Thorsen, 2014	Positive	
		Victor and Yang, 2012	Positive	
Living Arrangements	Living alone	Routasalo et al, 2006	Positive	Finds living alone to be the most powerful predictor of loneliness.
		Menec et al, 2019	Positive	
		Ferreira-Alves et al, 2014	Positive	
		Theeke, 2009	Positive	
		Scharf and de Jong Gierveld, 2008	Positive	
		Victor and Bowling, 2012	Positive	Suggests a "coming to terms" (p. 327) effect with the passing of time.
		Luhmann and Hawkley, 2016	Positive	Only at bivariate level, association is confounded with low income and single marital status.
		Jylha, 2004	Positive	Those who lived with partners were at lowest risk of loneliness, those who lived alone at the highest risk of loneliness.
		Victor and Yang, 2012	Positive	Those who lived with partners were at lowest risk of loneliness, those who lived alone at the highest risk of loneliness.
	Living in care	Jylha, 2004	Positive	Those in care are at higher risk of loneliness than those who live alone
		Savikko et al, 2005	Positive	
		Ferrier-Alves et al, 2014	Positive	
		Walters et al, 2004	Positive	Focussed on depression and loneliness.

Table 5 summarises a large array of studies that have investigated single marital status and consistently found it to be associated with loneliness. Single marital status, i.e. being divorced, widowed or never married, is one of the most agreed upon predictors of loneliness in the literature. Of these different categories, widowhood is commonly found to have a stronger effect on loneliness than simply never marrying or being divorced (Wenger and Burholt, 2004; Savikko et al, 2005; Victor et al, 2005; Routasalo et al, 2006; Victor and Bowling, 2012; Menec et al, 2019). There is a degree of disagreement over whether loneliness is felt most severely when one is recently widowed (Savikko et al, 2006; Victor and Bowling, 2012), or whether feelings of loneliness continue to deteriorate as widowhood continues (Wenger and Burholt, 2004). Despite this nuance, many studies find single marital status to be a risk factor for loneliness, regardless of methods used or countries investigated (Table 5).

Contrary to all the other studies investigating marital status, Theeke (2009) adds an extra marital status category, 'married – spouse absent'. This factor was found to be a more considerable predictor of loneliness than all the other categories, including widowhood. This demonstrates the importance of the quality of marriage and cohabitation. Furthermore, investigating the importance of living arrangements with regards to marriage, Jylha (2004) found that in a multivariate analysis the marital status is confounded with living arrangements so that it no longer had an independent effect on loneliness in their model. This finding suggests that marriage does not directly alleviate loneliness, rather married people are less likely to live alone, and it is this that reduces a married individual's propensity to be lonely. However, this finding is inconsistent with the broader literature, with most other studies finding single marital status to be independently associated with loneliness.

With regards to living alone, it is clear from the literature that it is also associated with loneliness, regardless of marital status. Routasalo et al (2006) finds that living alone is the strongest predictor of loneliness in a study that included a variety of demographic, socioeconomic and neighbourhood variables. They find that living alone increases the odds of loneliness 3.13 times, compared to widowhood which only increases the odds of being lonely by 1.55 in their model. Other studies find that living alone is independently associated with loneliness including Menec et al, (2019); Ferriera-Alves et al (2014); Theeke, (2009); Scharf and de Jong Gierveld (2008) and Victor and Bowling (2012). The latter finding, as with widowhood, that over time there is a "coming to terms" (p. 327) where one accepts their situation and adjusts their social expectations accordingly, ameliorating feelings of loneliness.

Whilst most studies dichotomise living arrangements into the variables of "living alone" and "not living alone", Jylha (2004) and Victor and Yang (2012) investigate who and how many people an individual is living with. They find that living only with a partner is the arrangement that is least conducive to loneliness, and living alone is the most conducive to loneliness, with those in multiple-person households occupying the middle ground. In addition, Jylha (2004), Walters (2004), Savikko et al (2005) and Ferreira-Alves et al (2014) all found that living in care homes was particularly conducive to loneliness as opposed to living in private housing. These studies demonstrate the difference between social isolation and loneliness, especially amongst older people, where it is not necessarily the number of people an individual lives with or has contact with, but the quality of those relationships which is especially important.

In summary, there are subtle variations between some of the investigations regarding marital status and living arrangements, for example, sometimes men are found to be affected by single marital status more than women (Menec et al, 2019); some find that an individual's loneliness can ameliorate over time after becoming widowed or divorced (Savikko et al, 2005; Victor and Bowling, 2012); and some find that living in multiple-person households is more conducive to loneliness than living in a couple (Jylha, 2004; Victor and Yang, 2012). The two variables of marital status and living arrangements also display a high degree of collinearity (Luhmann and Hawkley, 2016). However, the overwhelming consensus is that single marital status (especially widowhood), living alone, and living in a care home are independently and considerably associated with loneliness.

3.5. Loneliness and Health

Table 6: Summary table of the literature referring to the relationship between loneliness and a variety of health indicators.

Characteristic	Summary of Characteristic	Study	Correlation with Loneliness	Additional Notes
Health	Having poor health	Burholt and Scharf, 2014	Positive	Measures health using presence of chronic diseases.
		Menec et al, 2019	Positive	Measures health using presence of chronic diseases and limitations with ADL.
		Ferrier-Alves et al, 2014	Positive	Measures health using presence of chronic diseases and limitations with ADL.
		Dahlberg and Mckee, 2014	Positive	Measures health using limitations with ADL.
		Theeke, 2009	Positive	Measures health using presence of chronic diseases and limitations with ADLs. Also measures frequency of doctor's visits, which is not found to be a significant indicator.
		Wenger and Burholt, 2004	Positive	Concludes that failing eyesight and hearing can increase feelings of loneliness.
		Cohen-Mansfied et al, 2009	Positive	Presence of chronic diseases and high frequency of doctor's visits were independently associated with loneliness.
		Savikko et al, 2005	Positive	Qualitative study reporting on what characteristics older populations perceive as contributing to loneliness.
	Mental health and psychological wellbeing	Burholt and Scharf, 2014	Positive	Uses a multi-item sale of depressive symptoms
		Aylaz et al, 2012	Positive	Uses a multi-item sale of depressive symptoms
		O'Luanaigh and Lawlor, 2008	Positive	Literature review
		Dahlberg and Mckee, 2014	Positive	Using the WHO-5 scale of psychological wellbeing and a self-reported measure of self-esteem.
		Aartsen and Jylha, 2011	Positive	Those who self-reported as experiencing frequent low mood, nervousness and irritability.
		Victor and Yang, 2012	Positive	

	Poor perceived mental health	Routasalo et al, 2006	Positive	
	Poor perceived health	Buecker, et al, 2020	Positive	
		Dahlberg and Mckee, 2014	Positive	
		Ferreira-Alves et al, 2014	Positive	
		Nicolaisen and Thorsen, 2014	Positive	
		Nummela et al, 2010	Positive	
		Scharf and de Jong Gierveld, 2008	Positive	
		Victor and Bowling, 2012	Positive	
		Routasalo et al, 2006	Positive	
		Cohen-Mansfield et al, 2009	Positive	
		Theeke, 2009	Positive	
		Heylen, 2010	Positive	Finds that subjective health is a greater barrier to social activity than objective health.
		Macdonld et al, 2018	Positive	Relationship is stronger in lower socioeconomic classes where perceptions of ill health have a greater impact on feelings of loneliness.
		Victor et al, 2005	Positive	Asked respondents whether their health in older age is worse than they would have anticipated a decade before.
		Deeg and Bath, 2003	Positive	Perceived health is a useful summary of all other health indicators.
	Substance use	Aylaz et al, 2012	Positive	Smokers are more likely to be lonely. Although the direction of this relationship is unclear.
	Receipt of care	Dahlberg and Mckee, 2014	Negative	Negative relationship between the receipt of informal care and loneliness.
	Informal caregiving	Wenger and Burholt, 2004	Positive	Those who become informal carers for a dependent spouse are more likely to be lonely.

Much like marital status and living arrangements, having poor health is consistently found to be a considerable contributor towards feelings of loneliness. In fact, when asked, older populations commonly report that they understand poor health to be one of the primary contributors to loneliness amongst their generation (Savikko et al, 2005). One of the challenges in understanding how this characteristic relates to loneliness is how exactly to measure health, and which facets of poor health have the greatest impact on loneliness. Two primary methods are used in measuring health, first, measuring the number of chronic diseases a person has, these usually include diseases such as suffering from cancer, stroke, diabetes, arthritis and heart disease (Burholt and Scharf, 2014). A second method is using a multi-item scale of functionality, usually measured by limitations in ADL. Issues with ADL refer to lack of mobility and autonomy in completing everyday tasks such as washing, dressing and climbing stairs (Ferriera-Alves et al, 2014). These two measures of poor health are found to be associated with loneliness in a range of studies (Burholt and Scharf, 2004; Menec et al, 2019; Ferreira-Alves et al, 2014; Theeke, 2009; Dahlberg and Mckee, 2014). Cohen-Mansfield et al (2009) also point out that when measuring chronic disease, comorbidity has a greater effect on loneliness than having a single chronic disease. Wenger and Burholt (2004) focus on sensory impairment and find that failing eyesight and hearing are particularly effective predictors of loneliness. Presence of chronic diseases and difficulties with ADL are variably found to have a greater effect on loneliness than the other, with Theeke (2009) arguing that limitations in ADL are a more powerful predictor of loneliness than chronic diseases and Cohen-Mansfield et al (2009) arguing the reverse. Overall, there is broad agreement that both impact feelings of loneliness.

As loneliness is defined as a cognitive state, and thus it is experienced psychologically (de Jong Gierveld and Havens, 2004), it is important to investigate the association between indicators of mental health and psychological wellbeing with loneliness. O'Luanaigh and Lawlor (2008), in their review of the literature find the prevailing academic opinion to be that feelings of depression are associated with feelings of loneliness. Measurements of depression are often conducted in surveys with multi-item scales of depressive symptoms (Burholt and Scharf, 2014; Aylaz et al, 2012), or a self-reported measure, i.e. *"how often do you feel depressed?"* (Victor and Yang, 2012; Routasalo et al, 2006). Whilst all these studies found an association between depression and loneliness, the latter measure is imprecise as those of older populations who report as depressed, approximately half of these do not suffer from clinical depression (Garrard et al, 1998), therefore studies using this measure must be considered with caution.

Some studies measure other facets of mental health and psychological wellbeing. Dahlberg and Mckee (2014) measure psychological wellbeing using a World Health Organisation (WHO) developed multi-item scale known as the WHO-5. This scale asks respondents questions, including how often they feel *"cheerful and in good spirits"*, or if they have a daily life that is *"filled with things that interest me"* (Topp et al, 2015, p.168). Whilst Dahlberg and Mckee (2014) find this to be the most powerful predictor of loneliness of all the health indicators they use, the measure of loneliness they compare it with is the dJG scale (de Jong Gierveld and Kamphius, 1985). This scale asks questions such as *"I experience a general feeling of emptiness"* and *"I miss the pleasure of the company of others"* (Figure 3). Thus, the questions allude to similar experiences, and it is reasonable to expect that the WHO-5 wellbeing scale and the dJG loneliness scale are likely to be measuring a similar phenomenon. This calls into question the validity of their conclusion and lends further evidence to the discourse that such multi-item scales are imprecise in measuring loneliness specifically (Section 2.3.5). Similarly, Aartsen and Jylha (2011) find a strong relationship between those who experience emotions such as frequent low mood, irritability and a sense of uselessness, with increased feelings of loneliness. Unlike Dahlberg and Mckee (2014), they acknowledge that these emotional characteristics and loneliness have the potential to be considered as "two sides of the same coin" (p. 37). However, they argue that as the bivariate correlations between the emotional characteristics and loneliness are only weak to moderate, it is fair to conclude that these characteristics are not simply just proxy measures of loneliness.

Finally, the health indicator which is perhaps the most consistently found to be associated with loneliness is using a measure of subjective health. Researchers ask a question such as: *"How would you best describe your health?"* (Nicolaisen and Thorsen, 2014) or *"Would you say that for someone your age, your own health is…"* (Scharf and de Jong Gierveld, 2008). Respondents usually answer on a four or five-point ordinal scale ranging from poor to excellent. This is found to be a considerable predictor of loneliness in a multitude of studies (Buecker et al, 2020; Dahlberg and Mckee, 2014; Ferreira-Alves et al, 2014; Nicolaisen and Thorsen, 2014; Nummela et al, 2010; Scharf and de Jong Gierveld, 2008; Victor and Bowling, 2012; Routasalo et al, 2006; Cohen-Mansfield et al, 2009; Theeke, 2009; Heylen, 2010; Macdonald et al, 2018; Deeg and Bath, 2003; Victor et al, 2005). Deeg and Bath (2003) suggest that the reason that subjective health is a useful indicator is because it acts as a summary for all other health variables. Furthermore, using a self-evaluation of health fits within the cognitive theory of loneliness as what is important to loneliness is not one's actual circumstances, but how they evaluate their circumstances. Researchers have also investigated the relationship between smoking and receipt and provision of formal and informal care. These factors have been studied by few researchers. However, studies have found that loneliness is more prevalent amongst smokers and those providing informal care, but is not affected by receipt of informal care.

In summary, it seems unclear exactly which health indicators most severely impact feelings of loneliness. However, most studies find that lack of functionality or presence of chronic illness contributes to feelings of loneliness, as do poor psychological wellbeing, whilst using poor subjective health as a measure is likely to be a useful summary of all the above.

3.6. Loneliness, Income, Education and Employment

Table 7: Summary table of the literature referring to the relationship between loneliness, income, education and employment.

Characteristic	Summary of Characteristic	Study	Correlation with Loneliness	Additional Notes
Income	Having a higher household income	Aylaz et al, 2012	Negative	
		Buecker et al, 2020	Negative	
		Ferriera-Alves et al, 2014	Negative	
		Menec et al, 2019	Negative	
		Savikko et al, 2005	Negative	
		Cohen-Mansfield et al, 2009	Negative	
		Luhmann and Hakley, 2016	Negative	
		Macdonald et al, 2018	Negative	
		Dahlberg and Mckee, 2014	Negative	Uses a subjective, self-evaluating measure of whether an individual feels comfortable on their level of income.
		Burholt and Scharf, 2014	Negative	Review of the empirical literature.
Education	Having received higher level of formal education	Victor et al, 2005	Negative	
		Victor and Yang, 2012	Negative	
		Menec et al, 2019	Negative	
		Cohen-Mansfield et al, 2009	Negative	There is a negative bivariate correlation, however there is no correlation once covariates are controlled.
		Luhmann and Hawkley, 2016	Positive	
		Ferreira-Alves, 2014	No	
Employment	Being employed	Luhmann and Hawkley, 2016	No	
		Ferreira-Alves, 2014	Negative	

As Burholt and Scharf (2014) highlight, there is remarkable consistency in the literature regarding the relationship between loneliness and income levels in older populations (Table 7). Researchers tend to use a measure of household income, and either treat it as a binary variable, "high" and "low", or use a broader ordinal scale. All however find a negative relationship between high household income and loneliness (Aylaz et al, 2012; Buecker et al, 2020; Ferreira-Alves et al, 2014; Menec et al, 2019; Savikko et al, 2005; Cohen-Mansfield et al, 2009; Luhmann and Hawkley, 2016; Macdonald et al, 2018). The findings suggest that having a higher income protects against feelings of loneliness through characteristics such as spending behaviours (Luhmann and Hawkley, 2016). Lack of financial resources can limit an individual's ability to participate in social activities (Aylaz et al, 2012). The literature is conclusive, having low household income is a considerable predictor of loneliness in older populations.

Education, whilst often linked with household income, is a less understood variable in relation to loneliness. Menec et al (2019) and Victor et al (2005) report a negative association between higher education and loneliness, with the latter suggesting that the relationship is weak and should not be overstated. Victor and Yang (2012) are more assertive, describing the relationship as considerable, with those in the UK who were educated to the tertiary level having just a 3% prevalence of loneliness, whilst those who received only primary education having a loneliness prevalence rate of 20%. The authors state that more research is required in this area to ascertain whether education is acting as a proxy for access to material resources, or whether the phenomenon is something intrinsic to the receipt of higher education. The authors in this study do not control for other variables, they suggest that there is not enough understanding about the mechanisms through which variables interact with loneliness to justify the inclusion of any causal factors. However, not controlling for other variables can lead to false conclusions being drawn. This is a process proposed by Cohen-Mansfield et al (2009) who find no association between higher education and loneliness once income is controlled for, suggesting that bivariate associations between higher education and loneliness are simply a result of the collinearity between education and income. Luhmann and Hawkley (2016) find that once income is controlled for the relationship between education and loneliness is reversed so that more educated individuals are lonelier than less educated individuals who are on the same income. They argue that this is either because higher-educated individuals have higher standards for evaluating their social relationships, or it may be because they actually have fewer high-quality relationships. Furthermore, Ferreira-Alves et al (2014) fail to find an association even at the bivariate level between education and loneliness. Therefore, it is evident that unlike household income, there is no academic consensus on the relationship between education and loneliness.

Finally, employment is often cited as one of the most powerful risk factors for loneliness (Flood, 2005). When studying older populations, however, most of the study population is retired and as such factors of employment are often redundant. Accordingly, Luhmann and Hawkley (2016) find no statistical association between the number of hours worked and loneliness. Ferreira-Alves et al (2014) do find that those who are categorised as "working" are less lonely than those who are "retired" or "at home", although no explanation is given as to what distinguishes the "retired" category from the "at home" category. With the likelihood that the vast majority of those in the older populations are retired, coupled with the paucity of research on this characteristic, it can be concluded that employment is not a particularly influential factor relating to loneliness in older populations.

3.7. Loneliness and Internet Usage

Table 8: Summary table of the literature referring to the relationship between loneliness and internet usage.

Characteristic	Summary of Characteristic	Study	Correlation with Loneliness	Additional Notes
Use of the internet	Low use and poor understanding of the internet.	Cotton et al, 2013	Positive	
		Fokkema and Knipscheer, 2007	Positive	Research conducted through an experimental study.
		Luhmann and Hawkley, 2016	Negative	
		Aasrts et al, 2014	No	
		Aarts et al, 2018	No	

A range of studies have investigated the association between internet usage and loneliness in older populations (Table 8), with a diverse methodology being employed. Cotton et al (2013) use a self-reported measure of high frequency of internet usage and finds a weak negative association with loneliness. Fokkema and Knipscheer (2007) however create an experimental study where a sample of older Dutch individuals are trained in the use of the internet and compared to a control group who are not. The authors report that those who had been trained in the use of the internet experienced a reduction in loneliness scores. The internet helped participants maintain regular contact with friends and family, functioned as a pastime when alone, and increased their self-confidence.

Other studies have produced conflicting results. Luhmann and Hawkley (2016) found that those who frequently used the internet for communication showed higher loneliness scores. This is likely to be the result of a phenomenon that Aarts et al (2018) identified, whereby use of social media is a good aide to social activity but cannot replace physical social contact for older populations. Importantly, however, these studies focussed on use of social media, whilst the two previous studies investigated use of the internet more generally. Finally, Aarts et al (2014) failed to find a significant relationship between use of social networks and loneliness, despite a large sample size. In summary, the studies that have investigated the relationship between loneliness and internet usage have been diverse and inconclusive.

3.8. Loneliness and Social Activity

Table 9: Summary table of the literature referring to the relationship between loneliness and a variety of social activity indicators.

Characteristic	Summary of Characteristic	Study	Correlation with Loneliness	Additional Notes
Frequency of Social Contact	High frequency of social contact	Buecker et al, 2020	Negative	
		Nyqvist et al, 2016	Negative	
		Luhmann and Hawkley, 2016	Negative	Only for face-to-face contact, impersonal forms such as telephone calls and email do not help alleviate loneliness.
		Aartsen and Jylha, 2011	Negative	Uses an index regarding frequency of visits to specific events, e.g. theatre visits and family ceremonies.
		Dahlberg and Mckee, 2014	Negative	Uses an index of activity, that includes both social and physical characteristics.
		Victor and Yang, 2012	No	
Quality of Social Contact	Having access to a confiding relationship.	Victor and Yang, 2012	Negative	
		Victor and Bowling, 2012	Negative	
		Cornwel and Waite, 2009	Negative	
Size of Social Network	Having a large number of social contacts	Moorer and Suurmeijer, 2001	Negative	
		Luhmann and Hawkley, 2016	Negative	
		Victor and Bowling, 2012	Negative	Refers specifically to “confiding network”. Having a large confiding network can act as a remedy for loneliness, but a small network is not likely to be the cause of loneliness.

Satisfaction with Social Activities	Being satisfied with social activity	Routassalo et al, 2006	Negative	
		Ferreira-Alves et al, 2014	Negative	
Community Engagement	High frequency of engagement in community groups and activities	Luhmann and Hawkley, 2016	No	The variable is confounded with number of friends and frequency of social contact.
		Nyqvist et al, 2016	No	
		Cornwell and Waite, 2009	Negative	Only for participation in social organisations and volunteer activities, not religious events.
		Jylha, 2004	Negative	Used broader indices of social engagement, not all questions pertained to community engagement.
		Aartsen and Jylha, 2011	Negative	Used broader indices of social engagement, not all questions pertained to community engagement.

Intuitively, variables capturing social activity are amongst some of the most considerable predictors of loneliness, but there are many facets of social activity, with some being more pertinent than others (Table 9). Frequency of social contact is measured by respondents answering how often they see family, friends and/or neighbours. The literature regarding this characteristic is consistent in finding a relationship between the low frequency of social contact and loneliness (Buecker et al, 2020; Nyqvist et al, 2016). Luhmann and Hawkley (2016) agree but note that impersonal forms of contact such as telephone calls and emails do not protect against loneliness. Regarding quantity of social contacts, three studies have also found an association between having relatively few social contacts and loneliness (Moorer and Suurmeijer, 2001; Luhmann and Hawkley, 2016; Victor and Bowling, 2012).

Conflictingly, Victor and Yang (2012) do not find frequency of social contact to be an important variable regarding loneliness in older populations, instead, they find that having a confiding relationship is important. Hence, the authors argue for a quality over quantity framework, where feelings of the emotional dimension of loneliness are more important than the social dimension of loneliness for older populations, a theory addressed in Section 3.1. The theme of confiding relationships is identified in a small collection of studies. Victor and Bowling (2012) and Cornwell and Waite (2009) also find that access to confiding relationships and the ability to “open up to” and “rely on” (Cornwell and Waite, 2009, p. i43) family and friends to be negatively associated with loneliness.

Routasalo et al (2006) and Ferreira-Alves et al (2014) are the only researchers to include a variable measuring satisfaction with social activities. They find that this is a considerable and independent associate of loneliness, and also more important than frequency of social activity. However, working within the cognitive theory of loneliness, asking an individual whether they are satisfied with their social activity is very similar to asking an individual whether they are lonely, as loneliness is theorised to be a dissatisfaction with an individual’s social outcomes relative to expectations (see Section 2.1.4). This challenges the validity of the use of such a method in the first place when investigating characteristics associated with loneliness.

One final measure of social activity used in the literature is related to the frequency of community engagement. Luhmann and Hawkley (2016) find that whether an individual engages in religious services, political/civic organisations or volunteer groups is correlated with lower levels of loneliness. However, they find that community engagement is representing variables of quantity of social contacts and frequency of social activities and is not independently associated with loneliness. Cornwell and Waite (2009) find that those who engage with volunteer and social organisations are more socially connected than those who do not, but they did not go further and link these activities directly with loneliness, only social disconnectedness.

In summary, there are many different measures through which researchers have attempted to establish a link between social activity and loneliness. It appears that either frequency or quality of social contact are the most accurate social predictors of loneliness, as variables such as size of social network and community engagement have been researched less comprehensively and have a less robust academic consensus. However, the variables highlighted in Table 9 occupy a complex nexus and are interdependent. This makes it difficult to ascertain which variables are the most important to loneliness.

3.9. Loneliness, Rurality and Neighbourhood Factors

Table 10: Summary table of the literature referring to the relationship between loneliness, rurality and the neighbourhood environment.

Characteristic	Summary of Characteristic	Study	Correlation with Loneliness	Additional Notes
Rurality	Living in rural areas	Savikko et al, 2005	Positive	
		Routasalo et al, 2006	Positive	Association only found at bivariate level
		Ferreira-Alves et al, 2014	Negative	
		Menec et al, 2019	Negative	Association only found at bivariate level
		Beer et al, 2016	Non-linear	"U" shaped association, where rural and urban areas are most lonely, with suburban and regional towns the least lonely
		Van den Berg et al, 2015	No	
Socioeconomic status	Socioeconomically deprived areas	Scharf and de Jong Gierveld, 2008	Positive	Authors also note strong neighbourhood effects.
		Deeg and Thomese, 2005	Positive	Large discrepancy between personal status and neighbourhood status increases feelings of loneliness.
Subjective evaluation of the area	Poor subjective evaluation of the local area	Scharf and de Jong Gierveld, 2008	Positive	Uses a multi-item scale relating to satisfaction with the local area.
		Kearns et al, 2015	Positive	Uses a multi-item scale relating to satisfaction with the local area.
		Van den Berg et al, 2015	Positive	Uses a self-reported measure of satisfaction with the local area.
Perceived community integration and belonging	Those who perceive the community to be well integrated	Buecker et al, 2020	Negative	
		Dahlberg and Mckee, 2014	Negative	
		Nyqvist et al, 2016	Negative	

		Kearns et al, 2015	Negative	Only at bivariate level, in a multivariate model, other factors relating to perceptions of quality of the neighbourhood appear more important.
Community integration	Objective measures that suggest the community is well integrated	Buecker et al, 2020	Negative	Neighbourhoods that experience rapid population growth or decline.
		Deeg and Thomese, 2005	No	Using measures of high population turnover and percentage of residents over the age of 65 (age homogeneity).
Accessible environments	Environments that are accessible and usable for an elderly population	Park et al, 2020	Negative	Using measures of community integration, accessibility of health and social services and quality of built environment.
		Domènech-Abella et al, 2020	Negative	Quality of built environment and walkability of public transport and amenities are important.
		Rantakkoko et al, 2014	Negative	
		Buecker et al, 2020	Negative	Long walking distances to local amenities can increase loneliness.
		Kearns et al, 2015	Negative	Infrequent use of local amenities can increase loneliness.
		Van den Berg et al, 2015	Negative	Not using a mix of transport, i.e. car, foot, public transport or living far from a major highway can increase loneliness.

Discussion of the influence of neighbourhood variables and their impact on feelings of loneliness is lacking, with most research focussing on the relationship between individual characteristics and loneliness (Buecker et al, 2020). One neighbourhood variable which is commonly assumed to be linked to feelings of loneliness is rurality (Table 10). The relationship between rurality and loneliness has been investigated in few studies, and the association is not well understood, with researchers often citing unique local circumstances as the reason for any findings. For example, Savikko et al (2005) find a positive relationship between rurality and loneliness, but the Finnish study suggests that the fragmentation of rural communities in Finland due to high population turnover is a key reason for the association. Routasalo et al (2006) also find a positive association. The authors do not investigate which specific characteristics of loneliness are more common in rural areas, although they do find depression to be a considerable predictor of loneliness, whilst other researchers have found depression to be more common in rural areas (Walters et al, 2004).

A Portuguese study conducted by Ferreira-Alves et al (2014) find loneliness to be associated with urban areas, the authors cite higher levels of community integration in rural than urban Portugal. This is a direct contrast to Savikko et al's (2005) Finnish study. Furthermore, Menec et al (2019) also find an association between urbanity and loneliness, but they suggest that this is due to confounding factors such as socioeconomic deprivation which is more common in urban areas. Finally, Beer et al (2016) finds a non-linear association between rurality and loneliness, where the most rural and the most urbanised areas are the loneliest, with regional towns the least lonely. Whilst Van den Berg et al (2015) finds no association at all between loneliness and population density. These studies demonstrate that the academic literature on rurality and loneliness is thoroughly inconclusive, with country specific factors likely influencing any association.

Although an individual's income status is consistently found to be associated with loneliness (see Section 3.6), a couple of studies have investigated the relationship between neighbourhood socioeconomic status and loneliness (Table 10). Scharf and de Jong Gierveld (2008) highlight that socioeconomically deprived areas have a higher incidence of loneliness than non-deprived areas, but they also highlight a considerable local effect, where some areas of similar socioeconomic status are considerably lonelier than others. This suggests that socioeconomic status is an oversimplification, with other local factors such as population turnover, crime rates and the quality of housing also influencing loneliness prevalence at a neighbourhood level.

The effect of an individual's perception of the neighbourhood on loneliness has a stronger academic consensus (Table 10). Two studies use multi-item scales where respondents rate a variety of neighbourhood characteristics, such as perceptions of crime, quality of the urban fabric and general satisfaction with the local area. They find a strong negative association between high perceptions of neighbourhood quality and loneliness (Scharf and de Jong Gierveld, 2008; Kearns et al, 2015). Van den Berg et al (2015), uses a self-reported measure of perceived neighbourhood satisfaction where respondents directly answer a question asking how satisfied they are with the local area. The authors also find a negative association between satisfaction with the local area and loneliness; however, the interpretation of the question is likely to differ by respondents as the question could be understood in terms of neighbourhood integration and reputation, or an assessment of the physical quality of the neighbourhood.

Several studies investigate the relationship between perceptions of neighbourhood integration and belonging with loneliness, all of them find that those who perceive the community to be well integrated or perceive themselves as belonging to the community, are less lonely (Buecker et al, 2020; Dahlberg and Mckee, 2014; Nyqvist et al, 2016; Kearns et al, 2015). Two studies also use objective measures of community integration, with Buecker et al (2020) finding that areas that experience rapid population growth or decline having a higher tendency to loneliness. Deeg and Thomese (2005) use a measure of population turnover (the percentage of migration out of the neighbourhood in a year) and age homogeneity (percentage of residents over the age of 65), although they do not find any association with loneliness, this is likely because the characteristics measured did not differentiate enough across the sample to produce any significant results.

Finally, some studies investigate the relationship between accessible environments and loneliness. Park et al (2020), Domènech-Abella et al (2020) and Rantakkoko et al (2014) all find that areas that are accessible to older individuals, whether that be because of natural features such as flat land and no ice, or usability and accessibility of local amenities and services, show fewer incidence of loneliness. Van den Berg et al (2015) find that those who do not use a variety of transport methods such as public transport, cycling and driving are also lonelier than those who do. Whilst Kearns et al (2015) find that those who report infrequent use of local amenities and leisure facilities report higher prevalence of loneliness. However, the statistical models used to investigate the use of transport, amenities and leisure facilities did not include variables such as frequency of social contact, as such conclusions should not be drawn without further investigation, as it can reasonably be assumed that lack of social contact is contributing to infrequent use of leisure facilities or modes of transport.

The literature on the effect of neighbourhood-level characteristics on loneliness is underdeveloped. Even when studying the local area, variables used often refer to individual perceptions of the local area, and as such could be considered individual-level indicators. It appears that accessibility of the local area and perceptions of area quality and integration are likely to be the characteristics most reliably associated with loneliness, but research in these areas is lacking and poorly defined. Buecker et al (2020) argue that it is likely that neighbourhood influences on an individual's feelings of loneliness are weaker than the influence of individual characteristics.

3.10. Summary of Loneliness Associates

Research that has been conducted into the various individual and neighbourhood predictors of loneliness is rather disparate, there is a large array of characteristics that have been found to be associated with loneliness, although these are often measured in different ways and as such are not easily comparable. The indicators are summarised in Table 11 based on what the prevailing academic opinion is on the characteristic's relationship to loneliness. For several indicators there is no academic consensus as to whether they influence loneliness, these have been placed in the "rarely" category of Table 11. Some indicators are associated with loneliness, but in such a paucity of studies that it is difficult to draw any robust conclusions, these are listed in the "sometimes" category, whilst the "frequently" category comprises those characteristics with a strong academic consensus. This chapter has identified several variables that could be included in the composite index of loneliness at the small-area level. In Chapter 4, multivariate analysis is undertaken using the *Understanding Society* dataset to determine which of these characteristics are independently related to loneliness and should be included in an area-based composite index that predicts the prevalence of loneliness amongst older populations in England.

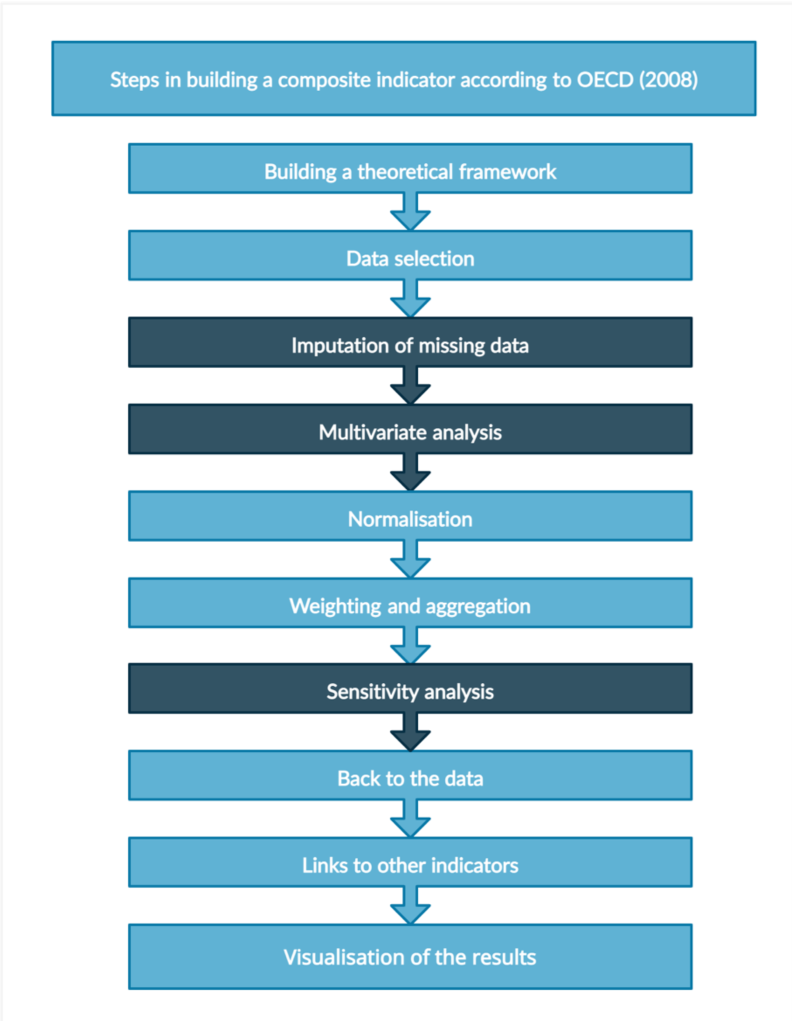
Table 11: Summary table of all the predictors of loneliness that have been identified in the literature and the prevailing academic opinion on their association with loneliness.

Characteristics frequently associated with loneliness	Characteristics sometimes associated with loneliness	Characteristics rarely associated with loneliness
Oldest age	Substance Use	Gender
Ethnic minorities	Provision of informal care	Employment
Migration	Low quantity of social contacts	Education
Single marital status (especially widowhood)	Socioeconomically deprived neighbourhood	Community engagement
Living alone	Poor community integration	Use of the internet
Living in care	Frequent use of amenities and leisure facilities	Rurality
Poor health		
Low income		
Low frequency of social contact		
Low quality of social contact		
Poor subjective evaluation of local area		
Poor perception of community integration		
Poor accessibility of local environment		

Chapter 4. Selecting the Indicators

The next stage in the construction of the index requires that the specific variables for inclusion are identified. Chapter 3 conducted a thorough literature review of characteristics associated with loneliness in older populations that have been included in existing empirical studies. However, the collection of potential variables for inclusion in this index is considerable, and as was shown in the previous chapter, the academic consensus for *some* variables is weak. As such it is necessary to conduct statistical analysis that considers the nature and size of relationships between variables. This will narrow the selection of variables and help to identify specific indicators for inclusion, and later will guide the weighting procedure in Chapter 5. Therefore, this chapter will review a variety of data sources and multivariate analysis will then be conducted to ascertain which indicators are most suitable for the index (Figure 6).

Figure 6: Flowchart outlining the steps that will be addressed in Chapter 4.



This chapter, as with Chapter 5, will also incorporate sensitivity analysis iteratively throughout by reviewing the effects of methodological decisions made on the overall index. Sensitivity analysis is important as value judgements occur throughout the construction process of a composite indicator; this can call into question the robustness of the index (OECD, 2008). The incorporation of sensitivity analysis into the construction process of a composite indicator can improve its structure and transparency (Chan et al, 2000). In this research, sensitivity analysis will mostly take the form of scatterplots and correlation analysis assessing the variance in results of the index when two opposing methodological decisions are taken (e.g. two different sets of indicators or two opposing weighting structures). Observational techniques are also employed to assess the effect of differing spatial granularity between indicators. This process contributes to the requirements of the theoretical framework by ensuring that the construction of the index is clear and transparent. Furthermore, stakeholder advice and the empirical literature will be considered when selecting indicators, this is also guided by the theoretical framework (Chapter 2). Such consultation is important as the purpose of the index is to be meaningful for real word application and thus stakeholder input adds credibility. Stakeholders consulted include the charities Independent Age and the British Red Cross, with consultation taking the form of virtual meetings and a review of initial results. Consultation with stakeholders and consideration of the wider literature was important when considering which variables to include in the index, as complete reliance on a social survey would limit the scope of possible variables for inclusion to those collected in the survey. Variables must be selected based on relevance to the phenomena being measured and not penalised solely because the data is not available (OECD, 2008), thus considering stakeholder opinion and the literature allows for consideration of proxy variables and the construction of a more comprehensive index.

4.1. Identifying data sources

A range of different surveys and data sources that allow for the investigation of demographic, social, economic, and environmental characteristics, and their relationship with loneliness were initially identified and reviewed. This requirement demanded that any survey used had a variable of loneliness, or similar, for such analysis to be conducted. The two main surveys conducted in England that include both a self-reported measure of loneliness and the 3-item UCLA scale are the *ELSA* and *Understanding Society*. Other surveys also include loneliness measures (ONS, 2018) but are focussed on investigating specific societal domains such as travel (National Travel Survey), or physical activity (Active Lives Adult Survey) and hence are not relevant to the context of this research. Both *ELSA* and *Understanding Society* have similar sample sizes in their most recent waves. *ELSA* having 8,736 records in Wave 9, which was conducted in 2018 (Banks et al, 2019). Wave 9 of *Understanding Society,* which took place between 2017-2019, has 8,848 observations once those surveyed under the age of 65 were discarded (University of Essex, 2020).

Age UK attempted to create an index for loneliness using *ELSA* (Iparraguirre, 2016), and whilst there are many useful variables, it does not contain any variables relating to the neighbourhood environment (Banks et al, 2019). As such, *Understanding Society* was chosen for analysis as it contains a broader range of variables across the demographic, social, economic and environmental domains and has not been used to create a loneliness index to date. It would be possible to use both surveys, but using both in parallel has limitations, namely as they both have a different set of respondents, they cannot be combined and thus confounding between variables cannot be investigated.

A logistic regression model was built using the self-reported loneliness measure as the dependent variable. The model is still implicitly bound by limitations of the direct, survey-based method of measuring loneliness outlined in Chapter 2. For example, it has been identified that certain demographic groups are less likely to describe themselves as lonely because it is a stigmatising concept (section 2.3). Therefore, the traits that cause these individuals to be lonelier will not be identified by the model. This is a further justification for being informed by the wider literature and stakeholder input when selecting variables.

The possibility of using the records from *Understanding Society* directly to build the index was explored. However, one of the core requirements that the index must satisfy according to the theoretical framework developed in Chapter 2, is that it is applicable for small spatial units, and specifically, Lower layer Super Output Areas (LSOAs), as desired by stakeholders. Using the 2011 Census geography there are 32,844 LSOAs in England. As noted, Wave 9 of the *Understanding Society* dataset contains only 8,848 records for individuals over the age of 65 in the UK, only 6,640 of which are in England, therefore too few LSOAs are represented in the dataset for it to be used directly to produce the index.

An alternative approach was considered, and this was to use *Understanding Society* with other area data to produce model-based area estimates. Several different estimation techniques were considered with the aim that the variables from *Understanding Society* could be used to create reliable estimates at the small-area level. Iterative Proportional Fitting (IPF) is a common technique used to create area estimates where a sample size is too small, however, it requires a complete population count of the same variable for a different year (Lomax and Norman, 2016), which was not available. A further issue was that the estimates are considered inaccurate if the input data has too many missing values, defined by Norman (1999) as more than 30% of areas. Wave 9 of *Understanding Society* has over 73% of LSOAs in England without a single observation. Thus, it was deemed that IPF was not a suitable tool for creating estimates in this study. A range of other small-area estimation techniques were reviewed, including the multilevel techniques proposed by Twigg et al (2000) and Bayesian methods reviewed in Rao (2008). It was concluded that these methods were too technically and computationally demanding as they would limit the reproducibility of the index by other parties, as well as them being beyond the scope of a one-year research project, thus necessitating the use of data from other more complete sources. Ultimately, it was decided that *Understanding Society* would be used to conduct the multivariate analysis and identify relevant variables, assess effect sizes and inform weighting. However, the data that would be integrated into the index would be gathered from other sources that had more comprehensive national coverage but whose variables reflected those measured in *Understanding Society*. This is the approach taken by Age UK who used *ELSA* to identify variables then sourced the indicators from the Census (Iparraguire, 2016).

Preliminary exploratory analysis was conducted between a range of variables and the self-reported measure of loneliness. These were included in the regression model with variables being dichotomised to reduce the number of categories and avoid issues of small numbers and statistical insignificance. The dependent variable, self-reported loneliness, was dichotomised into feels lonely "often" or "rarely". With those who felt lonely "some of the time" and "often" being combined, whilst those who felt lonely "hardly ever or never" comprised the "rarely" category. The results of the multiple logistic regression are displayed in Table 12. Variables related to loneliness within the model and thus considered for incorporation into the index include being widowed, living alone, not being satisfied with your level of income, categorising your health as fair or poor, having low neighbourhood cohesion, being non-British and smoking. Receiver operating characteristic (ROC) curves were drawn to ascertain the power of those seven indicators in predicting the presence of the dependent variable (self-reported loneliness) when it was applied to the original dataset. The area under the curve (AUC) statistic demonstrates the probability that the model will accurately predict the presence of the dependent variable for a given observation. The regression model presented in Table 12 has an AUC of 0.74 when applied to those over the age of 65 in Wave 9 of *Understanding Society,* suggesting that these seven variables are highly predictive of loneliness in older populations. The subsequent sections in this chapter will present the statistical interpretation of these variables and review them with reference to the literature and stakeholder consideration. Indicators from complete data sources will then be identified for each variable. Finally, this chapter will outline other candidate variables that were omitted from the model and offer justifications for this.

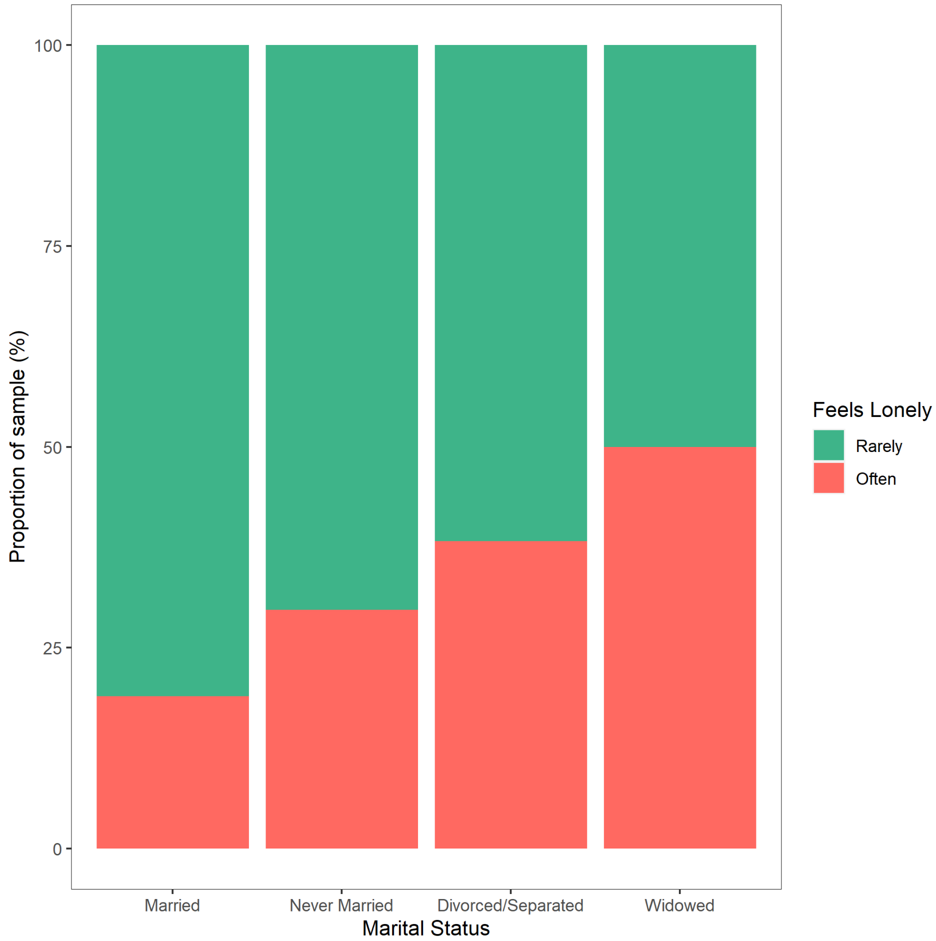
Table 12: Multiple logistic regression model with self-reported loneliness as the dependent variable, using data from Understanding Society.

Dependent Variable: Likelihood of self-reporting as lonely				
Variable	Odds Ratio	CI 2.50%	CI 97.50%	p-values
Intercept	0.04	0.03	0.05	<0.001
Widowhood Status				
No	1			
Yes	2.07	1.8	2.38	<0.001
Household Size				
2+	1			
Alone	2.6	2.29	2.96	<0.001
Income Satisfaction				
Satisfied	1			
Neutral/Dissatisfied	1.89	1.68	2.13	<0.001
Self-assessment of general health				
Good	1			
Fair/Poor	1.86	1.65	2.11	<0.001
Buckner's Neighbourhood Cohesion Instrument	1.59	1.47	1.73	<0.001
Ethnicity				
British	1			
Non-British	1.34	1.12	1.59	0.001
Smoker				
No	1			
Yes	1.45	1.21	1.74	<0.001

4.2. Widowhood

The widowhood variable is derived from the marital status field in *Understanding Society*. Initially, analysis was conducted with marital status as four different categories: married, never married, divorced/separated and widowed. Using four categories was attempted because there is a clear trend where those who are married are the least likely to report loneliness, those who had never married or were divorced were more likely, and widows were the most likely to report loneliness (Figure 7). However, upon inclusion in a multivariate model (Table 12), the never married and divorced categories lost significance and are therefore likely to be confounded with household size, suggesting that incidences of loneliness in these categories are more likely a result of their increased propensity to live alone, and not the characteristic of never marrying or being divorced itself. This was not the case for widowhood, which remained a considerable predictor of loneliness in the multivariate model. As both the data and the literature emphasised the importance of the characteristic of widowhood to the prevalence of loneliness (Wenger and Burholt, 2004; Victor et al, 2005; Savikko et al, 2005; Menec et al, 2019), the decision was made not to omit the marital status category, but to recode it into a widowhood status category, aggregating all other marital statuses. This produced more meaningful results, as seen in Table 12. Data are nationally and readily available on the number of widows over the age of 65 by LSOA in the 2011 Census. This was thus selected as the indicator for the widowhood variable and included in the index.

Figure 7: Bar chart showing the proportion of lonely individuals over the age of 65 by martial category.



4.3. Living Alone

Household size was a continuous variable in the original *Understanding Society* dataset (University of Essex, 2020), and was recoded as: living alone or living with two or more people. This decision was made following the literature which emphasised the impact of living alone on an increased likelihood of being lonely (Routasalo et al, 2006; Victor and Yang, 2012; Ferreira-Alves et al, 2014). However, the research did not distinguish clearly between the likelihood of being lonely in households of two or more people, with few researchers investigating this relationship. In Table 12 living alone remained one of the most consistent and considerable predictors of loneliness, this was also the findings of the empirical literature. Therefore, there is a clear basis for its inclusion in the loneliness index. Data on the number of over 65s who live in a one person household is again nationally available in the 2011 Census, and therefore this indicator was selected for inclusion in the index.

4.4. Variables of Income

There are two measures of income in *Understanding Society*, one is absolute household income, and the other is satisfaction with level of income. The literature suggests that both are covariates of loneliness (Section 3.6) with low absolute household income being among the most consistently agreed upon predictors of loneliness (Burholt and Scharf, 2014). Unexpectedly, statistical models revealed no association between household income and self-reported loneliness. This was initially assumed to be the product of outliers. As Figure 8 shows, the range of observations is large and positively skewed with outliers higher above median household incomes. Therefore, outliers were discarded according to Tukey (1977), where if they are more than three times outside the interquartile range and are considered extreme outliers. The resultant distribution of the data is shown in Figure 9. However, even after outliers had been treated, household income still showed no association with loneliness.

In contrast, the satisfaction with income variable demonstrated a strong association with loneliness in the multivariate model (Table 12). This is an interesting finding that points to the importance of subjective assessments of an individual's personal circumstances as being more indicative of loneliness than objective measures. The conclusion was drawn that satisfaction with income would add value to the loneliness index, operating as the variable that indicates material wealth. However, no dataset in England that contains observations of the number of individuals who are dissatisfied with their income level that is suitable for indexing at the small-area level. Therefore, despite findings reported in this section, absolute income rates were sourced from the ONS at Middle layer Super Output Area (MSOA) and chosen as the indicator to represent material wealth in the loneliness index. This was acceptable to stakeholders and is in keeping with the wider literature that consistently found absolute low household income to be related to loneliness in older populations.

Figure 8: Box plot showing the distribution of values within the absolute household income variable.

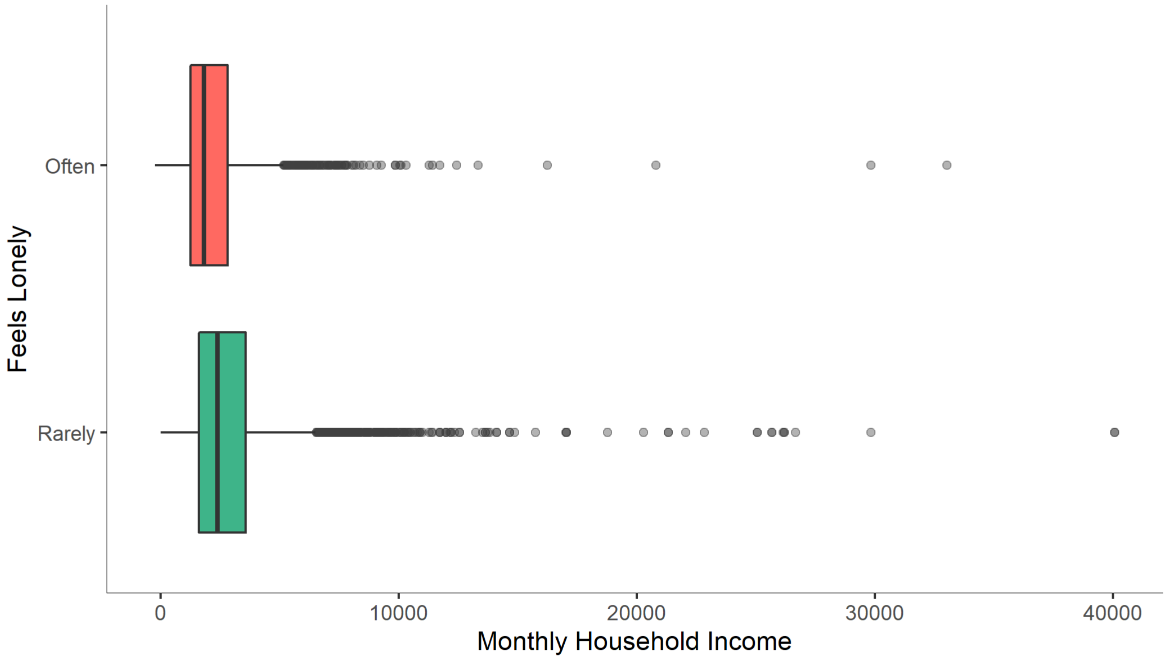
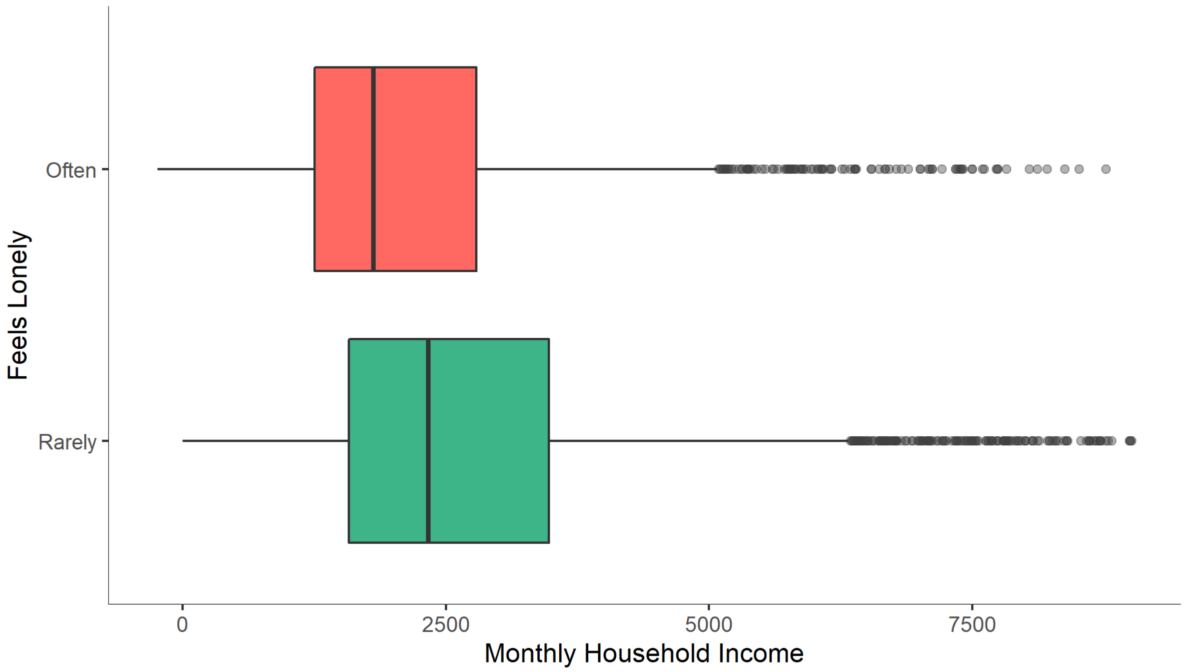


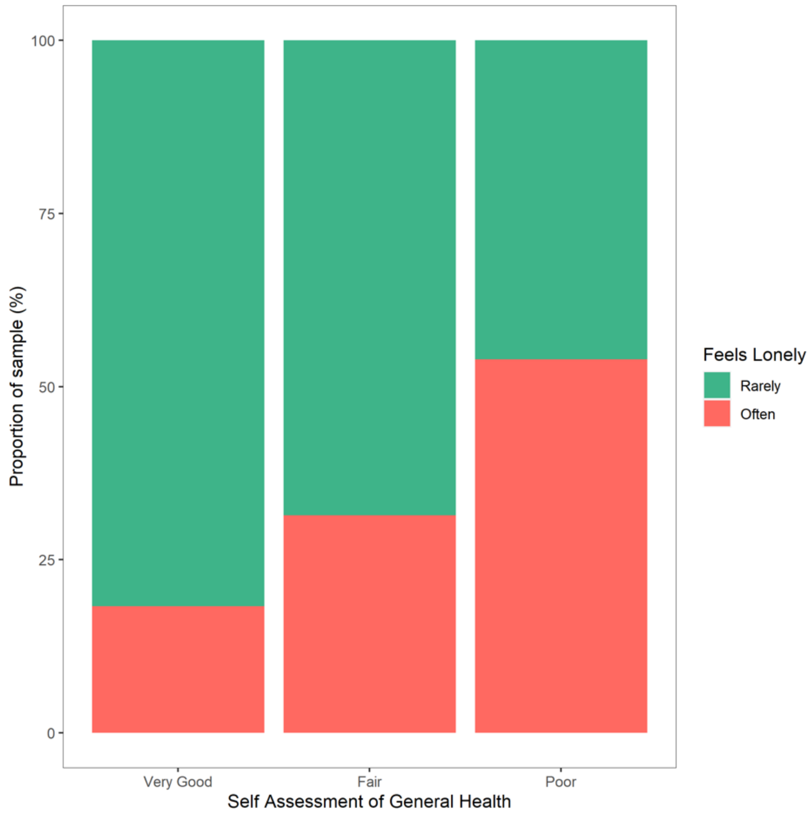
Figure 9: Box plot showing the distribution of values within the absolute household income variable after treatment of outliers.



4.5. Variables of health

There are several health variables included in *Understanding Society*, these include a measure of limiting long-term health issues, a measure of self-assessed general health, a measure of perceived satisfaction with health and a measure of whether someone's physical and mental health has interfered with their social life in the last four weeks. There are also several measures of ADLs.

Figure 10: Bar chart showing the proportion of lonely individuals over the age of 65 by self-assessed general health.



Preliminary bivariate analysis identified self-assessment of general health (Figure 10) and whether a respondent claimed that their health had interfered with their social life in the last four weeks as having the strongest association with loneliness. Sequentially, all variables of health were added into the models and the initial assessment of these relationships was confirmed, showing that the indicators of self-assessment of general health and whether their health had interfered with their social life showed the most considerable effect on loneliness of the different health indicators. Theoretically, these variables are closely aligned to the concept of loneliness as one variable alludes to the impact of health on social life, and the other acts as a summary of all health indicators, such as chronic illness, ADLs and mental health, an approach favoured in the literature (Deeg and Bath, 2003).

ROC curves were used to ascertain the predictive power of the model when both health indicators were included compared to the inclusion of just one health indicator. The results suggested that there was no statistical basis for retaining both variables relating to health in the index as the predicative power of the index was not increased when both were included. The self-assessment of general health variable was retained over the measure of relating to the respondent's social life. This decision was made because there is a strong academic consensus for the inclusion of this indicator (Section 3.5), and because the indicator is available in the 2011 Census. Consequently, the indicator of over 65s who report as having "fair" or "poor" general health is included in the Census and was selected for inclusion in the index.

4.6. Neighbourhood Cohesion

Buckner's (1988) neighbourhood cohesion instrument is an index of subjective neighbourhood cohesion. *Understanding Society* includes a shortened version comprising of eight items covering three dimensions of neighbourhood cohesion as outlined in Table 13. This variable is shown to have a strong association with loneliness (Table 12), where those who responded negatively, displaying a lower sense of neighbourhood cohesion, were found to be more likely to be lonely. Individual indicators of neighbourhood cohesion were also investigated but were found to be less reliable predictors of loneliness.

Table 13: Survey items included in Buckner's Neighbourhood Cohesion Instrument in Understanding Society

Attraction to the neighbourhood

- Plans to remain a resident of the neighbourhood for several years

Neighbouring relations

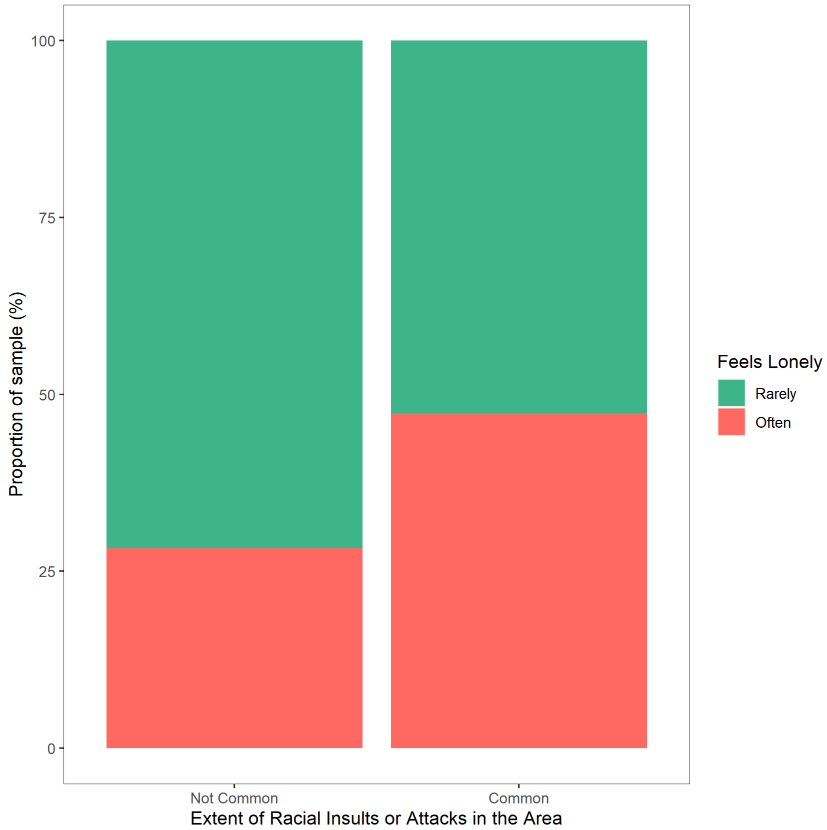
- Can borrow from and exchange favours with neighbours
- Can ask for advice from neighbours
- Regularly talks to people from the neighbourhood

Sense of community

- Perceives themselves to be similar to others in the neighbourhood
- Feels as though they belong to neighbourhood
- Friendships with neighbours mean a lot to respondent
- Would work together to improve neighbourhood with others.

The literature has shown that neighbourhood factors are not as considerable predictors of loneliness as individual characteristics (Buecker et al, 2020). However, many researchers have shown a relationship between loneliness and factors such as a sense of community (Nyqvist et al, 2016), attraction to the neighbourhood (Kearns et al, 2015) and neighbourly relations (Buecker et al, 2020), and therefore it should not be overlooked in the construction of a loneliness index.

Figure 11: Bar chart showing the proportion of lonely individuals over the age of 65 by perceived frequency of racially aggravated insults or attacks in the local area.

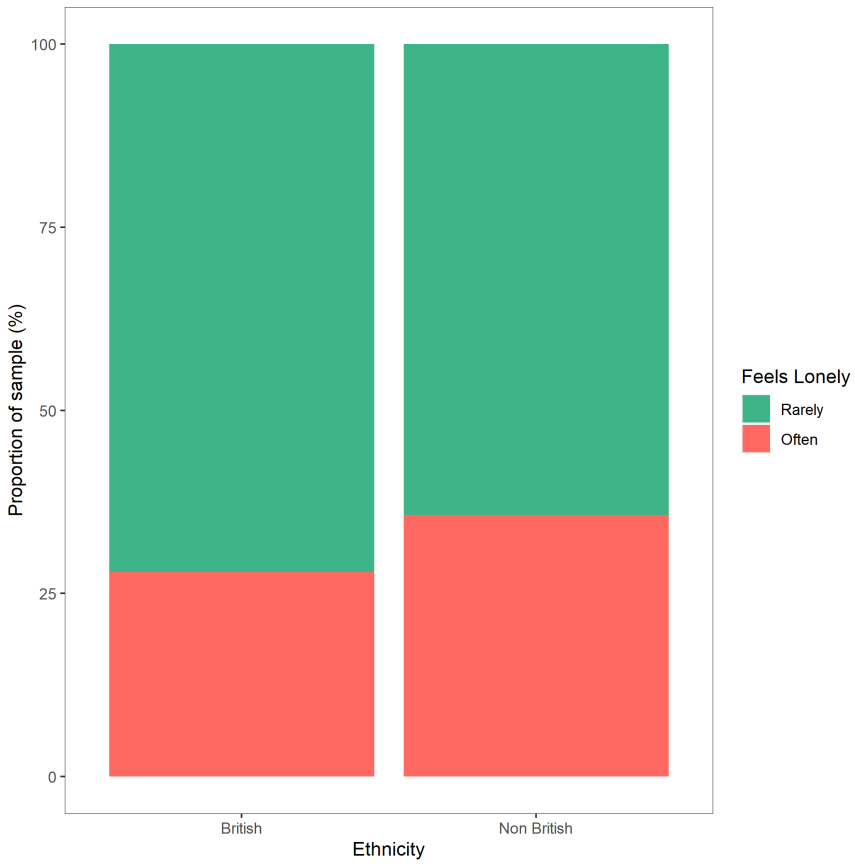


However, Buckner's Neighbourhood Cohesion Index is not available in datasets with full national coverage at the small-area level in England. Therefore, it cannot be included directly in the composite index. It was still considered important to include a measure that reflected community cohesion, and so stakeholders were consulted. Stakeholders were presented with a variety of potential proxy variables to represent low neighbourhood cohesion, including high rates of population turnover and low percentage of individuals over the age of 65 in the neighbourhood. Stakeholders lacked enthusiasm for many of the variables suggested but showed broad support for the inclusion of one indicator: high rates of hate crime. Furthermore, the survey data revealed a strong association between those who were lonely and those who reported that their neighbourhoods had high rates of racially aggravated incidents (Figure 11). There is also a strong relationship between Buckner's Neighbourhood Cohesion Index and the perception that racially aggravated incidents are frequent in the local area within the survey data. Those who reported low neighbourhood cohesion were 2.27 times more likely to report high rates of racially aggravated incidents than those who reported high neighbourhood cohesion (OR = 2.27, p = <0.001). Statistics on hate crimes are available from the Home Office for 2019 at the police area level, data for Greater Manchester is missing, and was imputed using hate crime statistics from the same area for 2018. Each LSOA was assigned the rate of hate crime for the police area in which it is located.

4.7. Ethnicity

In the literature, belonging to an ethnic minority is consistently found to be associated with loneliness (Section 3.3). Initially, the ethnicity variable was coded into several categories to assess the relationships between loneliness and a variety of different ethnic minority communities in England, as differences were found by Victor et al (2012). However, these categories yielded statistically insignificant results due to small sample sizes. Consequently, the variable was dichotomised into "British" and "Non-British". This variable was shown to be only weakly associated with loneliness (Figure 12) but was statistically significant within the multivariate model (Table 12). The theoretical basis for its inclusion in the index is robust, and therefore the variable was retained in the model.

Figure 12: Bar chart showing the proportion of lonely individuals over the age of 65 by ethnicity.

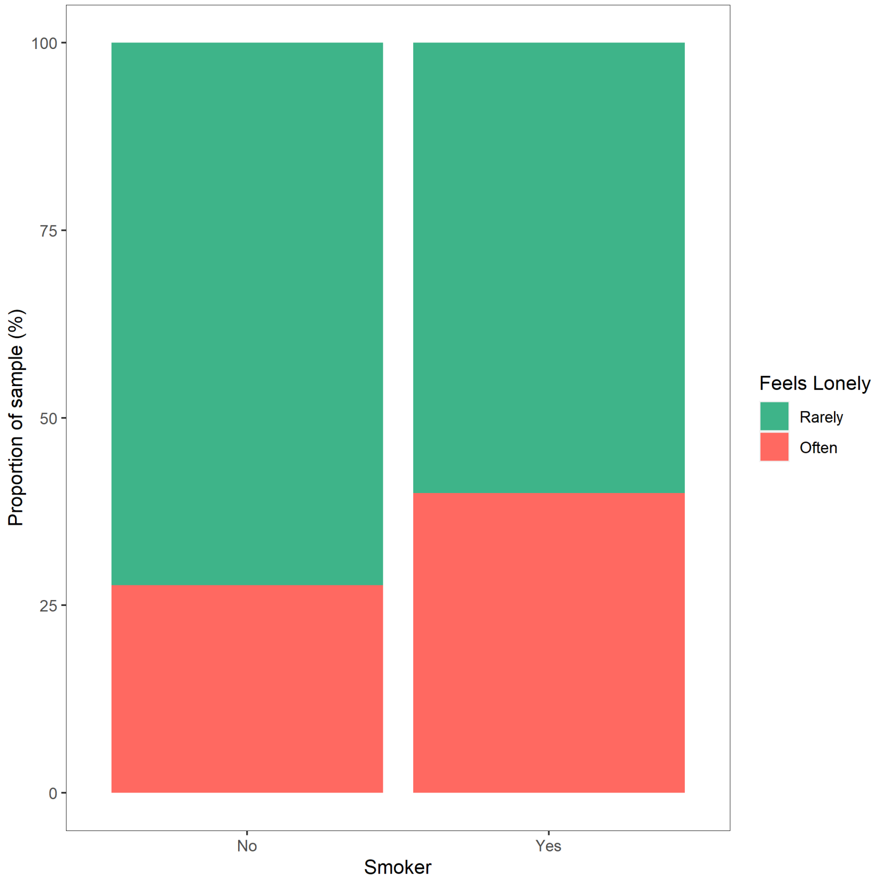


During stakeholder consultation, the importance of English language ability over ethnicity was emphasised. Stakeholders were concerned that using the variable of ethnic minority may limit the value of the index in areas with a high proportion of ethnic minority populations. This alludes to the findings of Victor et al (2012) who proposed that different settlement patterns amongst certain ethnicities may negate feelings of loneliness induced by being a minority. Furthermore, there was a theme in the literature that found that national language ability had a strong relationship with loneliness (Wu and Penning, 2015; de Jong Gierveld et al, 2015). *Understanding Society* does not include English language proficiency data for all participants and thus was not analysed in the regression model. However, heeding stakeholder advice, as well as considering the wider literature, English language ability was substituted for ethnicity and included in the index, with data available for those over the age of 65 in the 2011 Census by LSOA.

4.8. Smoking

As Table 12 shows, the model estimate for smoking is statistically significant and a considerable predictor of loneliness. The theoretical basis for its inclusion in the loneliness index is less robust than some of the previously reviewed characteristics. The literature has identified that smokers are more likely to be lonely than non-smokers (Aylaz et al, 2012). Whilst the survey data also finds this association (Figure 13). However, the direction and reason for this relationship is poorly understood. It is unknown whether being lonely is causing people to smoke, or their loneliness is a product of their smoking, or whether smoking is merely representing some other unidentified characteristic (Aylaz et al, 2012). Stakeholders expressed scepticism over the inclusion of this variable, suggesting it was likely to be representing socioeconomic factors such as health or income levels. However, smoking was found to be independently related to loneliness within the model (Table 12), even when variables relating to health and wealth were controlled for. Moreover, the purpose of the new index is to locate the neighbourhoods that contain the highest concentration of lonely older people and not the precise causes of their loneliness. Therefore, even though it is likely that smoking is acting as a proxy variable for another latent characteristic, it does increase the predictive power of the index. The ONS produces estimates on the percentage of adults who smoke by local authority. These were incorporated into the index, with LSOAs being assigned the same percentage as the local authority they sit within.

Figure 13: Bar chart showing the proportion of lonely individuals over the age of 65 by smoking status.



4.9. Informal care provides

Stakeholders believed informal care providers deserved a dimension in the index. This is a variable that was highlighted in the literature as being associated with loneliness (Wenger and Burholt, 2004), however, it was not represented in *Understanding Society* and thus could not be statistically analysed. The theoretical framework advised that the index should be comprehensive and descriptive. Furthermore, the OECD (2008) advise that the inclusion of variables should not be solely reliant on data as this could unfairly penalise those domains where data is not available. Further investigation revealed that research conducted by several charities that were not directly consulted had also found that informal caregiving increased an individual's propensity to be lonely. These included reports by The Campaign to End Loneliness (Goodman et al, 2015), Age UK (Davidson and Rossall, 2015) and Carers UK (2017). Following stakeholder advice and the findings in the wider academic and charitable literature, 2011 Census counts on the number of informal care providers over the age of 65 were included in the index. However, recognition that this variable was included without primary statistical evidence is considered at the weighting stage (Chapter 5), as advised by the OECD (2008).

4.10. Omitted variables

Table 14 summarises the key variables that are commonly associated with loneliness in the literature but were omitted from the index after further analysis. The second column offers a brief rationale for their omission.

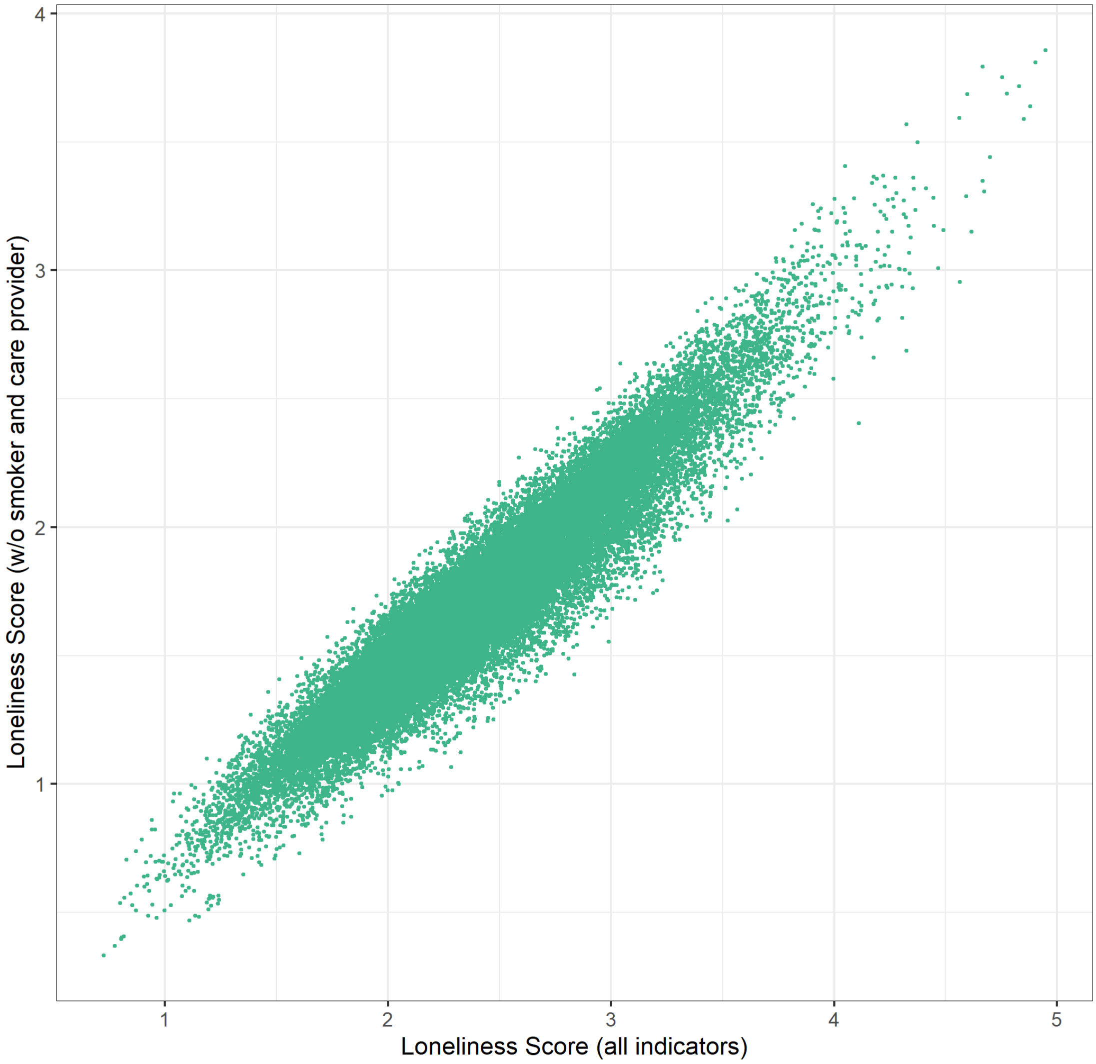
Table 14: Variables omitted from the index after data analysis and stakeholder consultation.

Variable	Reason for omission
Oldest age	No relationship found when other social characteristics were controlled for.
Being female	This did have an effect in the multivariate analysis. However, literature lacks academic consensus on the relationship between sex and loneliness, and stakeholders did not support its inclusion in the index.
Number of close friends	Variable did not have an effect on loneliness in the multivariate analysis. Variable had an irregular distribution, and the survey question was somewhat arbitrary, with no common understanding of what constitutes a “close” friend.
Educational Attainment	Educational attainment appeared to be confounded with household income in the survey data, this is a finding also highlighted in the literature.
Number of journeys taken	Stakeholders proposed this indicator to represent activity and frequency of social contact. No data is available on the travel patterns of over 65s at the area level, so it could not be included.

4.11. Validating the Variables

Most of the variables selected for inclusion were identified following statistical analysis and then validated by consulting with stakeholders. Two of the variables selected require further consideration. Firstly, the smoking variable was met with a degree of scepticism by stakeholders, and secondly, the informal care providers variable was only included based on stakeholder opinion and the wider literature, and not statistically analysed. Therefore, sensitivity analysis was conducted to ascertain whether either of the two variables would exert too much influence on the index and therefore require further analysis and possible omission. The sensitivity analysis involved constructing two indices, one included all the variables selected for inclusion in sections 4.2 – 4.9, and the other omitted the variables of smoking and informal care provision. They were constructed using the min-max normalisation techniques, equal weighting and a simple linear aggregation (see Chapter 5). The two indices were then plotted against each other with the results shown in Figure 14. The plot demonstrates that the two methods display a strong correlation ($r = 0.96$, $p= <0.05$), which means that the inclusion of the smoking and informal care providers variable are not overly distorting the results of the index. The variables were therefore retained on the justification that stakeholders and the literature have emphasised the wide variety of causes of loneliness in older populations and therefore the theoretical framework favoured the creation of a comprehensive and descriptive index over a more parsimonious index.

Figure 14: Scatter plot showing the influence of the informal care provider and smoking variables on the overall index.



4.12. Summary of indicators

The final collection of variables that have been identified for inclusion in the index according to statistical analysis on national survey data, the empirical literature, and stakeholder consultation, are summarised in Table 15. The table also indicates the spatial level at which the data is collected, the age groups that the data are applied to, the source of the data, the year in which it was collected and with relevant citations. The next chapter reviews different normalisation, weighting and aggregation techniques and then selects appropriate methods, this will produce the final index.

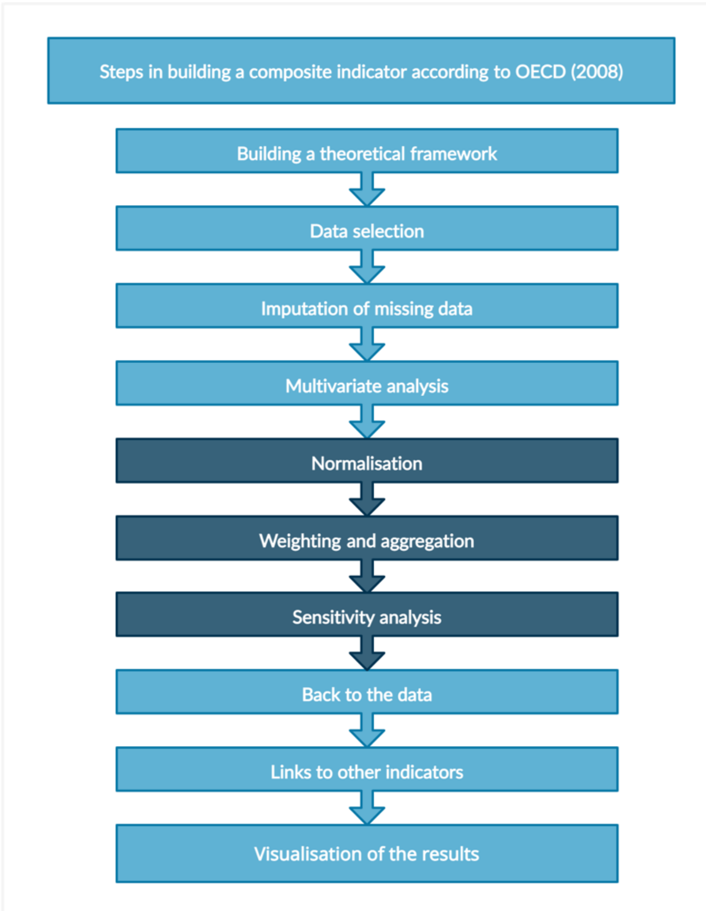
Table 15: Indicators selected for inclusion with metadata

Variable	Age group	Spatial level	Source	Year	Citation
Being widowed	Over 65s	LSOA	Census	2011	(ONS et al, 2016)
Living Alone	Over 65s	LSOA	Census	2011	(ONS et al, 2016)
Poor or fair self-assessed general health	Over 65s	LSOA	Census	2011	(ONS et al, 2016)
Poor English language ability	Over 65s	LSOA	Census	2011	(ONS et al, 2016)
Informal care provider	Over 65s	LSOA	Census	2011	(ONS et al, 2016)
Low household income	All households	MSOA	ONS	2018	(ONS, 2020)
High prevalence of smoking	Over 18s	Local Authority	ONS	2018	(ONS, 2019)
High rates of hate crime	All age groups	Police Area	Home Office	2019 (2018 for Greater Manchester)	(Home Office, 2020; 2019)

Chapter 5. Normalisation, Weighting and Aggregation

The previous chapter identified the specific indicators of loneliness in older populations that will be incorporated into the index. It is now necessary to begin the construction process. This involves processing the data so it is fit for aggregation and then collating it into a single index. Specifically, this chapter will outline the steps taken in normalisation (Section 5.1), weighting (Section 5.2) and aggregation (Section 5.3) (Figure 15). The key arguments and approaches in the literature for each step will be reviewed before deciding upon an appropriate method. Methodological decisions will be made with reference to the theoretical framework and the structure of the data being incorporated into the index. Sensitivity analysis will be conducted to provide validation and transparency for the effects of methodological decisions made on the results of the index.

Figure 15: Flowchart outlining the steps addressed in Chapter 5.



5.1. Normalisation

The indicators selected for inclusion are expressed in different forms and on different numerical scales. Some are percentages, others are expressed as an average, and some are raw counts. For the purposes of aggregation, raw counts must be converted into percentages to ensure that the size of spatial units is not influencing the index scores. For example, for each LSOA, the number of widows was divided by the total number of inhabitants in that LSOA and multiplied by 100. This calculation was completed to ensure that all data for LSOAs, MSOAs, local authorities and police areas were not implicitly weighted in the final index dependent on the size of their population. Following the deriving of percentages, normalisation was applied to ensure all variables were expressed on the same numerical scale. This process ensures that any one indicator was not given an implicitly higher weight simply because it had higher values. For example, the widowhood variable is measured as a percentage and therefore cannot have a value greater than 100, whilst average monthly household incomes are measured in Great British Pounds (£) and thus have much larger raw figures. If not normalised onto the same numerical scale, upon aggregation the household income variable would have a much greater influence over the index. The OECD (2008) handbook suggests three main methods of normalisation, all of which are also well explored in academic literature, as presented in subsections 5.1.1 to 5.1.3:

1. Ranking
2. Z-Scores
3. Min-Max

The advantages and disadvantages of these three separate methods will now be considered.

5.1.1. Ranking

Ranking is the simplest normalisation method. In the context of this research, it would assign each LSOA a rank between one and 32,844 for each indicator presented in Table 15, where one would represent the score with the highest propensity for loneliness. A key drawback of this method is that it loses the absolute data (Saisana and Tarantola 2002), that is, the LSOA ranked in the first position has a “worse” score than the LSOA ranked in the second position, but it would not indicate how much worse the score is. In other words, information is lost as values move from a ratio to a strong ordinal scale of measurement. It is argued here that for the purpose of measuring loneliness, the retention of absolute data is of high importance, as some of the characteristics measured are highly concentrated in certain areas. For example, poor English language proficiency is highly concentrated in cities such as Leicester, where in one neighbourhood there are 14.78% of over 65s who speak little or no English. However, 98.17% of English LSOAs have less than 2% of their populations who speak little or no English. It is necessary to allow these extreme values to be represented to identify loneliness hotspots, where ranking would result in a levelling off within the data so that the index would not as clearly distinguish those areas at extreme risk. Therefore, ranking was not deemed an appropriate method of normalisation for this research.

5.1.2. Z-Scores

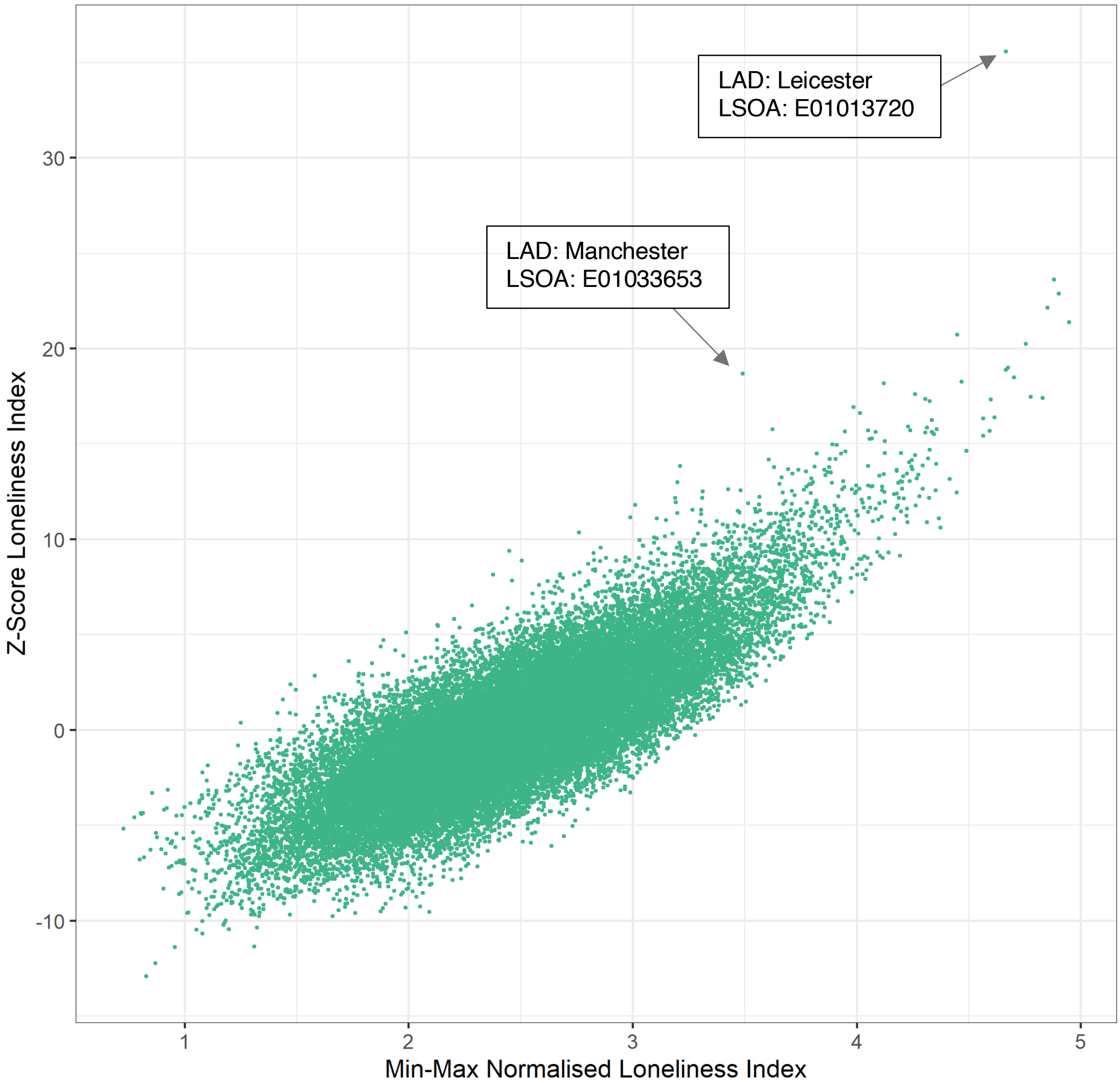
Z-scores are one of the most widely used normalisation techniques. Z-scores convert each indicator onto a common scale such that it has a mean of zero and a standard deviation of one (Senior, 1991). The scale is then measured in standard deviations, such that a Z-score of two would represent an LSOA with conditions two standard deviations higher than the mean for a given variable. Z-scores result in indicators with extreme values exerting greater influence on the indicator (OECD, 2008). For the purposes of measuring loneliness, this could be problematic. Returning to the example of English language proficiency, the same LSOA in Leicester that has 14.78% of its older residents who do not speak good English would have a Z-score of 27.87. However, the highest Z-score for average income (i.e. the LSOA with the lowest average income) would be 2.32 for a neighbourhood in Humberside. The smaller score is a result of a smaller range of values in the income indicator, compared to the English language indicator which has a large range and is highly skewed. This means that the extreme values in the language ability indicator are further from the mean than the extreme values in the income indicator. When aggregated, this would cause English language proficiency to have a higher influence on the overall indicator, even though this research has found that the average income indicator is considered more important to the concept of loneliness in older populations than language ability (Chapters 3 and 4). This could be fixed by applying weights before the aggregation stage; however, using weights to account for skewed data adds another uncertainty into the weighting stage of construction, a process that is already criticised as being somewhat arbitrary (Greco et al, 2019). Moreover, a measurement unit of standard deviations is not particularly intuitive to the general public which may inhibit interpretation and usability of the index.

5.1.3. Minimum-Maximum (Min-Max)

The min-max form of normalisation (also regularly referred to as scale normalisation or feature scaling) converts all scores onto a sliding numeric scale from zero to one by subtracting the minimum value and then dividing by the range, where the area with the “worst” score for a given indicator is assigned a value of one, and the “best” a value of zero (OECD, 2008). The method is still vulnerable to outliers, for example, the same neighbourhood in Leicester as described above would have a min-max value of 1 for the English language proficiency indicator, whilst the nearest score is 0.59 for a neighbourhood in Manchester. However, the method is not vulnerable to the differing distribution of values across indicators, it will not offer greater influence in the final index to those indicators that have larger ranges or are highly skewed, as the maximum value will always be one. Furthermore, min-max normalisation also maintains the absolute information that the ranking system does not as it is still expressed as a ratio. Lastly, working on a scale of zero to one is easily interpreted by any user, and this is particularly important when creating public-facing applications and encouraging their replication and updating. For these reasons, the min-max method was chosen as the preferred method of normalisation.

For the purposes of robustness, sensitivity analysis was conducted to ascertain the influence of using the min-max normalisation methods instead of Z-scores on the results of the index. All indicators were given an equal weighting (see Section 5.2) and linearly aggregated (see Section 5.3), however one index was normalised using Z-scores and the other using min-max normalisation. The results of this analysis are displayed in Figure 16. The plot exhibits a strong correlation ($r = 0.81$, $p = <0.05$) between the two normalisation methods. However, it also demonstrates the influence that the highly skewed indicators, such as English language proficiency, can have on the overall index. For example, the two aforementioned neighbourhoods in Leicester and Manchester with highest rates of poor English language proficiency are highlighted in Figure 16. They are shown to have a higher risk of loneliness using the Z-score normalisation compared to the min-max method. The other variables included will also be exerting more or less influence on the composite indicator normalised by Z-scores based on their distributions and skewness. Therefore, this analysis reaffirms the decision to use the min-max method which is not so vulnerable to skewness and is more readily interpretable by users.

Figure 16: Scatterplot showing the relationship between the index when opposing normalisation methods (Z-scores or min-max normalisation) are applied.



5.1.4. Reviewing the distributions and polarity

Choosing the min-max normalisation method required a review of the distribution of the values within each indicator to ensure that outliers were not exerting undue influence and distorting the scores of other observations. One problem was highlighted in the rates of hate crime indicator. The issue was in the City of London, which is a separate police area from Greater London. In the earlier stages of normalisation, the number of hate crimes in each area was divided by the number of people who reside in the area to derive a percentage, this led to the allocation of a much higher hate crime score for the City of London compared to the rest of the country. This is because very few people actually live in the City and the increased crime rate is associated with the daytime working population. The higher rate for the City of London distorted the scores for the other Police Areas in England and did not allow for the variance between them to be well represented

(Figure 17). The City of London was therefore assigned the same hate crime rate as the Metropolitan Police Area to remedy the issue, the resulting distribution of scores is summarised in Figure 18.

Finally, the polarity of the indicators had to be reviewed. For all indicators, a higher value is equal to a score that represents an increased risk of loneliness, except for the household income indicator, where a higher average household income is equal to a reduced chance of loneliness. To correct this, the normalised household income scores were subtracted from 1, so that a score of 1 represented the neighbourhood with the lowest average household income and 0 represented the neighbourhood with the highest average household income. With the normalisation process complete, the subsequent sections of this chapter will discuss the process of weighting and aggregation to complete the construction of the index.

Figure 17: bar chart showing the rate of hate crime scores by Police Area before treatment for outliers.

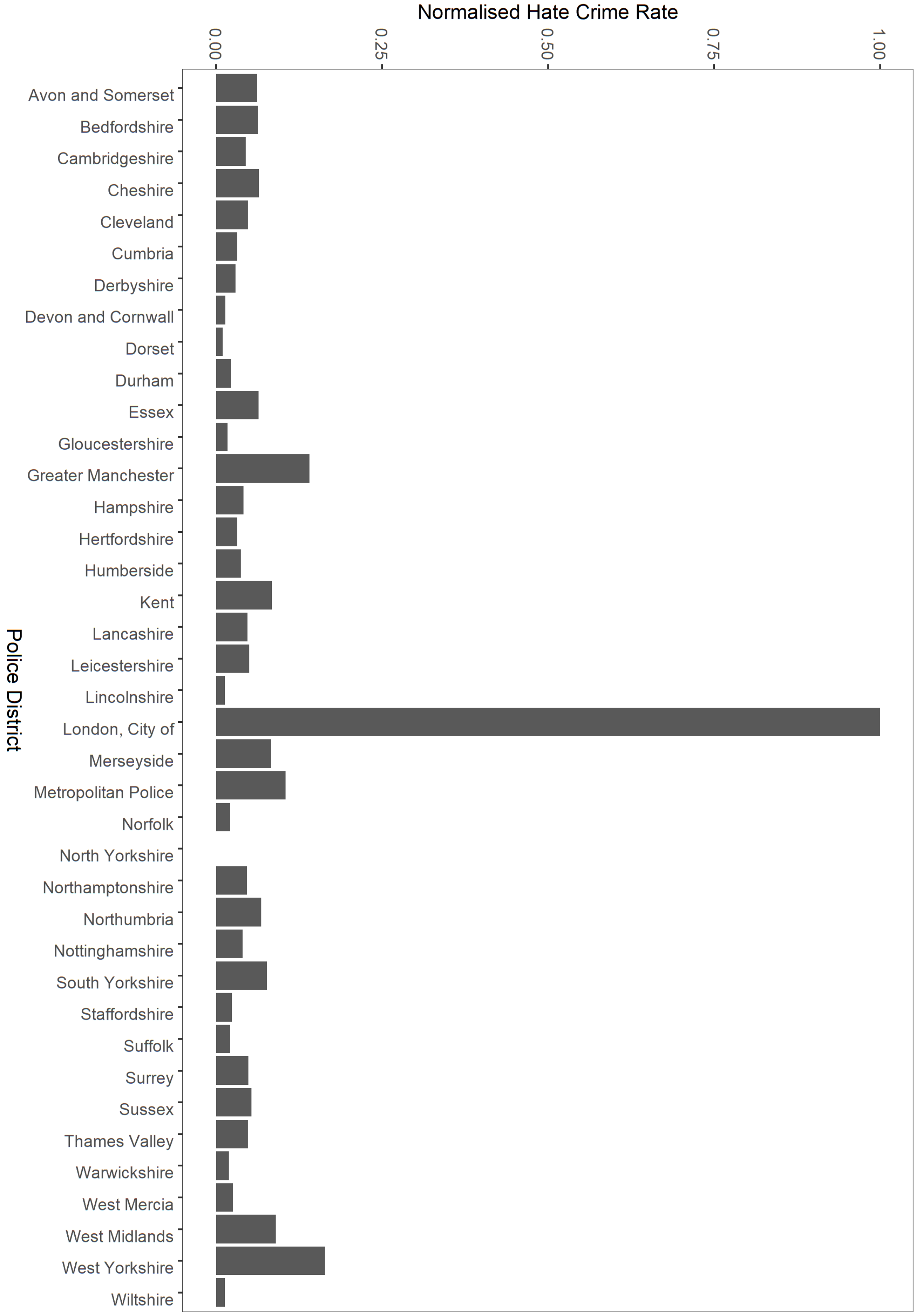
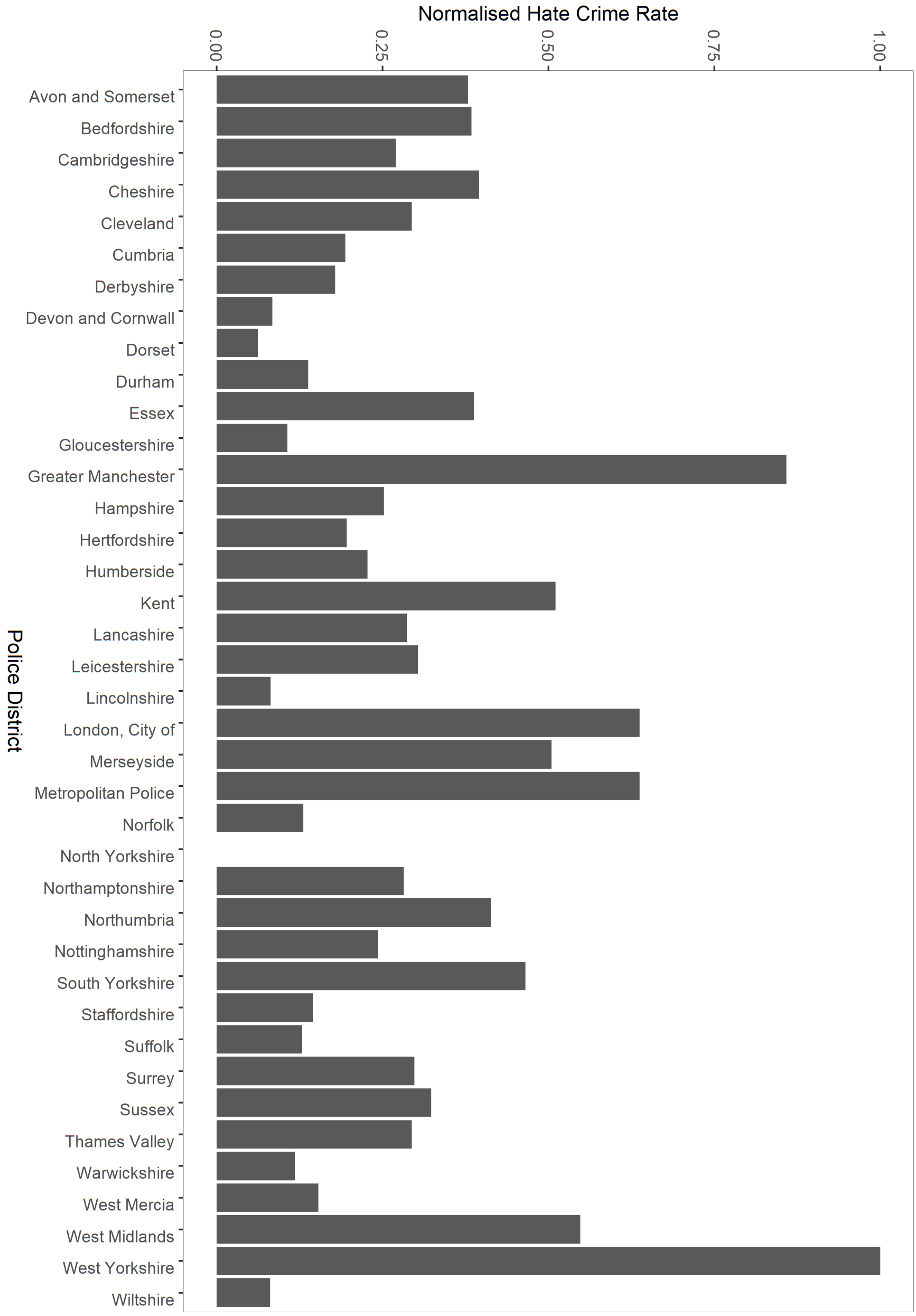


Figure 18: bar chart showing the rate of hate crime scores by Police Area after treatment for outliers.



5.2. Weighting

This section will review the advantages and disadvantages of applying weights to the different indicators before aggregating them into a composite index. It will then decide upon an appropriate weighting method based on the nature of the indicators being incorporated and the theoretical framework that was outlined in Chapter 2.

5.2.1 Different approaches to weighting

All weighting applied in the construction of composite indicators involves value judgements (OECD, 2008). The most common approach is to not apply weights at all, however, to do so implicitly assigns equal weighting to all indicators (Bandura, 2008). This approach is often favoured for its simplicity; where there is a lack of theoretical, stakeholder, or statistical evidence to justify a weighting structure; or because of its alleged objectivity (Maggino and Ruviglioni 2009; Decancq and Lugo 2013). However, there are major criticisms of this approach. Favouring equal weighting over a weighting structure that is grounded in sound theoretical or methodological justifications is a considerable concession in the name of simplicity (Paruolo et al. 2013). Other commentators argue that it does not achieve objectivity either, as it is an equally subjective decision to applying specific weights (Mikulić et al, 2015). Whilst an equal weighting approach also ignores the fact that many indicators will include some essential variables and some which are more peripheral to the concept being measured (Greco et al, 2019). Such arguments led Chowdhury and Squire (2006, p. 762) to conclude that equal weighting is *"obviously convenient, but also universally considered to be wrong"*.

Other indices have derived weights from statistical analysis, an example includes the IMD in England (McLennan et al, 2019). It is argued that this is a more objective approach as it does not depend on the subjective evaluation of the researcher (Zhou et al, 2007). However, this approach is not without criticism. Commentators have pointed out that an index constructor should be cautious of taking statistical outputs as fact, as an association between a set of indicators does not always represent a true relationship as confounding factors and proxy variables may be present (Decancq and Lugo, 2013; Saisana and Tarantola, 2002).

Some commentators also stress how it is advisable to consider data quality during the weighting process, with higher quality (and hence more reliable) data being assigned more importance (Freudenberg, 2003). However, this penalises those indicators that are harder to measure, without accounting for the theoretical value of a given indicator towards the construct that a researcher is trying to measure (Greco et al, 2019). Finally, some researchers favour participatory methods, using expert and stakeholder opinion to distinguish which variables are most important to a given phenomenon. The use of stakeholders in the weighting process is a conventional way to ensure transparency and justify subjective decisions (Greco et al, 2019). There is no one-size-fits-all solution to the problem of weighting in the construction of composite indicators, it is up to the developer to decide which is most appropriate for their index based on the theoretical framework (OECD, 2008).

5.2.2. Applying weights

For the concept of loneliness, it does not seem sensible to take an equal weighting approach when considering the variables that have been identified, as some are more central to the concept of loneliness than others. For example, the statistical and theoretical basis for including variables such as high rate of smoking in a particular area is less robust than including a measure of whether a person is widowed or lives alone. It is important therefore that this is reflected in the index. Research in Section 4.1 has already generated odds ratios (OR) for most of the indicators being used through multivariate logistic regression. Deriving weights from regression analysis has a precedent in the construction of composite indicators and is used in the National Innovative Capacity Index (Porter and Stern, 2001). The OR is a coefficient that represents the importance of each variable towards the concept of loneliness.

Table 16 presents the weights for each variable, this was assigned following consideration of the OR for each variable, stakeholder consultation and the quality of the input data, thus using a multi-criteria approach by combining statistical weighting with participatory methods and consideration of data quality. It should be noted that for the proxy/substitute variables of poor English language ability, low household income, and high rates of hate crime, the OR given is in fact for the variable that they are replacing, i.e., having a non-British ethnicity, being dissatisfied with your level of income, and living in a neighbourhood that has a low Buckner's cohesion score. The variable of informal care provider has no OR as it was not included in the survey data. The process that led to the selection of the specific weights will now be described.

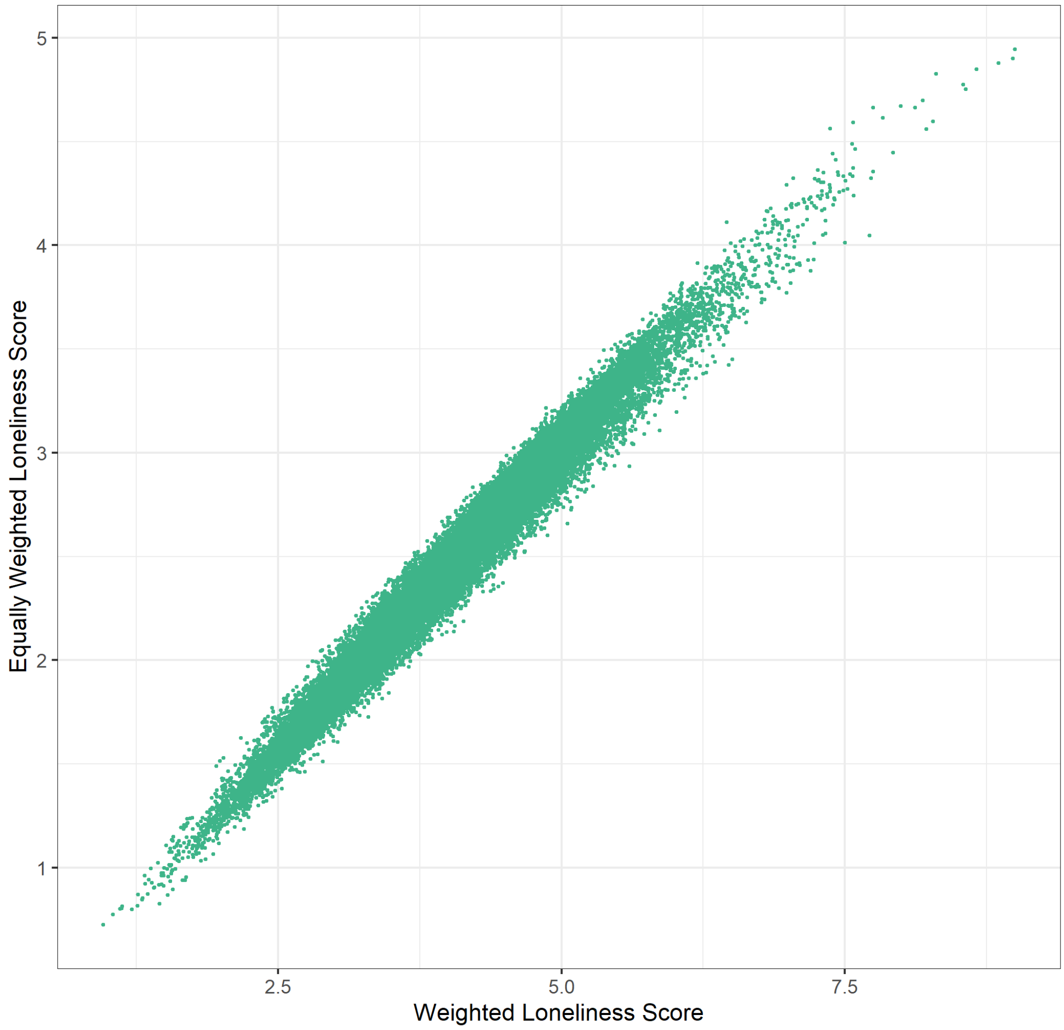
Table 16: Indicators selected for inclusion with assigned weight

Variable	OR	Adjusted weights	% of Composite Indicator
Living Alone	2.6	2.6	21.2%
Being widowed	2.07	2.07	16.9%
Low household income	1.89	1.89	15.4%
Poor or fair self-assessed general health	1.86	1.86	15.1%
Poor English language ability	1.34	1.34	10.9%
High prevalence of smoking	1.45	1	8.2%
Informal care provider	N/A	1	8.2%
High rates of hate crime	1.59	0.5	4.1%

There are a few methodological issues that are encountered from simply taking the OR at face value and using these as weights within the index. Firstly, they are derived from a closed statistical model, as the literature cautioned, it is important not to simply consider statistical outputs as fact (Decancq and Lugo, 2013; Saisana and Tarantola, 2002). Secondly, the dependent variable used for the regression model was self-reported loneliness, as discussed in Chapter 2, this method is subject to several conceptual limitations. Finally, stakeholder input has added the provision of informal care variable that has no OR and highlighted concern about the smoking variable. Therefore, value judgements are required to account for these issues, with these value judgements reflected in the weights presented in Table 16 and the rationale for the adjustments given below.

In the absence of any robust information to assign a greater or lesser weight to the informal provision of care indicator, it is assigned a default weight of one, implicitly giving it one of the lowest weights in the index. Similarly, the theoretical basis for the variable of smoking is not profound, no causal relationship has been established, and stakeholders expressed a degree of reservation over its inclusion. Therefore, the smoking variable is also assigned a weight of one. Lastly, the high rates in the hate crime variable were problematic as this variable is collected at the coarse geographical level of police areas. The variable gave too much emphasis to the LSOAs that sat within Greater Manchester and West Yorkshire, the police areas with the highest rates of hate crime. Loneliness index scores were clustering around police areas due to the coarse geography, given there is no theoretical justification that suggests that an individual's propensity to be lonely is influenced by the police area they reside in, it was clear that this was a methodological issue influencing the index. However, the variable was supported for inclusion by stakeholders, and it is theoretically important to retain a variable relating to the neighbourhood environment. Consequently, due to the poorer quality of the data, as advised by Freudenberg (2003), the variable of high rates of hate crimes was reweighted to 0.5 to give it the least influence on the overall index due to the lack of granularity that it offers. As a further means of sensitivity analysis, Figure 19 shows the influence that the weighting structure has on the overall composite index compared to if equal weighting was applied using a simple linear aggregation. Although the two methods display a high degree of correlation ($r = 0.98$, $p = <0.05$), the resounding support in the literature for an evidence-based weighting system suggests the weights should remain in place to create a more accurate measure of loneliness.

Figure 19: Scatterplot showing the relationship between the index scores by LSOA using equal weighting and the weighting structure presented in Table 16.



In summary, the literature expressed the view that applying equal weights (i.e. not applying weights at all) is conceptually flawed, this index has therefore derived weights from statistical analysis, but adjusted them for stakeholder opinion and based on the quality of the data that is being incorporated. Finally, the indicators are now ready for aggregation into a single index.

5.3. Aggregation

Following the processes of normalisation and weighting, the indicators must be aggregated into the composite index. There are several means of aggregation that will be reviewed here. As with the previous sections in this chapter, a method of aggregation will then be decided upon and sensitivity analysis will be conducted to ensure the robustness of the methodological decisions and offer transparency.

5.3.1. Approaches to aggregation

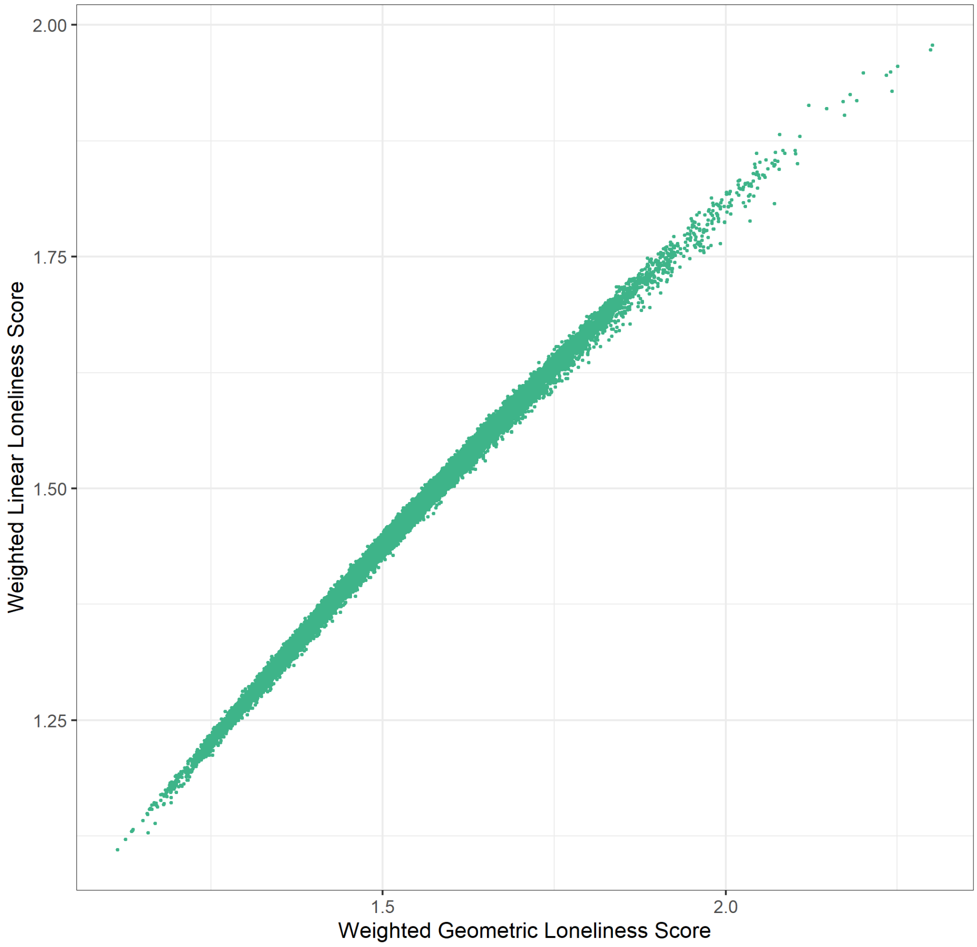
According to OECD (2008) guidance, there is one broad theme to be considered when aggregating indicators: compensability. In this instance, compensability refers to the amount that a low score in one variable can be compensated for by a high score in another variable. Methods that allow for varying degrees of compensability include a linear and a geometric approach. Non-compensatory methods are more technical and often computationally demanding (Greco et al, 2019). A non-compensatory approach is desirable when different dimensions of the same composite index differ greatly. For example, a sustainability index may include economic, social and environmental dimensions, where an analyst may decide that sound economic performance cannot compensate for declining social or environmental conditions (Munda, 2012). The OECD (2008) find that non-compensatory approaches are not particularly popular and suggest that one of the reasons for this is their complexity and high computational costs. Munda (2012) finds that the non-compensatory approaches have a large influence on those units ranked in the middle positions, however, those with the highest and lowest scores tend to remain similar compared to when compensatory approaches are used. For the purposes of this project, a degree of compensability is admissible. All variables included are socioeconomic in nature, and it is reasonable to assume that, for example, having a vulnerability to loneliness through poor health can be ameliorated by marriage and high income. Furthermore, the theoretical framework outlines the aim of the index as identifying those places at highest risk of loneliness and is less concerned with those neighbourhoods in the middle positions. Finally, the more technical non-compensatory approaches may limit the accessibility and reproducibility of the index to the wider user, a quality identified as being important in the theoretical framework outlined in Chapter 2.

The two techniques that allow for compensability are a linear approach, that is simply summing the different indicators, or a geometric approach, which finds the geometric mean of the different indicators. The linear approach offers a constant amount of compensability between variables, meaning that a lower score in one domain can be wholly offset by a higher score in another, and it is the most commonly employed method of aggregation (OECD, 2008). In geometric aggregation, compensability is lower for the composite indicators with lower values (van Puyenbroeck and Rogge, 2017). This is because the geometric mean produces a lower score for units with a sparse distribution (UNDP, 2015). In the context of a composite indicator, this means that those neighbourhoods with, for example, half of indicators with very good scores and half with very poor scores will be identified as less likely to be lonely than those with consistently poor scores but less extreme values across most indicators. The theoretical idea behind this being that loneliness (or a given phenomenon) is more likely to occur in neighbourhoods that suffer from a range of inadequate conditions as opposed to average conditions in most variables but severely inadequate conditions in a single variable. This was a notion highlighted by The Campaign to End Loneliness who emphasised the need to identify those experiencing multiple loneliness risk factors (Goodman et al, 2015). The geometric approach is adopted by the United Nations (UN) in the construction of the most well-known composite indicator, the Human Development Index (HDI) (Greco et al, 2019). Thus, geometric aggregation offers a third option between linear aggregation which offers full compensability and those approaches that offer no compensability.

5.3.2. Aggregating the indicators

For this research, based on the context in Section 5.3.1, it seems theoretically sensible to use a geometric aggregation approach, as full compensability in the real world is unlikely. However, sensitivity analysis was conducted, and aggregation was completed using both methods, geometric and linear, with the two resultant indices compared in Figure 20. The plot in Figure 20 demonstrates an extremely strong correlation ($r = 0.99$, $p = < 0.05$) between the results of the two aggregation methods. Furthermore, the top ten loneliest neighbourhoods identified remained the same regardless of which aggregation method was used. Meanwhile, the loneliest 100 neighbourhoods also achieved a 94% match and the loneliest 1,000 neighbourhoods achieved a 93% match using the differing methods. Despite the theoretical advantages of geometric aggregation, because the results using the two methods are so similar, taking the linear approach was favoured for ease of interpretation and reproduction by other users.

Figure 20: Scatterplot showing the relationship between the index scores by LSOA using linear and geometric aggregation methods.



Thus, the scores for the different variables are weighted as described in Section 5.2, then summed together to produce the loneliness index. Finally, the resultant scores for each LSOA were then rescaled using the min-max normalisation process so that they were on a scale from zero to one for ease of interpretation.

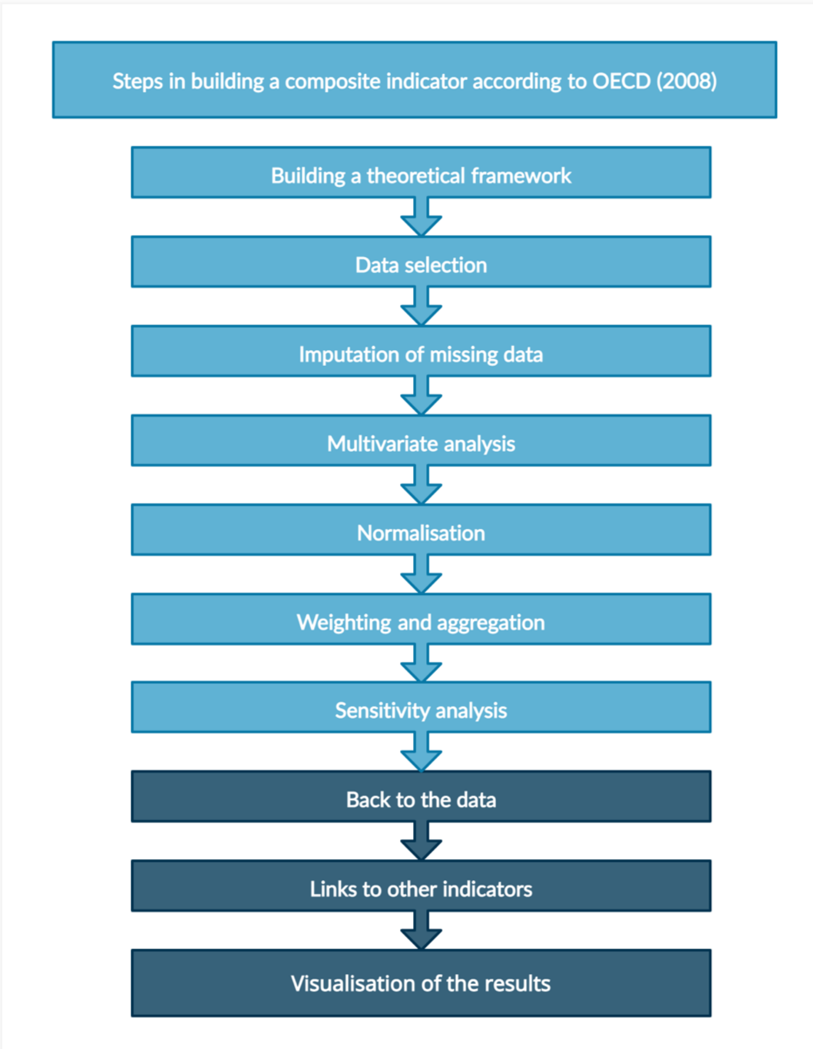
5.4. Summary of index construction

This chapter has outlined the construction steps in the building of the composite indicator. It reviewed a range of normalisation, weighting and aggregation methods, and decided on min-max normalisation, a weighting structure derived from a multi-criteria approach that incorporated statistical analysis, stakeholder opinion and consideration of the quality of the data being incorporated. Finally, the indicators were aggregated into a single composite index using a simple linear (additive) approach. This has created the new loneliness index that assesses loneliness risk for older populations at the neighbourhood level, hereafter referred to as the Hall index.

Chapter 6. Results, Analysis and Validation

This chapter will present the results of the Hall loneliness index in England. Firstly, it will summarise the process taken in the construction of the index (Section 6.1). Secondly, it will fulfil the final three steps in the construction of a composite index as outlined by the OECD (2008) (Figure 21).

Figure 21: Flowchart outlining the steps addressed in Chapter 6.

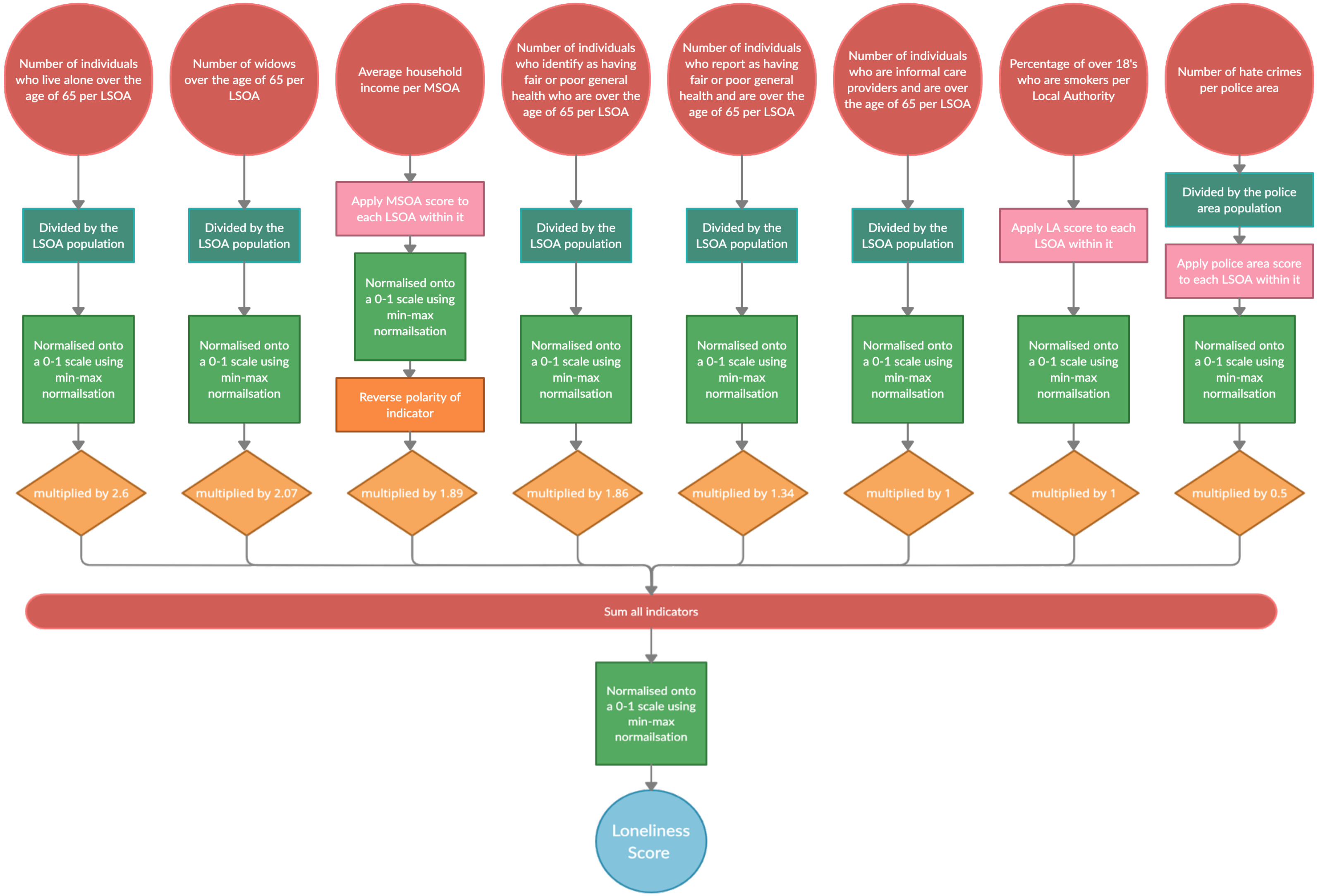


This process includes visualising and analysing the spatial distribution of loneliness risk at the national level (Section 6.2) and at the small-area level (LSOA) in England. In doing so, this chapter will compare the results of this index with the Age UK Index (AUKI) (Subsection 6.3.1), the Lucy and Burns Index (LBI) (Subsection 6.3.2.1) and the Essex County Council Index (EECI) (Subsection 6.3.2.2). Through this process the chapter will provide further validation for the Hall loneliness index presented in this thesis. Next, the chapter will analyse the fine detail of the index by deconstructing it. This is a useful technique as it allows a user to profile neighbourhood performance in order to understand the key drivers of a given score which can be useful in policy formulation. Finally, this chapter will also link loneliness to other social and economic indicators and phenomena using the Hall index (Section 6.4). This demonstrates the explanatory power of the index and allows loneliness to be linked to other constructs such as deprivation, rurality, and coastal proximity in England.

6.1. Summarising the construction stage

Figure 22 presents a flowchart that describes the exact steps taken in the construction of the index. It is useful for any user seeking to reproduce the construction of the Hall index and for clearly summarising the steps taken in Chapters 4 and 5. Each red circle represents the indicators selected, with the steps taken in normalisation being represented in green and pink colours, the weighting stage being represented by yellow diamonds, and then all the indicators summed where the arrows converge. The sum of all the indicators is normalised onto a zero to one scale for ease of interpretation. The output is then Hall loneliness score for each LSOA, where a higher score represents a neighbourhood with a higher risk of loneliness

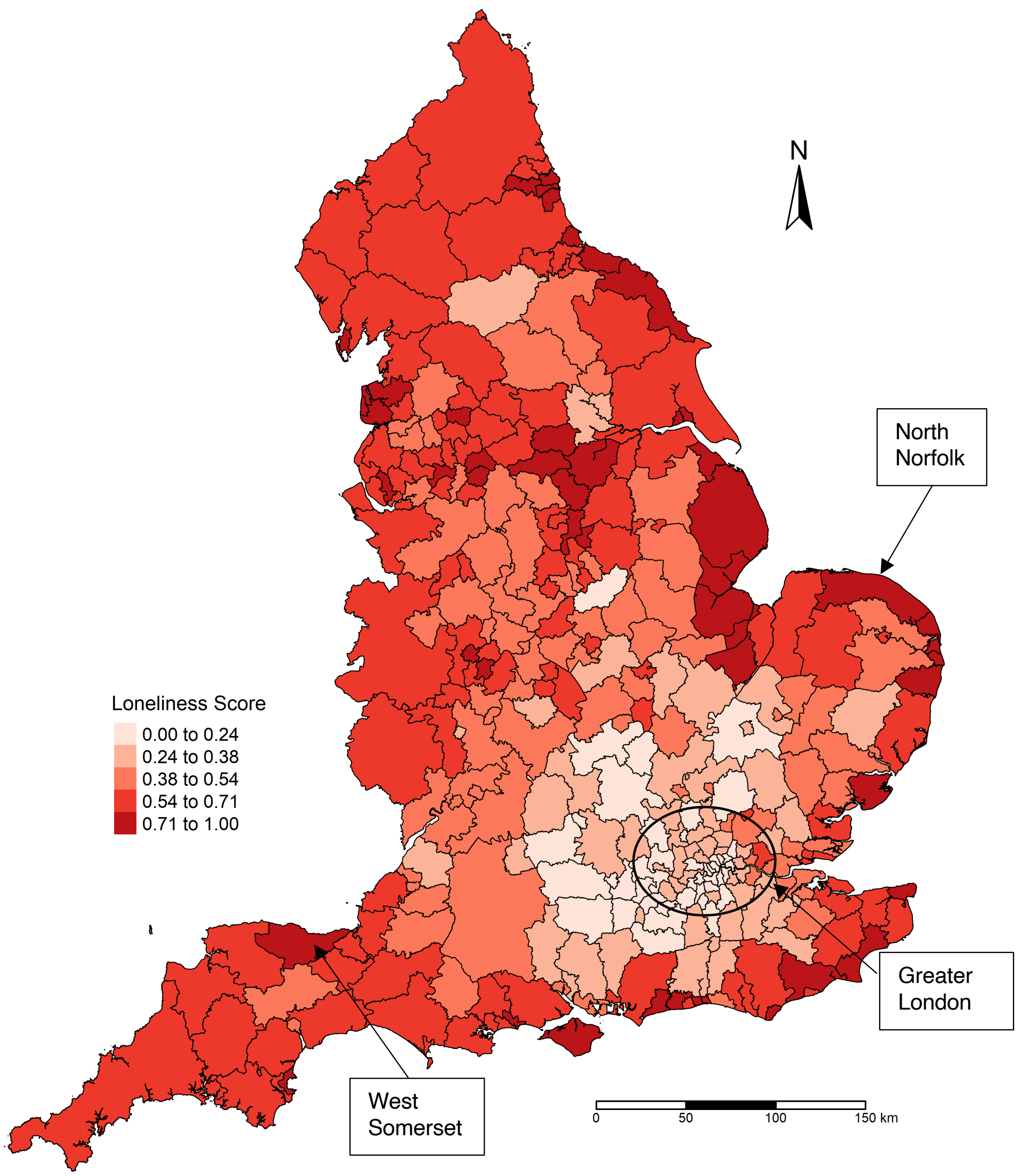
Figure 22: Flowchart describing the precise steps in the construction of the Hall loneliness index



6.2. The National Distribution of Loneliness Risk

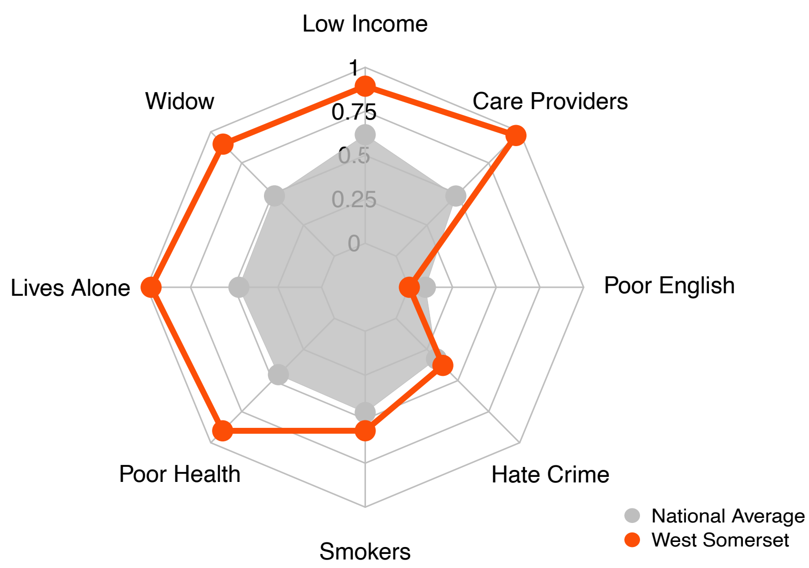
Figure 23 shows the Hall index mapped at local authority level for England. This map is a result of the mean loneliness score of all LSOAs within each local authority, the aggregated values were then rescaled using the min-max normalisation method to ensure they were on a scale from zero to one for ease of interpretability. The data has been aggregated to local authority level so that the overall spatial distribution of loneliness risk in England is visible. A higher score implies a greater risk of loneliness whereas a lower score implies the reverse.

Figure 23: The spatial distribution of loneliness in England by local authority.



A clear spatial pattern of loneliness risk in England is exhibited in Figure 23, with the coastal areas in the South and East of England fairing particularly badly. There also appears to be an urban North versus South divide, where areas in the North of England, particularly those urban areas such as Knowsley, Barrow, Salford and Tameside in the North-West; Doncaster, Barnsley and Rotherham in Yorkshire; and Newcastle and Hartlepool in the North-East, appear to be at high risk of loneliness. However, urban areas in the South, such as London, Oxford and Cambridge do not seem to have as high of a risk of loneliness. The Home Counties and Greater London display the lowest risk of loneliness in the new index. The local authority at highest risk of loneliness in England is West Somerset. The radar chart shown in Figure 24 displays the scores for each variable in the index for West Somerset. It shows that west somerset has amongst the highest rate of over 65s who are widows, live alone, categorise their health as fair or poor or are informal care providers. Finally, it also has one of the lowest average household incomes in the country. The rate of hate crimes in West Somerset is also marginally above average, whilst the rate of over 65s with poor English language ability is below average. These two variables are the indicators that suffer from the greatest skewness and so most neighbourhoods will display a score below the mean, as poor scores in these indicators are very concentrated in specific areas, such as those in West Yorkshire and Greater Manchester for hate crime, and areas in Leicester and Ealing for poor English Language ability. Figure 24 also shows the effect that the weighting process has had on the index, as the loneliest local authority displays the highest scores in the most heavily weighted domains, e.g. widowhood, living alone, low income and poor health. Whilst it tends to demonstrate lower or more average scores in the lesser weighted domains, e.g. English language ability, smoking and rates of hate crimes.

Figure 24: Radar chart showing the indicator scores for West Somerset compared to the national average.



6.3. Comparison with existing indices

The Hall index will now be compared with pre-existing loneliness indices (AUKI, LBI and ECCI). There is particular consideration given to the local authorities and LSOAs identified with differing loneliness scores by the different indices. The reasons for differences in the areas that are identified will also be considered.

6.3.1. National comparisons with the Age UK index

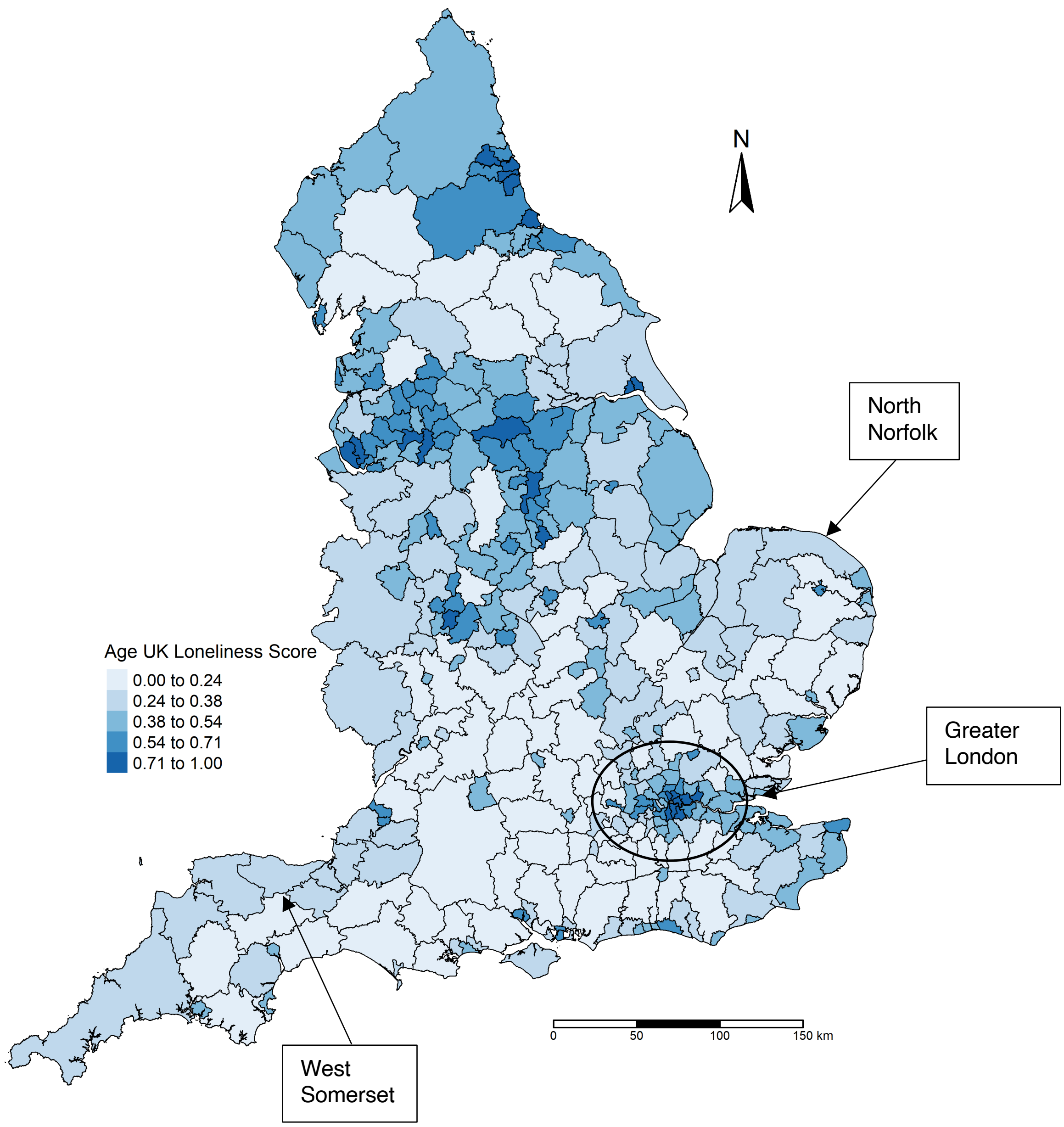
As a means of validation, the Hall index will be compared to the existing loneliness index created by Age UK in 2016. Figure 25 displays the AUKI, as described by Iparraguirre (2016), with the data available from The National Archives (2015). The values are supplied as log odds, so for means of comparison, they have been normalised using the min-max method. The variables included in the new index and the AUKI are listed in Table 17.

Table 17: The variables included in the Hall index compared with those in the Age UK Index.

Variables included the Hall index	Variables included in the AUKI
Living alone	Living alone
Being widowed	Being widowed, divorced or separated
Low household income	Being of ages 65-74 or 80 and over
Poor or fair self-assessed general health	Poor or fair self-assessed general health
Poor English language ability	
Informal care provider	
High prevalence of smoking	
High rates of hate crime	

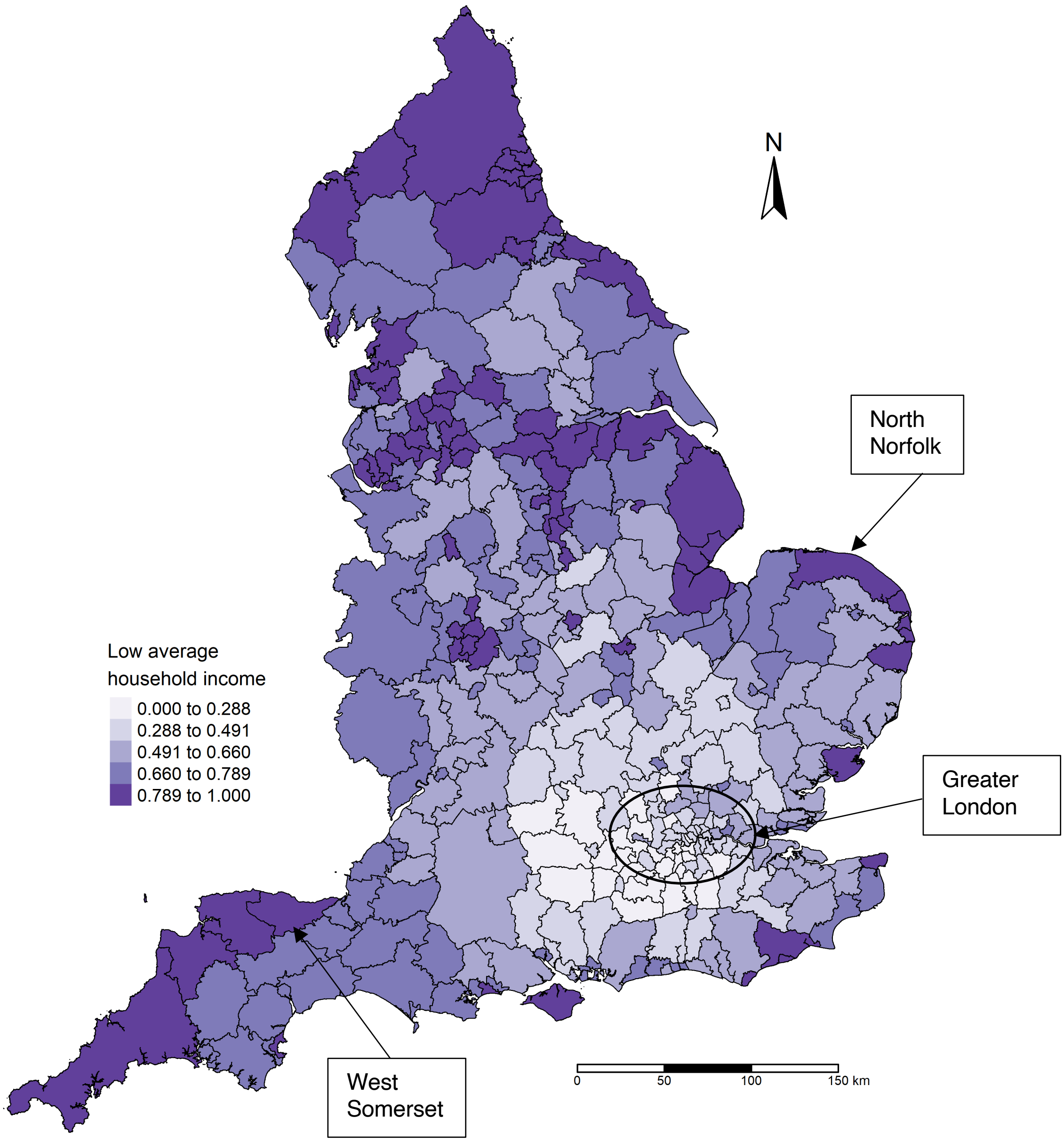
Both indices identify the urban areas of the North as having a high risk of loneliness, specifically areas clustered around Merseyside (Knowsley), Greater Manchester (Salford and Tameside), Yorkshire (Barnsley, Rotherham and Doncaster) and Newcastle and Hartlepool. However, the AUKI does not identify the strong coastal pattern that has been revealed with the Hall index (Figure 23), and it also identifies Greater London as an area at high risk of loneliness, which is found to be one of the least likely regions to suffer from high rates of loneliness according to the Hall index.

Figure 25: The spatial distribution of loneliness in England by local authority according to the Age UK Index.



Regarding Greater London, it is likely that a key reason for it being identified as low risk in the Hall index is the inclusion of the low household income variable. With London having higher than average household incomes compared to most areas outside of the South-East, this is demonstrated in Figure 26, which maps average household income in England. A similar development has led to the identification of some of the coastal authorities as having a high risk of loneliness, for example, West Somerset and North Norfolk, who both have low average household incomes and are found to be at high risk of loneliness in the Hall index but are not by the AUKI. No variable representing income is included in the AUKI, despite the literature finding conclusively that it is associated with loneliness (see Section 3.6). Thus, it appears that the inclusion of the low household income variable is a robust addition to the index. Many other variables included in the Hall index also tend to present higher rates in these coastal districts, for example, widowhood, informal care providers, individuals who live alone and self-reported poor health all demonstrate a coastal pattern, although the latter two variables were also included in the AUKI.

Figure 26: The spatial distribution of low household income in England by local authority.



6.3.2. Neighbourhood level comparisons

The application of the Hall index at the neighbourhood (local) level allows local authorities to extract the LSOAs belonging only to their districts, and then rescale using the min-max method. This allows for the identification of neighbourhoods at highest risk of loneliness, with scores relative to their local authority, as opposed to nationally. Therefore, aiding the implementation of more informed policy and planning and provides a much richer level of geographical detail compared to working with geographical units as large as local authorities as presented in Figure 23. This is demonstrated using the London Borough of Southwark and Essex County. These areas were chosen as they already have existing indices, with the opportunity for comparison providing further means of validation. The Hall index will be compared to the LBI using Southwark, and the ECCI using Essex County.

6.3.2.1. Southwark – Comparison with Lucy and Burns (2017)

Southwark was chosen as an example here as it is also analysed in Lucy and Burns (2017). The authors created a London-based loneliness index and demonstrate it by examining the distribution of loneliness in Southwark. This provides an opportunity to validate the Hall index for Southwark through comparison with the existing LBI. Whilst the construction process of the Lucy and Burns (2017) index is clearly presented, it makes little use of statistical analysis to justify decisions made in the construction. Table 18 compares the variables included in the Hall index with those in the LBI, whilst Figure 27 displays the spatial distribution of loneliness risk according to the Hall index and Figure 28 shows the loneliness map of Southwark according to the LBI.

Table 18: Variables included in the Hall index compared to those in the Lucy and Burns Index.

Variables included Hall index	Variables included in the LBI
Living alone	Living alone
Being widowed	No qualifications
Low household income	Index of Multiple Deprivation
Poor or fair self-assessed general health	Bad or very bad self-assessed health
Poor English language ability	Public Transport Accessibility Level
Informal care provider	
High prevalence of smoking	
High rates of hate crime	

Figure 27:The spatial distribution of loneliness by LSOA in Southwark according to the Hall index.

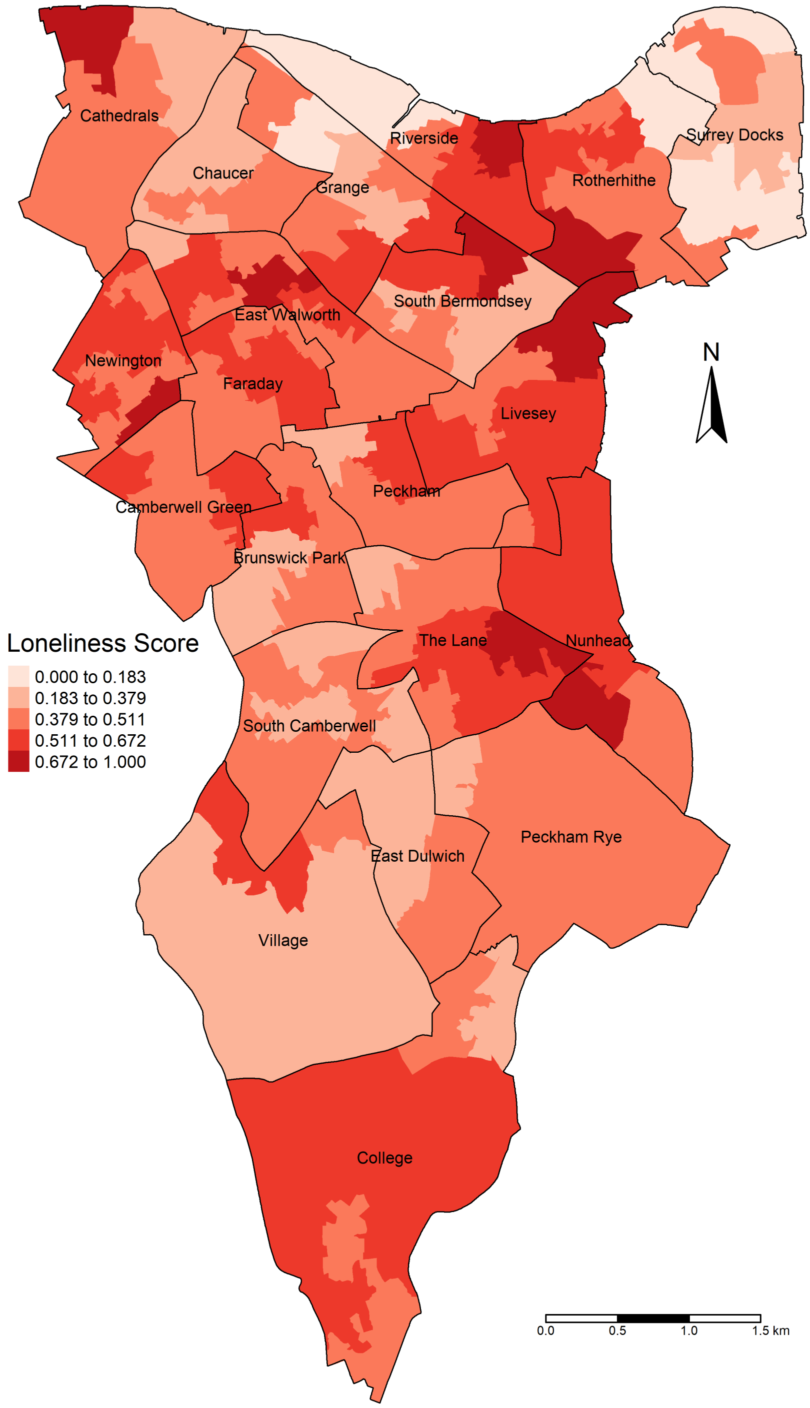
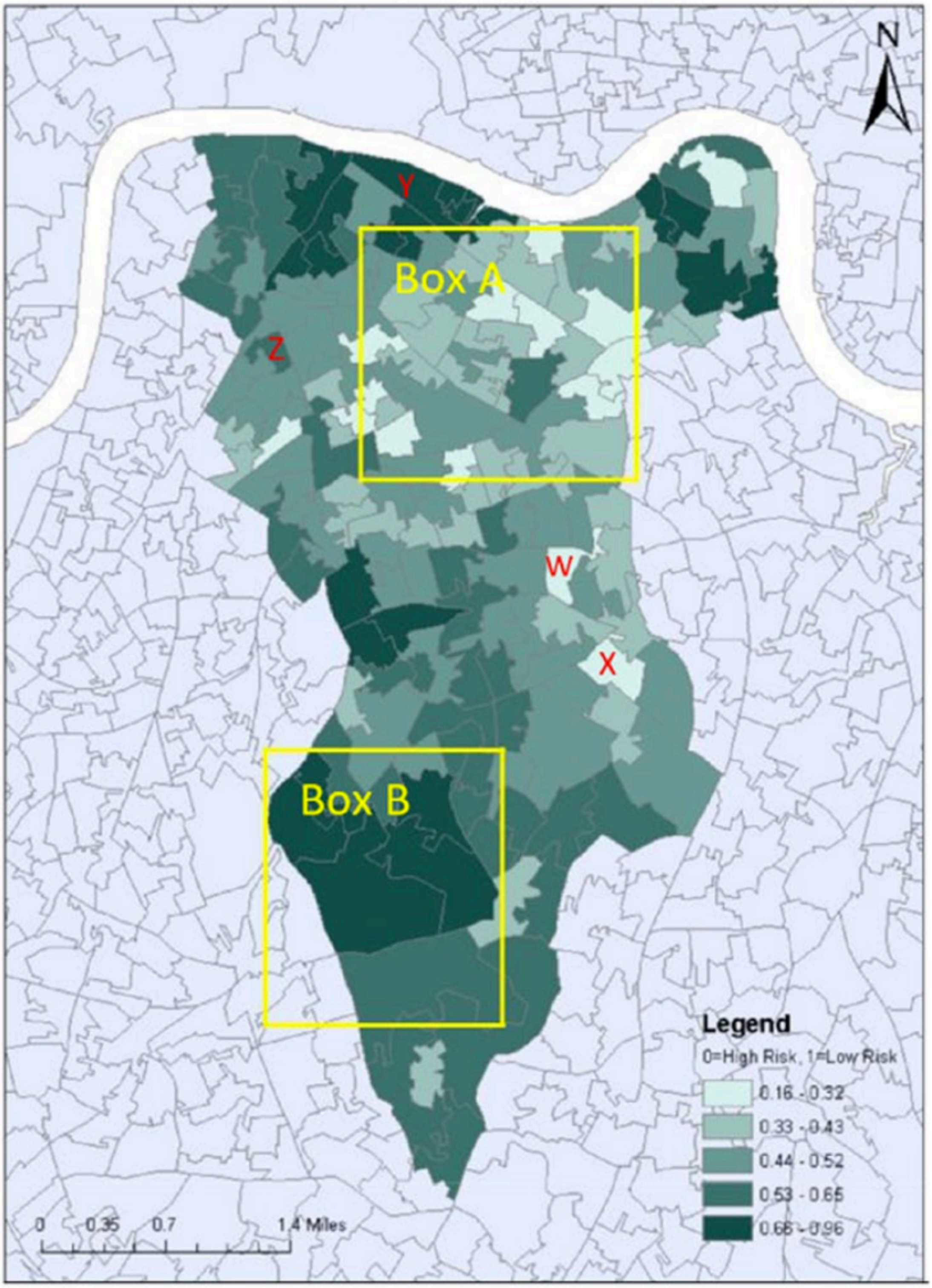
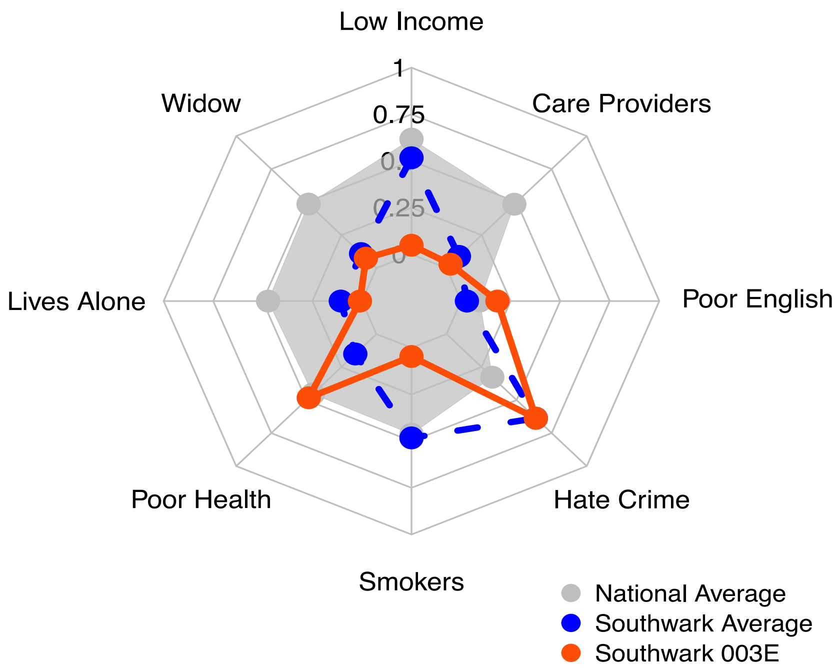


Figure 28: The spatial distribution of loneliness by LSOA in Southwark according to Lucy and Burns (2017)



It should be noted that the colour scale in Figure 28 is inverted when compared to Figure 27, so that darker colours represent lower risk of loneliness in the LBI. There are several key similarities between the two figures, the ward of Village, outlined in Box B in Figure 28, is found to have low risk of loneliness in both indices, whilst both indices also find high risk of loneliness in the areas marked W and X in Figure 28, which can be seen in west Nunhead and east The Lane. Rotherhithe and north Livesey (Figure 27) are also found to have low rates of loneliness in both indices, which are displayed in the eastern side of Box A in Figure 28. Similarly, the western side of Riverside, LSOA Southwark 003E, is found to have very low risk of loneliness in both figures (marked Y in Figure 28). The low risk of loneliness in western Riverside in both the Hall index and the LBI is particularly noteworthy as the AUKI found it to be of medium risk. Lucy and Burns (2017) highlight this finding as a possible flaw to their index, as the neighbourhood contains London Bridge station, a key travel hub in London, and they pose that the LBI may therefore be too vulnerable to the inclusion of the Public Transport Accessibility Level variable. However, the Hall index, despite not including a variable relating to transport, also finds this neighbourhood to be particularly low risk. Figure 29 displays a radar chart showing the indicator scores for each variable for Southwark 003E. It shows that the two primary drivers for the low loneliness score for the LSOA are the higher-than-average household income and lower rates of smoking for the neighbourhood compared to the rest of Southwark. The likely correlation between high income and a low decile rank on the IMD is probably the reason for the similarity in the score for the LSOA in both the Hall index and the LBI, when compared to the AUKI, which didn't include a measure of affluence.

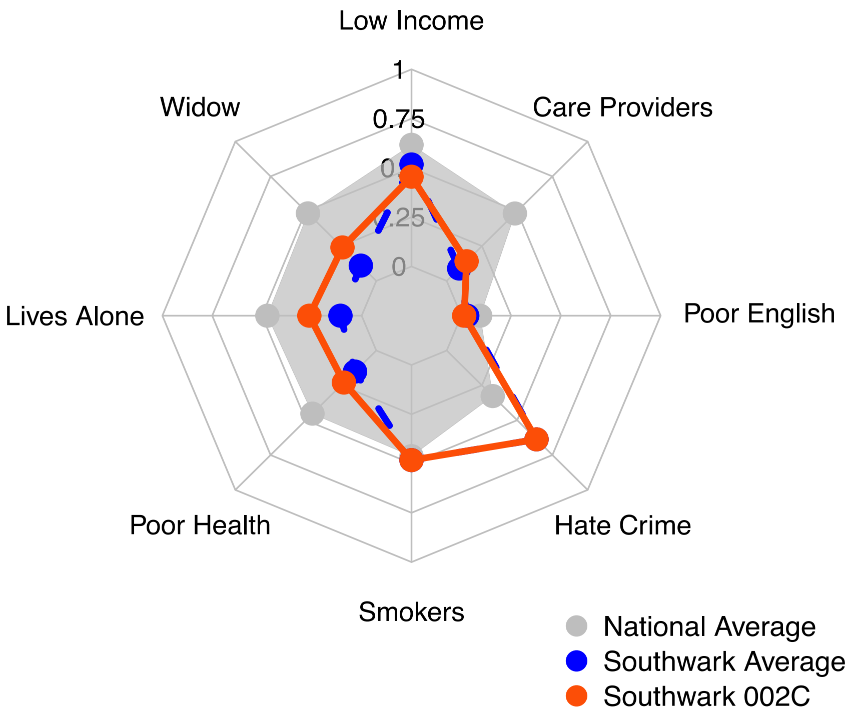
Figure 29: Radar chart showing the indicator scores for LSOA, Southwark 003E, compared to the national average and the average for Southwark.



The Hall index and the LBI do differ in some areas. For example, the LSOA named Southwark 002C which can be found in the far north-western corner of Figures 27 and 28, in the ward named

Cathedrals. Southwark 002C is in the highest category of loneliness risk in Southwark according to the Hall index, and the second lowest risk category according to the LBI. The radar chart in Figure 30 shows the normalised scores that the LSOA received for each variable included in the Hall index compared to the national average and the Southwark average. The chart shows that, relative to the other neighbourhoods in the borough, Southwark 002C has high rates of widows, single person households, and people who characterise their health as fair or poor. The differing results between the two indices being compared here are therefore likely a result of the inclusion of the widowhood variable in the present index (not included in the LBI), and the weighting which increases the influence of the three variables listed above, which received equal weighting in the LBI. Further, the national rail hub, Blackfriars, sits within the Southwark 002C and thus will influence the score for LBI through the inclusion of the transport accessibility variable. There was very little evidence identified in the literature to suggest that transport connectivity reduced the chances of loneliness in old age calling into question the validity of the inclusion of this variable in the LBI.

Figure 30: Radar chart showing the indicator scores for the LSOA, Southwark 002C, compared to the national average and the average for Southwark.



6.3.2.2. Essex – Comparison with Essex County Council (2013)

It is also useful to compare with the ECCI as a further means of validation. As outlined in Chapter 2, Essex County Council created their loneliness index using both the IMD and Mosaic geodemographic data (from Experian). The index is extremely comprehensive, incorporating fifteen different variables, however, some of the data are collected from commercial sources, thus it is not well suited for use by other charities or local authorities due to the cost involved, nor is it easy to replicate. Further, it is not clear how variables were selected for inclusion, calling into question the transparency of the index. Table 19 summarises the variables included in the ECCI compared to the Hall index.

Table 19: Variables included in the Hall index compared with those included in the Essex County Council Index.

Variables included Hall index	Variables included in Essex Loneliness Index
Living alone	Index of Multiple Deprivation
Being widowed	Single pensioners
Low household income	Widowed
Poor or fair self-assessed general health	Retired
Poor English language ability	Unlikely to meet friends/family regularly
Informal care provider	Unlikely to interact with neighbours
High prevalence of smoking	Poor health
High rates of hate crime	Permanently sick
	Suffering from depression
	Suffering from poor mobility
	Visually impaired
	Hard of hearing
	Struggling financially
	Not employed
	Less education

Many of the variables included in the ECCI are interrelated which could lead to issues of unintended increased weighting (or compounding) for certain domains with no rationale provided for this decision. For example, the ECCI includes six different variables pertaining to health: poor health; permanently sick; suffering from depression; suffering from poor mobility; visually impaired; and hard of hearing. Deeg and Bath (2003) argue that the variable relating to self-assessment of general health is a useful summary of all other health indicators, and thus encompasses those other health variables which are also included in the ECCI. Furthermore, the variable relating to retirement is implicitly included in the Hall index as only those over the age of 65 are included in most of the indicators, with the UK state pension age currently at 66 (Osbourne, 2020). The only variables, therefore, included in the ECCI which are not accounted for in the Hall index are those relating to social life: likelihood of interacting with friends or family regularly; and likelihood of interacting with neighbours regularly. Thus, the Hall index reflects a similar understanding of loneliness but employs a more parsimonious selection of variables, from free and open data sets. It was thus hypothesised that the two indices would demonstrate a similar spatial distribution of loneliness for Essex County. However, the Hall index is more readily reproducible and is well suited to widespread uptake by local authorities and charities, for use at both the neighbourhood and the national level. For means of spatial comparison Figure 31 maps loneliness using the Hall index and Figure 32 displays the ECCI mapped in Essex County courtesy of a report from the BBC (2015), where green indicates low risk of loneliness and red indicates high risk.

Figure 31: The spatial distribution of loneliness by LSOA in Essex County according to the Hall index.

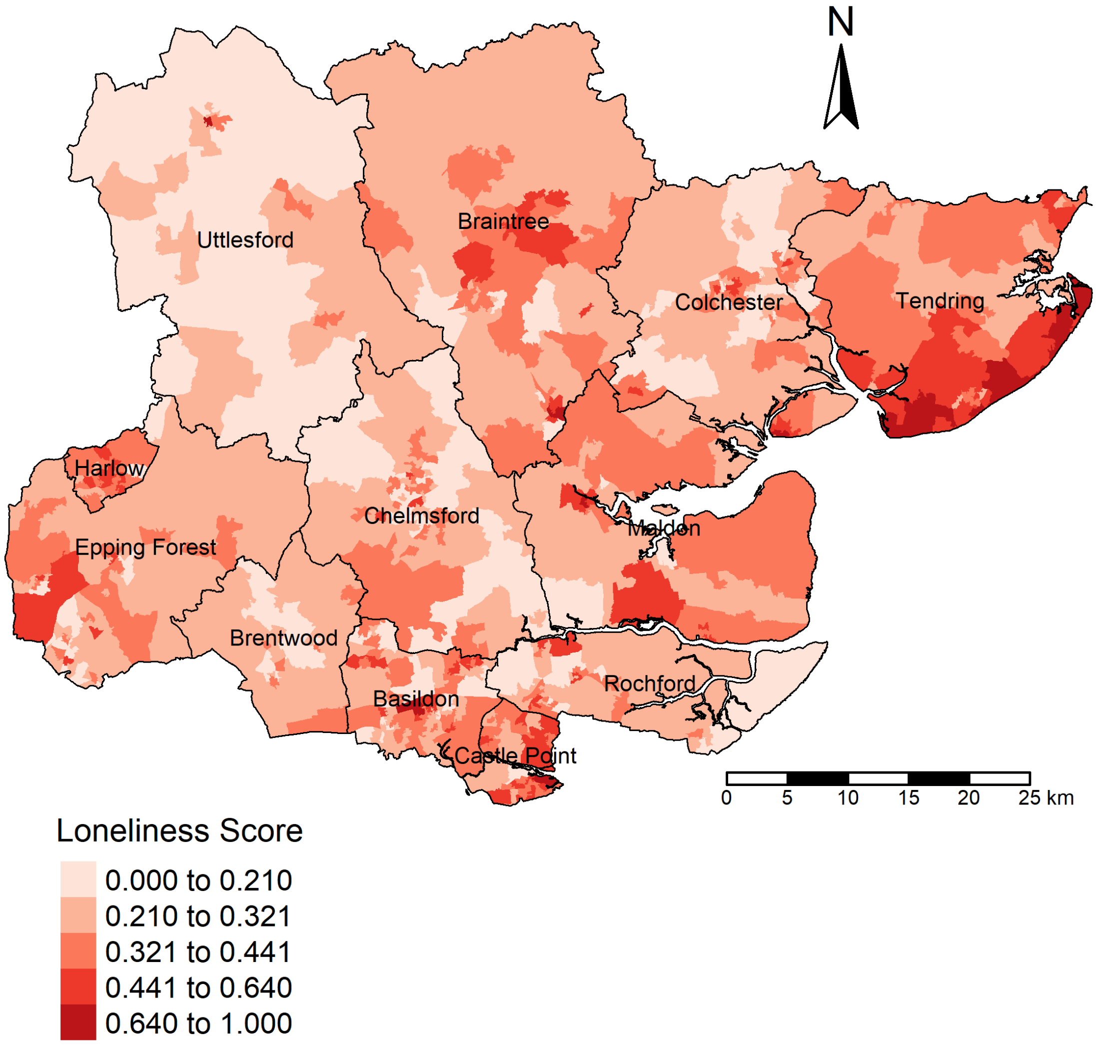
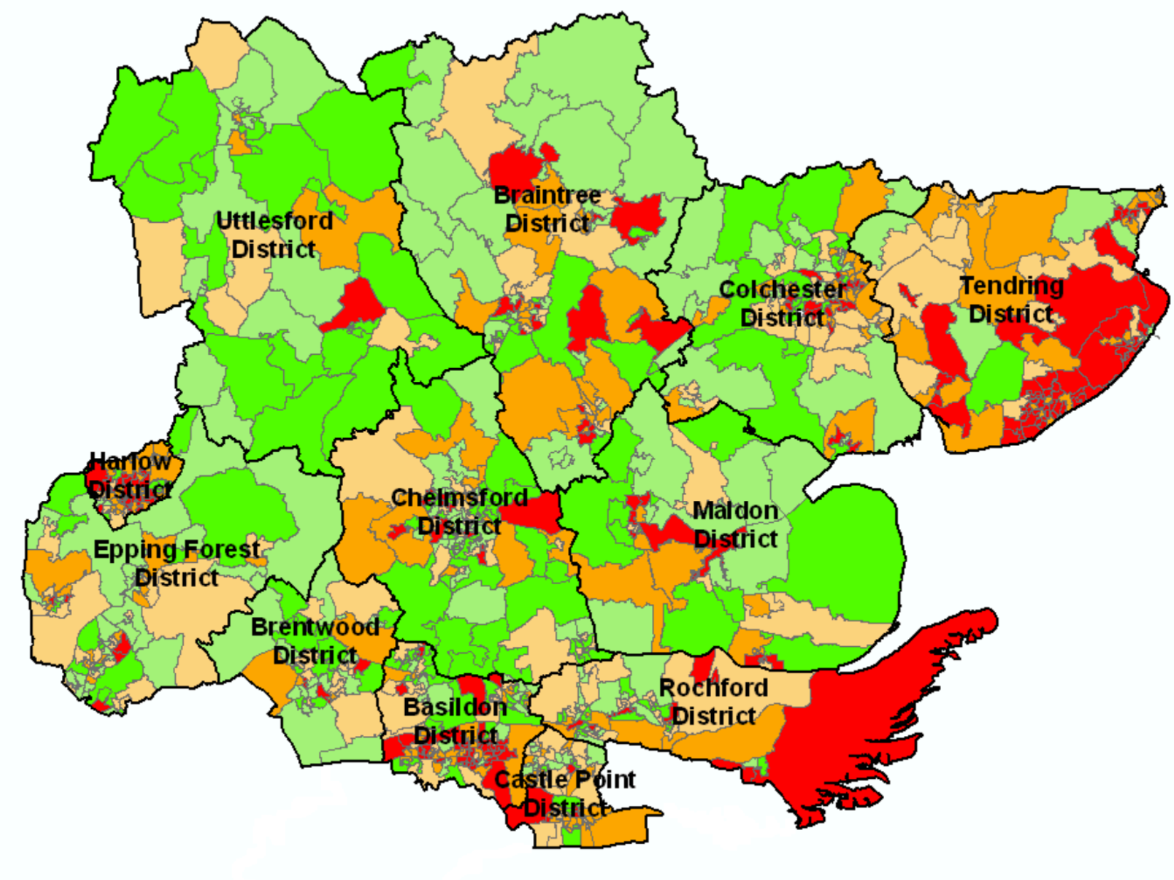
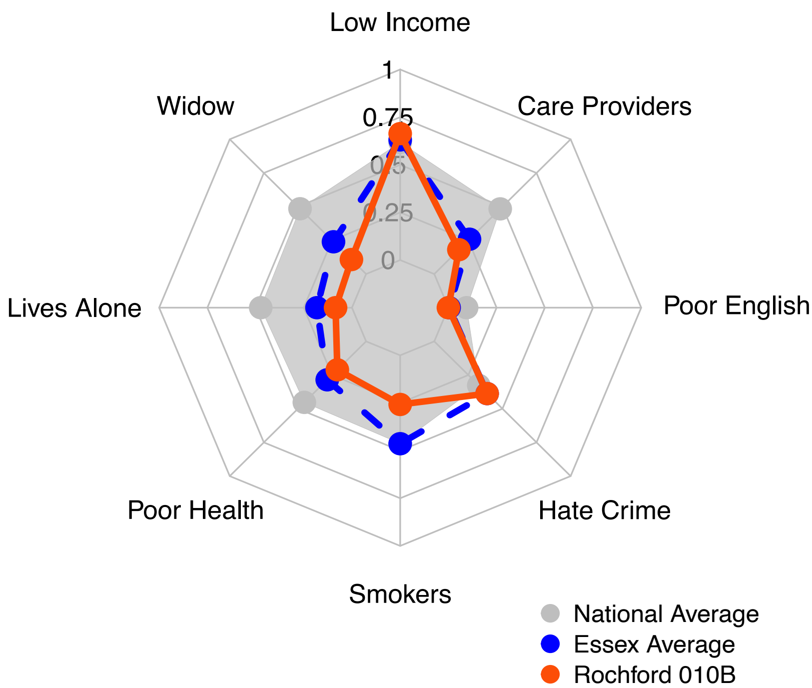


Figure 32: The spatial distribution of loneliness by LSOA in Essex County, using the Essex County Council Index (Source: BBC, 2015).



Comparisons of the two maps display a high degree of similarity. Both indices highlight the coast of Tendring as being the most at-risk area for loneliness in the county. They also both show a high risk of loneliness in Harlow, Castle Point, central Basildon and central Maldon. Naturally, scores diverge in some neighbourhoods, most notably in the large LSOA on the coast of Rochford, named Rochford 010B, which the Hall index finds to be in the lowest risk category in Essex County, and the ECCI index finds to be in the highest risk category. The radar chart in Figure 33 shows that indicator scores for Rochford 010B are either the same or below the Essex County average for all variables except low income, although this difference is incredibly marginal. It has fewer smokers than the Essex County average, but a similar rate to the national average. However, given the decreased influence of this variable in the overall index through reduced weighting, it is unlikely that this variable is greatly contributing to the differences in ranking between the two indices. Without access to the raw index scores for the ECCI, it is impossible to determine what has caused the difference in ranking. It is likely a result of the weighting system employed by the Hall index, where the ECCI uses equal weighting (but inadvertently compounds certain domains through the inclusion of multiple indicators representing the same domain, e.g. health). It could also be a consequence of the different time frames at which the data was collected, the ECCI was constructed in 2013 whilst the Hall index has data from 2011, 2018 and 2019. Finally, the differences may be a result of the inclusion of the indicators relating to frequency of social engagement in the ECCI. The literature suggested that frequency of social contact is important to the concept of loneliness in older populations. However, due to a lack of freely available data at the national level this could not be included in the Hall index.

Figure 33: Radar chart showing the indicator scores for LSOA, Rochford 010B, compared to the national average and the average for Essex County.



6.3.3. Summary of national and neighbourhood comparisons

This section has demonstrated the power of the Hall index in identifying at risk regions on both the national and neighbourhood level. Through comparison with existing indices, it has provided validation for the Hall index and explored the primary drivers behind the loneliness scores in certain regions. It has found that loneliness nationally tends to be concentrated in coastal regions and Northern former industrial cities. Principally, however, it has demonstrated that a plausible and reproducible loneliness index can be created using free and open data by charities and local authorities. It has shown how the index can then be disaggregated to identify the primary drivers behind the loneliness score for a given geographical unit, which can then be used to inform policy and resource allocation.

6.4. Associated characteristics

A key power of composite indicators is that they can be compared with other characteristics to help describe the phenomenon that is being measured and test associations between different characteristics (OECD, 2008). Two of the most debated characteristics relating to loneliness in older populations is the relationship between loneliness and deprivation, and loneliness and rurality (see Sections 3.6 and 3.9). These associations will be examined using the Hall index in this section.

6.4.1. Association with the Index of Multiple Deprivation

As has been discussed in this thesis, loneliness is a phenomenon often associated with deprivation, particularly socioeconomic deprivation (Scharf and de Jong Gierveld, 2008). The Hall index allows for the measurement of loneliness risk in relation to deprivation, as calculated in the IMD. The graph in Figure 34 provides boxplots for the Hall index by 2019 IMD deciles (Ministry of Housing, Communities and Local Government, 2019). It shows that a higher risk of loneliness is found in areas with higher multiple deprivation. However, the relationship is weak, with only marginal increases in median loneliness scores as IMD decile decreases (denoting higher levels of deprivation). Furthermore, the LSOA with the highest risk of loneliness in England, Christchurch 003A, falls into the eighth decile of the IMD, which suggests that it is in the least deprived 30% of neighbourhoods in the country. It is likely that a key reason for the relationship between the Hall index and the IMD is the inclusion of the measure of low income in the Hall index. Figure 35, therefore, shows the relationship between the Hall index when the income variable is removed and IMD decile, as a form of sensitivity analysis. The boxplots show a weaker relationship when the income variable is removed from the Hall index, with there now being little variation in the median loneliness score between different deciles. This suggests that loneliness is only loosely related to notions of area deprivation and is more closely related to levels of income. This phenomenon was described by Scharf and de Jong Gierveld (2008) who found that differing characteristics at the local level, factors such as housing, local policy and population composition, are more important to the concept of loneliness than a one-dimensional view that greater deprivation is equal to greater loneliness.

Figure 34: Boxplots showing the median loneliness score and variation by 2019 IMD deciles.

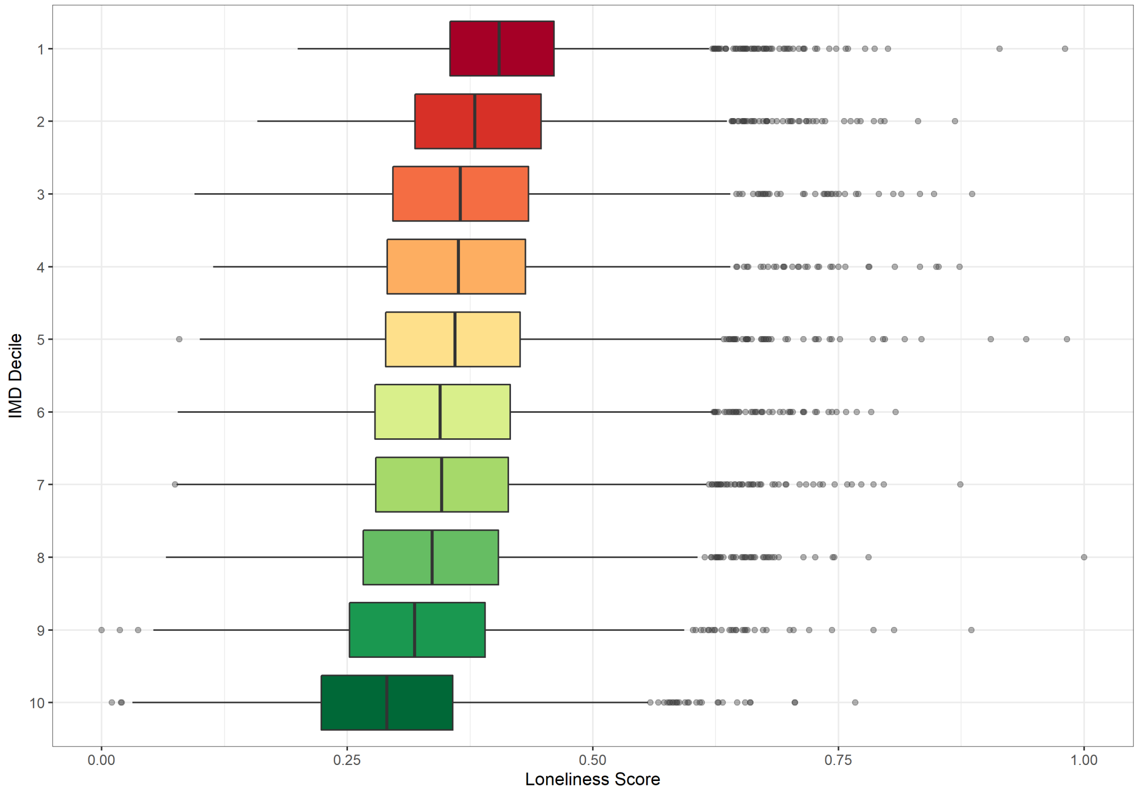
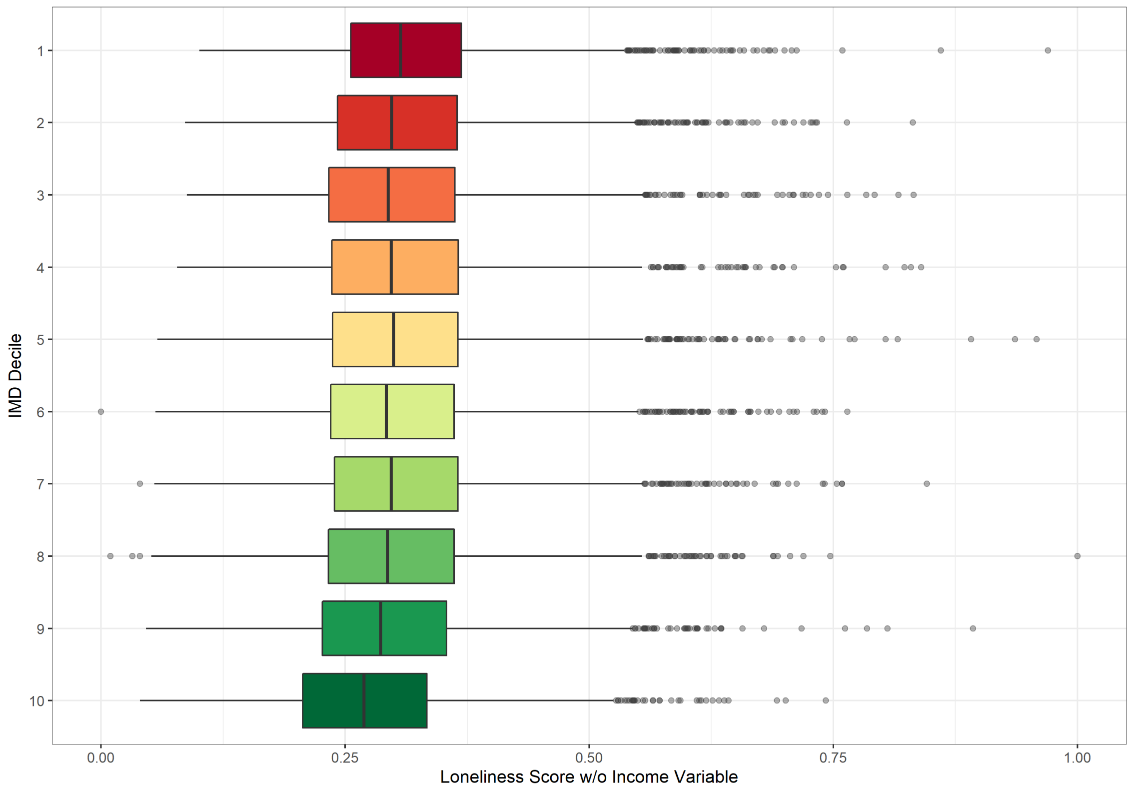


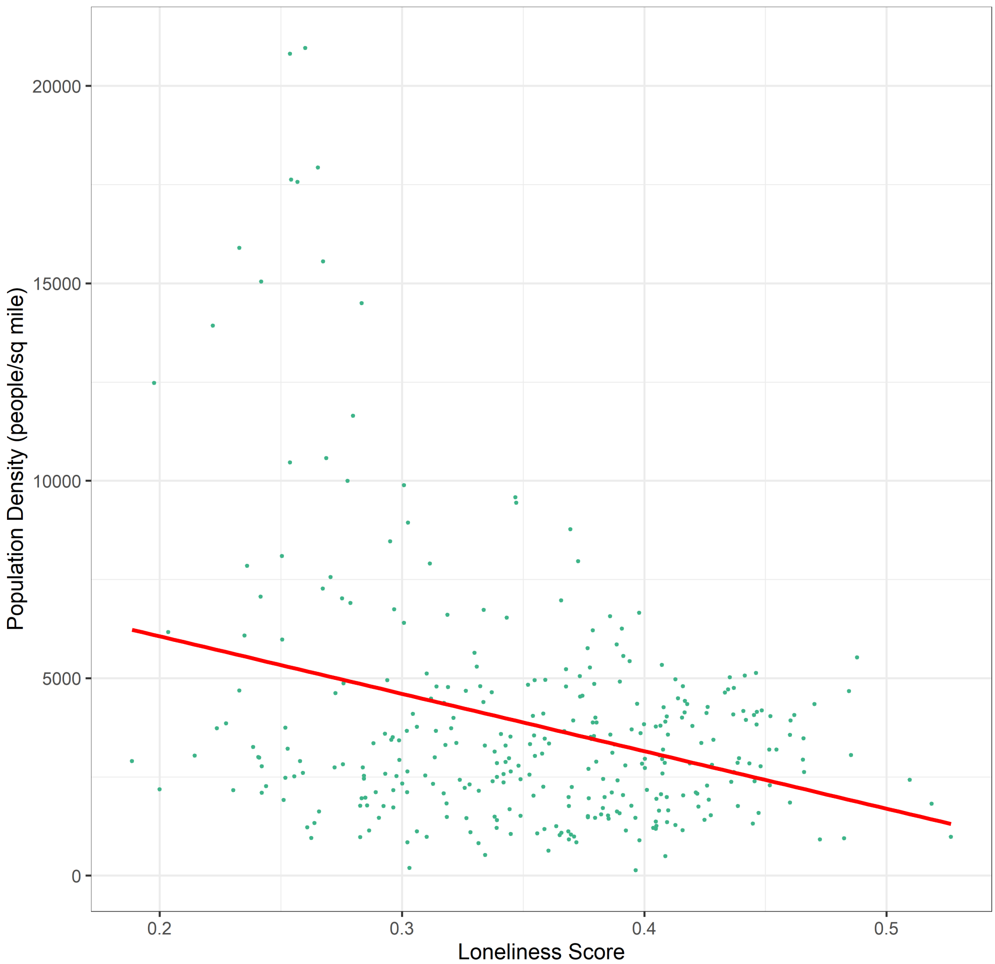
Figure 35: Boxplots showing the median loneliness score when the income variable is removed by 2019 IMD deciles.



6.4.2. Association with rurality and coastal proximity

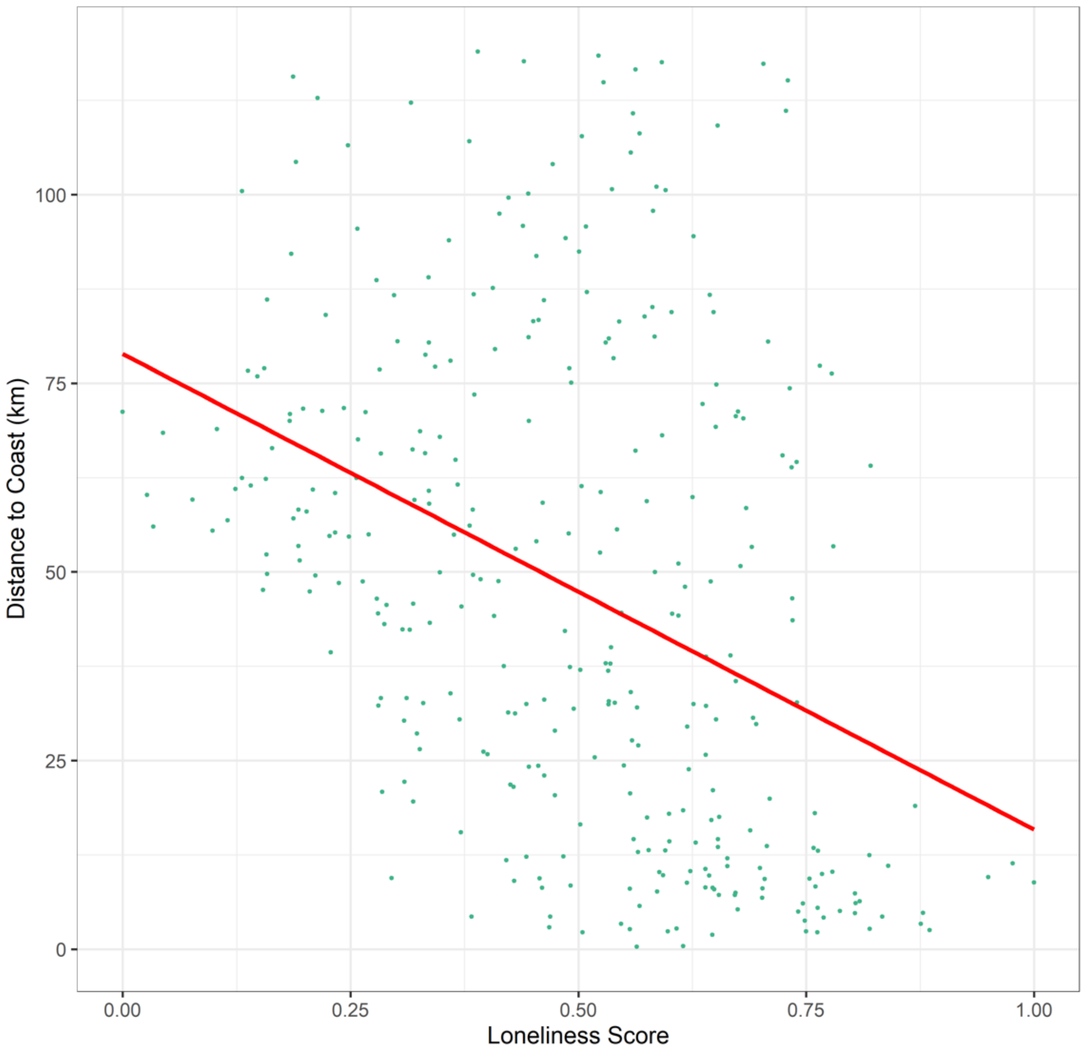
Rurality is a highly debated topic with regards to loneliness. It is usually assumed in public discourse that rural areas have a higher presence of loneliness, although academic opinion on the matter is lacking consensus. Some researchers find rurality to be associated with loneliness (Savikko et al, 2005; Routasalo et al, 2006), some find urban areas to have a higher presence of loneliness (Ferreira-Alves et al, 2014; Menec et al 2019), with others finding non-linear relationships or no relationship at all (Van den Berg et al, 2015; Beer et al 2016). Furthermore, certain researchers suggest that their findings are the result of characteristics unique to the national context due to unique social characteristics (Savikko et al, 2005; Ferreira-Alves et al, 2014). Figure 36 plots local authority population density estimates for 2019 (ONS, 2020) against the Hall index. It finds a moderate negative correlation ($r = -0.31$, $p = < 0.05$), suggesting that in England, loneliness in older populations is more likely to occur in areas of low population density, and therefore, more rural areas.

Figure 36: Scatterplot showing the relationship between population density and the Hall index by local authority in England.



Section 6.2 reviewed the spatial distribution of loneliness at the national level and suggested there was an increased risk of loneliness in coastal areas. Figure 37 displays the relationship between the Hall index and the distance from the local authority centroid to the nearest coast. The results suggest that the relationship between loneliness and coastal proximity is slightly stronger than the relationship between loneliness and rurality ($r = -0.38$, $p = < 0.05$ compared to $r = -0.31$, $p = < 0.05$). Furthermore, it is not the case that rurality is confounded with coastal proximity, as analysis between population density and coastal proximity in England suggest that the two are not closely related ($r = 0.03$, $p = < 0.05$). This, therefore, suggests that loneliness risk in England is related to both low population density and coastal proximity.

Figure 37: Scatterplot showing the relationship between coastal proximity and the loneliness index by Local Authority in England.



6.5. Summary of results

This chapter provided a clear and concise summary of the steps involved in constructing the Hall index to ensure its reproducibility and accessibility for other interested users. It then continued to visualise the results of the Hall index. In doing so it has identified that loneliness in older populations tends to be clustered in coastal areas and in former industrial Northern towns. Next, it closely compared and analysed the results of the Hall index against existing loneliness indices. This demonstrated that the Hall index is a valid and useful tool, by explaining where the Hall index differed from existing indices and the reasons for the divergence. It was found to be most similar to the ECCI, however, it is more accessible and clearer in its construction phase ensuring its validity and reproducibility. Furthermore, the Hall index scores were disaggregated to identify the primary drivers of area scores, demonstrating the usability of the index for local authorities and charities. Finally, the Hall index was compared to other social and environmental characteristics on the national scale, identifying that it is loosely related to area deprivation, but has a stronger relationship with coastal proximity and rurality. This thesis will now be concluded in the final chapter.

Chapter 7. Conclusion

This chapter will summarise the key findings of this research, and its contributions to the wider literature, before outlining the key limitations of the study. Finally, it will present the primary recommendations to both extend and improve upon the research presented in this thesis, in both the field of loneliness and in wider quantitative social studies.

7.1. Findings and Contributions

The key contributions of this thesis to the literature include the further consolidation of knowledge regarding the primary associates and risk factors that influence loneliness in older populations. The research has presented a new measure of loneliness through the development of a composite index comprising entirely freely available data. The index has been proven to be both valid, robust and reproducible as evidenced in its analysis and validation. As outlined by the OECD (2008), composite indices of this nature have the ability to: allow for ease of interpretation of a multidimensional issue; benchmark between regions and across time; place the issue of performance at the centre of public policy; and facilitate communication with the public. It has also fulfilled The Campaign to End Loneliness' call for the creation of loneliness maps (Goodman et al, 2015), and added a new tool that can be used instead of or in conjunction with existing loneliness measures to inform policy and intervention strategies aimed at limiting loneliness.

This research has created a measure of loneliness that used rigorous statistical analysis in cooperation with stakeholders to ensure the index is valid and meaningful. The index is applicable to the whole of England and can be applied at any level of Census geography. It has been constructed such that it is easily reproducible by charities and local authorities and can be used to identify differences in the prevalence of loneliness at the neighbourhood level and identify the primary drivers of loneliness risk in different areas. The index is theoretically sound, following advice from the theoretical literature, it has created a multidimensional measure, considering both emotional and social variables, thus accounting for the social and emotional dimensions of loneliness as first theorised by Weiss (1973). Furthermore, this research appreciates loneliness to be the result of a perceived discrepancy between desired and achieved social outcomes as identified by Peplau and Perlman (1982). This was achieved by using the self-reported loneliness measure as the dependent variable in the logistic regression model (Chapter 4). Consequently, the study has worked within a combination of the interactionalist and cognitive frameworks as advised for research into loneliness amongst older populations by Donaldson and Watson (1996).

The development of the Hall index has been achieved through two broad steps. The first was the identification of the primary correlates for loneliness amongst older populations. This was achieved through a thorough literature review that outlined a broad range of social, demographic, economic and environmental characteristics that have been associated with loneliness in previous research (Chapter 3). Multivariate analysis was then conducted in Chapter 4 using *Understanding Society* data, a household survey that offered the most comprehensive range of variables that had been identified in Chapter 3 for possible inclusion in the index. This analysis allowed for the assessment of the nature and size of the relationships between such characteristics and loneliness. Stakeholders, including Independent Age and the British Red Cross, were then consulted, and this offered a level of validation of those indicators that were identified, as well as an opportunity to include variables in the index that were not available in the survey data and therefore had not been included in the multivariate analysis.

The process of identifying variables primarily highlighted social and demographic factors as the key correlates of loneliness amongst older populations, specifically: living alone, being widowed, having poor health and low income. Factors such as poor English language ability, lack of neighbourhood cohesion, being an informal care provider and being a smoker were identified as peripheral characteristics that were associated with loneliness amongst older populations. Although it was concluded that smoking was unlikely to have a direct relationship with loneliness, and this was likely acting as a proxy variable for another unknown characteristic. The identification of these characteristics through a rigorous process involving statistical analysis, review of the wider literature and stakeholder consultation ensured no theoretical assumptions between loneliness and certain characteristics were made, and this is a common criticism of current survey-based methods of measuring loneliness (Victor et al, 2005).

Building on this research, the second broad step in the development of the index was the construction phase. Indicators that represented those characteristics that had been identified for inclusion in the index were selected from open data sources. Most indicators did not need a proxy variable and were available in the 2011 Census or from the ONS. However, lack of neighbourhood cohesion needed a suitable proxy and following stakeholder consultation, review of the literature and statistical analysis, high rates of hate crime was identified. Thus, eight variables were incorporated into the index: living alone; being widowed; being of fair or poor self-assessed health; having low household income; having poor English language ability; being a smoker; being an informal care provider; and living in an area with high rates of hate crime (Chapter 4). The construction step involved identifying a method of normalisation, weighting, and aggregation (Chapter 5). Indicators were normalised using a min-max method to place all variables onto a common numeric scale, weights were derived from regression analysis and informed by the quality of the data and stakeholder advice, and aggregation was conducted with a simple linear process. These steps were informed by the literature, the structure of the data, and the theoretical framework. As proposed by OECD (2008), sensitivity analysis was conducted throughout to ensure transparency and validity. The index construction was closely informed by the OECD (2008) *Handbook on the Construction of Composite Indicators*, thus ensuring the construction process is robust, valid and transparent. Furthermore, the process of aggregating the eight variables means that the Hall index highlights those areas that experience multiple risk factors and are therefore at highest risk of loneliness. This was a key necessity outlined by The Campaign to End Loneliness when they called for the creation of a new loneliness measure (Goodman et al, 2015).

Once the index had been constructed, it was then used to analyse the spatial distribution of loneliness in England. The key patterns identified were that loneliness risk tended to be higher in coastal areas and in former industrial Northern cities. The lowest risk of loneliness in older populations was found in London and the Home Counties. The index was then compared to existing loneliness indicators such as those created by Essex County Council (2013), Age UK (Iparraguirre, 2016) and Lucy and Burns (2017). This provided further validation and demonstrated the power of the Hall index as it analysed loneliness risk at the neighbourhood level and was used to identify the primary drivers of loneliness in different neighbourhoods. Finally, the Hall index was compared to other socioeconomic and environmental factors for a macro-analysis of the relationship between loneliness risk and rurality, coastal proximity and multiple deprivation in England. It was found to have a moderate relationship with coastal proximity, a slightly weaker relationship with rurality, and only a very loose, but still positive, relationship with multiple deprivation.

7.2. Limitations

This section will discuss the key limitations of this research with regards to the Hall index. The primary obstacle in the construction of the index was access to suitable data. It was expected that survey data could be used as it would provide a broad array of up-to-date variables for inclusion in the index, and thus would allow for the building of an index that directly reflected the results of the statistical analysis. It would also have allowed for the inclusion of variables relating to social activity. However, sample sizes in national social surveys are not large enough to be applicable at the neighbourhood level, and a key tenet of the theoretical framework was that the index could be used to map loneliness at the small-area level. Consequently, many of the variables were acquired from the 2011 Census and other open sources. Census data are limited in both scope and reproducibility, as it contains a narrow set of variables that are updated decennially. At the time of writing (2021), five of the eight variables included in the index are ten years out of date (with the latest 2021 Census data currently being processed). Other data sources were incorporated, these included statistics on hate crime from the Home Office (2018 and 2019) as well as household income estimates (2018) and smoking prevalence estimates (2018) sourced from the ONS. The variables accessed from the Home Office and the ONS were not available at the desired level of geography, LSOA, and therefore did not allow for the full variation of characteristics measured in the index to be revealed at neighbourhood level. However, they are updated more regularly, allowing for more frequent reproducibility. These limitations are important as they limit two of the key desires of stakeholders: that the index can be regularly reproducible and applicable at the small area level. However, in the current data climate, there was no feasible way to include indicators that are updated more regularly, measurable at LSOA level and theoretically important to the concept of loneliness. Therefore, the indicators included in the index are considered the most appropriate available indicators.

A further limitation exists with the inclusion of the household income variable. This is a measure of absolute household income and is not relative to the local cost of living, thus introducing a vulnerability into the index. The variable would be of greater use if it scored household incomes for a neighbourhood compared to a regional average. This is because there is a considerable disparity in the cost of living across England, meaning that lower incomes can afford more in some areas than they can in others. Therefore, the index may be unduly penalising neighbourhoods with low average household income that sit within regions of lower cost of living, for example, those in the former industrial Northern cities, and not giving enough emphasis to those areas of low household income that sit within regions with a high cost of living, for example, certain areas of London.

Restrictions in accessing data also meant that the index had to make use of proxy variables, specifically in the neighbourhood cohesion domain. Where proxy variables were employed, they were done so after consideration of statistical evidence and stakeholder advice (Section 4.6). Inevitably, however, the inclusion of proxy variables does introduce a vulnerability into the index, and a more direct indicator, or a collection of indicators, that represent neighbourhood cohesion would have been desirable. Similarly, the use of proxy variables meant that weights applied could not be wholly derived from statistical outputs as no odds ratios were available to represent the importance of the proxy variable's relationship to loneliness when other variables incorporated into the index were considered. Consequently, the hate crime indicator was weighted following a value judgement after the quality of the data was assessed, and its weight was reduced because it was measured at a high level of geography. As with all composite indices, construction involves several value judgements (Sasiana and Tarantola, 2002). However, to make this index less vulnerable to these common criticisms, the construction has been closely advised by the OECD (2008). The research has followed the steps and techniques advised by the handbook, with sensitivity analysis applied throughout, to ensure transparency and to help to produce a valid and robust index.

Furthermore, this research and the resultant index has focused exclusively on loneliness amongst older populations. It has not investigated the risk factors or geographical variations in loneliness in younger generations, and most of the variables included in the index do not account for those under the age of 65. This research and index should not be used to inform or assess policy that is intended to alleviate issues of loneliness in younger populations that remain pervasive. Similarly, it has been designed specifically for the English context, as the literature has demonstrated, characteristics associated with loneliness and even a clear understanding of what defines loneliness varies across cultures (Jylha, 2004; Savikko et al, 2005; Ferreira-Alves et al, 2014). It is not recommended that the Hall index be used in other countries without further research and validation of the index in other cultures.

Moreover, as with all spatially aggregate data, the index is susceptible to the modifiable area unit problem (MAUP). The concept of MAUP is that the boundaries of geographical analysis are arbitrary and can influence the data produced and the outcomes of spatial analysis (Wong, 2004). LSOAs have been used as the unit of analysis to help mitigate this problem. Using LSOAs allows for aggregation to other levels of geography, from ward up to government office region, meaning that the index can be applied to any level of geography for a given analysis. Furthermore, LSOA boundaries consider population characteristics and aim to create geographical units that contain similar demographics, unlike administrative units, such as wards or postcodes (Lloyd, 2016). In doing so, the effects of the MAUP are mitigated, although not eradicated. Similarly, a limitation that applies to all aggregate analyses is ecological fallacy. An ecological fallacy may be present where the results of an aggregate analysis are applied at the individual level (Tranmer and Steel, 1998). Therefore, any use of this index to formulate policy and intervention strategies must remain cognisant of the fact that an area that is identified as having very low risk of loneliness by the index may still contain very lonely older individuals. Similarly, not all older people in high-risk areas will suffer from loneliness. Lastly, the following section will offer recommendations for future research and policy.

7.3. Recommendations

There are lots of opportunities to improve upon the understanding of the social phenomena of loneliness and how it can be best alleviated. The key recommendations that have arisen from this research will now be discussed. Firstly, more research needs to be conducted into the causes and locations of loneliness in younger generations. The body of literature regarding loneliness in older generations is large, however, very few have investigated the effects and whereabouts of loneliness in the young and middle aged, even though some estimates suggest that loneliness is more pervasive in younger generations than older ones (Flood, 2005). It is imperative that society learns more about the causes and geographical variations in loneliness in these generations to understand how best to alleviate it.

Secondly, research into how best to use the Hall index in conjunction with other loneliness measures would be useful. This index is not necessarily the most appropriate measure of loneliness in all circumstances. It is likely that using a combination of self-reported loneliness measures or multi-item scales in conjunction with the Hall index will add greater value to the understanding of loneliness in older populations. Doing so would allow for the analysis of both inputs (those characteristics included in the Hall index) and output (self-reported loneliness) in conjunction. This could help evaluate the efficacy of intervention strategies and add further knowledge to our understanding of the causes and correlates of loneliness.

Thirdly, this thesis is a further example of the growing need for more data to be made freely and widely accessible. More up-to-date indicators measuring the same characteristics that have been included in the Hall index are accessible from other commercial sources in the UK such as Experian and CACI. However, such data are expensive to obtain and as such are not easily accessible to researchers, charities, or local authorities. By restricting these data, such organisations are impeding the formation of more informed policy tools and understanding of issues such as loneliness, or any other given social phenomena. Similarly, if government surveys such as *Understanding Society* were applied to a larger sample of people, or other less onerous means of acquiring data than surveys was more readily employed, then more informative data could be accessible for researchers, charities and local authorities.

Finally, this thesis has presented a robust, plausible and easily replicable index that can be used to measure the risk of loneliness in older populations by local area. The challenge now is to encourage local authorities and charities to use the index to create more informed policy and more accurate allocation of resources. This research has not investigated or recommended policy strategies for alleviating loneliness in society, it has merely identified neighbourhoods that these policies need to be enacted in. Further research on which policies or intervention strategies most effectively combat feelings of loneliness in older populations is encouraged. Furthermore, updating of the Hall index following the release of the 2021 Census data is encouraged to analyse the changing (or constant) spatial distribution of loneliness amongst older population in England.

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