Unveiling Liveability: Exploring Liveability Profiles of Neighbourhoods and Travel Patterns in London

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Abstract

The increasing significance of cities in addressing climate crisis and the transition towards human-scale urban planning have brought neighbourhoods into the spotlight. The constraints imposed by pandemic-induced movement restrictions confined individuals to their immediate surroundings, underscoring the pressing need for urban transformation. In response, the concept of 15-minute city has emerged as a viable approach to reshape urban structures and create liveable neighbourhoods.

This study aimed to construct a comprehensive Liveability Index based on the principles of the 15-minute city paradigm, encompassing diversity, density, proximity, and digitalisation. The transparent development process of the Liveability Index was shared throughout the research. The final index effectively captured the intricate liveability profiles of London's neighbourhoods. Notably, the analysis found that neighbourhoods with elevated liveability scores are generally clustered in Inner London. Furthermore, the study demonstrated the Liveability Index's potential as a valuable instrument to guide local government urban planning policies. Additionally, the results of the Mann-Whitney U test underscored significant disparities in active travel patterns among neighbourhoods with differing liveability profiles. This emphasises the tangible impact of neighbourhood design on residents' mobility pattern.

The assessment of neighbourhoods' liveability through the Liveability Index can help urban planners better understand neighbourhood dynamics, enabling neighbourhood-specific actions to foster the development of diverse, walkable and liveable neighbourhoods. By providing a holistic perspective, this research contributes to the creation of urban spaces that enhance residents' well-being and quality of life.

Declaration

I, Philyoung Jeong, hereby declare that this dissertation is all my own original work and that all sources have been acknowledged. It is 11,632 words in length.

정 필 영

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Acronyms

CI Composite Index

OECD Organization for Economic Cooperation and Development

LI Liveability Index

UA Uncertainty Analysis

1. Introduction

1.1 Research Background

In the face of unprecedented urbanisation, cities across the globe are confronted with multifaceted challenges that transcend conventional boundaries. UN-Habitat (2022) projects that by 2050, seven out of ten individuals will reside in urban areas. This escalating concentration of population in cities not only reduces the quality of human life, but also underscores the pressing demand for resources and larger spaces, potentially triggering substantial urban expansion. As cities are responsible for approximately two-thirds of global energy consumption and contribute to over 70% of carbon emissions (World Bank, 2023), the imperative to establish sustainable and resilient urban environment has never been more compelling. The latest Intergovernmental Panel on Climate Change (IPCC) report highlights the extensive ecological and human repercussions, underscoring cities' pivotal role in achieving net zero emissions (IPCC, 2023). These instances collectively emphasise the necessity for a profound transformation in how cities function and operate.

The urgency to re-envision city structures has grown more prominent as the pandemic-induced movement restrictions unveiled the vulnerabilities and unsustainability inherent in urban settings. Consequently, cities worldwide have begun to exhibit innovative local-based initiatives, shifting the focus away from large-scale projects. Instances such as the Netherlands' micro-markets and Austria's maze-like parks demonstrated how localised approaches can foster healthy and sustainable life styles whilst adhering to social distancing (Davies, 2020). Furthermore, Moreno's 15-minute city paradigm articulates essential dimensions for implementing proximity-based urban planning and highlights the significance of locally-scaled strategies in achieving sustainability (Moreno *et al.*, 2021). These instances highlight the potential of neighbourhoods in tackling climate challenges and enhancing residents' quality of life.

A neighbourhood serves as a small-scale enclave within a city, characterised by a distinct identity and functionality. Whilst the definition of neighbourhoods may vary across disciplines and perspectives, this study derives its inspiration from Jane Jacobs' influential work "The death and life of great American cities" (Jacobs, 1961). Jacobs championed the creation of diverse and dynamic neighbourhoods that prioritise their inhabitants. The emphasis on neighbourhoods mirrors the modern shift in urban planning towards a more human-scale approach (Gehl, 2013).

Given the increasing significance of neighbourhoods and local governments' endeavours to create liveable neighbourhoods, the assessment of neighbourhood liveability profiles has gained timely prominence. Therefore, this research aims to establish the Liveability Index – a composite index - to evaluate the liveability of London's neighbourhoods. This index draws its theoretical foundation from the 15-minute city concept. Through the illumination of distinct liveability profiles for each neighbourhood, this study endeavours to provide insights that can inform the development of tailored policies to each neighbourhood to enhance its distinctive

underperforming aspects.

1.2 Research Questions

This study aims to address the following research questions:

- From a built environment perspective, can we construct a comprehensive Liveability Index for London's neighbourhoods, based on the principles of the 15-minute city to portray their liveability profiles holistically?
- Do discernible disparities in active travel patterns exist between neighbourhoods with varying liveability scores?

1.3 Ethical Considerations

The datasets utilised in this study, such as amenity data, population data and the English Indices of Deprivation data, are publicly available and do not raise any ethical concerns. However, the raw mobility data inherently carries the potential for individual identification risk. To align with the ethical standards upheld in the UK, the data is transformed into aggregated flow data by the provider. This process ensures the complete removal of any potential risks of misuse. This study poses low ethical risk and received an approval.

2. Literature Review

2.1 Shift to Human-scale Urban Planning: The 15-minute City Paradigm

The widespread availability of affordable cars has profoundly transformed urban structure and functionality, leading to the proliferation of car-centred urban layouts. This transition has brought about environmental concerns and social exclusion within city designs, prompting urban planners to reconsider the structure of cities. For instance, Jacobs (1961) challenged the prevailing large-scale urban development and championed the idea of diverse, walkable and mixed-use neighbourhoods through a resident-inclusive approach. Meanwhile, Whyte (1980) focused on the observations of how people use and perceive public spaces, highlighting the value of small-scale, pedestrian-friendly areas that encourage social interactions and varied activities. Despite their distinct perspectives, Jacobs and Whyte played significant roles in shaping the emergence of New Urbanism. This movement called for a reconsideration of city inner structures by incorporating elements that prioritise community, sustainability and quality of life (Congress for the New Urbanism, 2000).

The urgency for a shift towards human-centred urban planning has grown more after the Covid-19. The pandemic exacerbated socio-economic disparities due to limited access to essential urban services, particularly impacting marginalised populations. Moreover, it unveiled the resident-exclusionary nature of modern city designs. The hygienic restrictions constrained individuals' activity radius around their homes, compelling contemporary urban planners to re-evaluate micro-level neighbourhoods and prioritise the creation of more liveable and inclusive neighbourhoods. Moreno's 15-minute city concept regards neighbourhoods as the essential and foundational spatial units in urban planning, where residents satisfy their fundamental necessities (Pozoukidou and Chatziyiannaki, 2021). Moreno *et al.* (2021) argue that neighbourhoods should be structured to support an ideal population density and provide an easy access to six crucial urban services: living, commerce, working, education, entertainment and healthcare. The neighbourhood-based approach diminishes dependence on vehicles, assisting cities in curbing carbon emissions, revitalising the local economy, attracting a diverse array of urban services, thereby enhancing residents' well-being (Allam *et al.*, 2022). The paradigm extends beyond proximity; it also highlights the importance of density, diversity and digitalisation. Density signifies the count of people per given area, whilst diversity embraces the richness of cultural diversity and mixed land-use (Moreno *et al.*, 2021). Lastly digitalisation plays a pivotal role in facilitating the aforementioned domains, enabling resident engagement and leveraging state-of-the-art technologies and data for paradigm implementation (ibid.). The 15-minute city concept is in harmony with key climate agendas. Its direct relevance to the Paris Agreement and Sustainable Development Goal 11 (Allam *et al.*, 2022), and its implementation in Paris has garnered international acclaim as an exemplary approach for post-pandemic urban revitalisation (Pozoukidou and Chatziyiannaki, 2021; Gongadze and Maassen, 2023).

However, the model also faces criticism for potentially segregating cities into isolated 15-

minute enclaves, hindering city-wide connectivity (Glaeser, 2021). Glaeser's argument (2021) that advocates for interconnected neighbourhoods to maximise opportunities highlights a crucial concern: how to strike a balance between the creation of self-sufficient neighbourhoods and ensuring the broader cohesiveness and accessibility of the entire urban landscape. Moreover, the concerns raised by O'Sullivan (2021) regarding the model's potential to amplify existing racial and socio-economic disparities whilst fostering gentrification are valid. Using GPS data, Abbiasov *et al.* (2022) identified a link between the 15-minute city land-use and socio-economic segregation, especially impacting lower-income populations. This underscores the necessity to fully consider the intricate interplay between social and economic dynamics shaping diverse urban regions. Neglecting these factors could inadvertently contribute to heightened polarisation.

Whilst the concept gained prominence in 2021, the notion of proximity-based urban planning has been acknowledged and put into practice in several cities. For example, Melbourne's 20-minute neighbourhoods prioritise local living by ensuring essential urban services within a 20-minute walk, fostering sustainability and well-being (Victoria State Government, 2017). Barcelona's SuperBlock Initiative designates car-free 400 * 400 metre blocks, equivalent to a 5-minute walk, to empower citizens, encourage active travels, and enhance urban ecosystems (Postaria, 2021). These cities showcase the transition in urban planning focus from prioritising the accessibility of urban functions across neighbourhoods to emphasising proximity within neighbourhoods. Furthermore, the adaptation made by these exemplary cities regarding the time frame illustrate their incorporation of the 15-minute city's principles whilst tailoring the model to suit their specific contexts.

In summary, the 15-minute city model offers a fundamental blueprint for establishing vibrant and liveable urban neighbourhoods. Nonetheless, critical scrutiny and the cases of exemplary cities offer valuable insights. Primarily, the need for a context-specific and resident-engaged bottom-up approach is paramount for the effective implementation of the model. Moreover, the strategic integration of robust transport networks, pedestrian-friendly pathways, and mixed-use urban design can uphold the benefits of self-sufficient neighbourhoods whilst simultaneously fostering urban cohesiveness and interconnectedness.

2.2 Defining Neighbourhoods

The concept of 'neighbourhood' in urban landscapes is intricate and can be understood from various perspectives. Sheppard (2015) elucidates this complexity through an epistemological lens that encompasses positivism, idealism, and structuralism, highlighting the multifaceted nature of our comprehension of urban space. Notably, research endeavours have sought to define and characterise neighbourhoods in diverse ways.

From the perspective of the built environment, neighbourhoods can be conceptualised as the agglomeration or clustering of various amenities. This emphasises the pivotal role of both the presence and arrangement of amenities in shaping the identity and functionality of a

neighbourhood. In an illustrative study, Sevtsuk (2014) delves into nuanced spatial patterns of amenity clustering, unravelling how different retail and food establishments coalesce within neighbourhoods. Building upon this, Hidalgo, Castañer and Sevtsuk (2020) employ a proximity-based clustering approach to identify neighbourhoods and their associated amenities. Their methodology aligns amenities with local peaks, characterised by their good accessibility and proximity to a greater number of other amenities (ibid.).

Neighbourhoods can be defined by subjective perceptions. Lynch (1964) emphasises the role of cognitive maps in shaping urban perceptions and spatial organisation. This underscores how individual perspectives influence the delineation and functional aspects of local urban areas. Nold (2009), in his research, employs biometric devices to capture personal emotional reactions within urban settings, leading to the creation of an "Emotion map". The work illustrates the interplay between personal experiences, emotions, and urban environments, thereby reshaping the understanding of neighbourhoods beyond physical attributes.

Recent research demonstrates the potential for identifying neighbourhoods using big data. For instance, Aras, Ouellette and Jain (2021) applied a hierarchical clustering to analyse road characteristics and barriers based on parcel data. This method effectively deconstructed American cities into distinct neighbourhoods, offering insights into strategies for fostering social interactions and blending among barrier-enclosed neighbourhoods. Moreover, González, Hidalgo and Barabási (2008) revealed that human mobility patterns are not random, showing a high degree of regularity wherein individuals frequently return to a few key locations. The study suggests the feasibility of utilising GPS data to create neighbourhoods based on activity spaces.

2.3 Liveability Assessment

Liveability assessment provides insight into the extent to which a place is desirable for habitation. Such evaluation can draw from a range of factors. For instance, the diversity and proximity of urban services can significantly shape liveability (Moreno *et al.*, 2021). Additionally, the accessibility and presence of urban green spaces (Niemelä *et al.*, 2010; Tian, Jim and Wang, 2014), and the promotion of a walkable environment (Shamsuddin, Hassan and Bilyamin, 2012) have been argued to contribute significantly to a city's overall liveability. Conversely, elements like the dispersion of retail establishments (Rotem-Mindali, 2012) and the sense of insecurity within urban environment (Leby and Hashim, 2010) can detrimentally affect liveability.

Extensive research endeavours have been directed towards conducting city-wide or large-scale assessments of liveability. The widely recognised Global Liveability Index assesses global cities by considering diverse factors that collectively influence a city's liveability (Economist Intelligence Unit, 2023). Whilst this index is valuable for cities to benchmark their status in distinct domains compared to others, the city-wide assessments may overlook subtle differences existing at the neighbourhood level within a city. This limitation highlights the

need for liveability assessments conducted at a more localised scale, such as the neighbourhood level, which is still relatively uncommon.

Higgs *et al.* (2019) constructed the Urban Liveability Index by integrating health indicators relevant to policies for residential addresses in Melbourne, highlighting its positive association with active travel behaviours. This incorporation of policy-related indicators into a neighbourhood-level index underscores its effectiveness in assessing policy impacts at a fine-grained scale, particularly challenging contexts like the neighbourhood level. Moreover, Norouzian-Maleki *et al.* (2015) underscore the importance of incorporating environmental attributes into the evaluation of neighbourhood liveability, and propose that indicator weights should be tailored to the unique contextual characteristics of each neighbourhood. This study recognises the intricate dynamics of urban spaces and acknowledges that a one-size-fits-all approach to assessing liveability might overlook crucial factors that shape residents' experiences.

Given that this research specifically aims to evaluate liveability through the lens of the built environment, the preceding literatures play a crucial role in identifying and prioritising liveability elements that are directly aligned with the research goal. Furthermore, the scarcity of liveability assessment at a granular level reinforces the compelling need for assessing neighbourhood liveability within the context of London. It highlights the importance of selecting pertinent indicators and recognising their context-specific importance in constructing the index.

3. Methodology

3.1. Outline

A multitude of literature underlines the multi-dimensional nature of liveability. In this regard, the utilisation of a Composite Index (CI) to present liveability seems beneficial. The CI can incorporate complex aspects of liveability and encapsulate them into a single indicator. The easy interpretation and the condensed presentation of diverse separate indicators through a CI have attracted the interest of the public and policymakers. Consequently, it has been frequently adopted by national or international organisations (Saisana, Saltelli and Tarantola, 2005). Seemingly simple, building a CI is, however complicated. The construction of a CI involves numerous processes which require subjective judgements and transparency (Saltelli, 2007). Whilst there is no absolute rule to follow in building a CI, the OECD guidelines on constructing a CI are popularly cited and provide the best practices. Whilst the construction of Liveability Index will be in accordance with the OECD's 10-step technical guidelines, there will be some modifications. This research aims to provide a holistic assessment of London's neighbourhoods' liveability, which necessitates the inclusion of the neighbourhood construction process. In this context, it is vital to recognise that the guidelines serve as an overall skeleton of the CI building process, and one needs to make context-specific adjustments to the guideline in order to achieve one's research aim.

3.2. Theoretical Framework

Although each step described in the OECD guidelines is of importance in building a CI, the quality of a CI is largely determined by the robustness of the theoretical framework (Joint Research Centre-European Commission, 2008). The framework helps understand the relevant domains that a CI needs to account for, and frame overall structure of building process. This is particularly crucial in deciding the datasets that will be used to build a CI.

The Liveability Index is grounded on the 15-minute city concept that opines the encouragement of mixed land-use and proximity-based urban planning for urban residents' well-being (Moreno *et al.*, 2021). The paradigm highlights the importance of four dimensions – Diversity, Proximity, Population Density and digitalisation – in facilitating the 15-minute city, and claims that successful implementation of the concept can provide residents with six essential urban services (Moreno *et al.*, 2021). However, this study excludes 'working' service due to the growing prevalence of teleworking among companies following the pandemic (Eurofound, 2022). The key domains of the 15-minute concept can also be found in policy documents including the London Plan 2021 (Greater London Authority, 2021) and the National Planning Policy Framework (Ministry of Housing, Communities & Local Government, 2021). Table 3.1. presents a compilation of quotes extracted from these government documents, aligning with the key domains of the 15-minute city concept. Notably, within each domain, a diverse range of quotes addresses various dimensions, all of which are intrinsically linked to the provision of essential urban services.

Table 3.1 A list of the 15-minute city concept related quotes from the policy frameworks

Domain	***Policy Reference (quoted)***	***Page***	***Policy Document***
Diversity	'Encouraging a mix of land uses, and co-locating different uses'	p.15	London Plan
	'High-density, mixed-use places support the clustering effect of businesses'	p.15	London Plan
	'creating vibrant and active places and ensuring a compact and well-functioning city'	p.16	London Plan
	'identify and allocate a range of sites to deliver housing locally'	p.22	London Plan
	'promote and support London's rich heritage and cultural assets'	p.24	London Plan
	'ensure the public realm is well-designed, safe, accessible, inclusive'	p.134	London Plan
	'maximise the extended or multiple use of educational facilities'	p.223	London Plan
	'sufficient supply of good quality sports and recreation facilities'	p.229	London Plan
	'A successful, competitive and diverse retail sector, which promotes sustainable access to goods and services for all Londoners'	p.267	London Plan
	'support strong, vibrant and healthy communities'	p.5	NPPF
	'enable and support healthy lifestyles … through the provision of safe and accessible green infrastructure, sports facilities, local shops, access to healthier food'	p.27	NPPF
	'To provide the social, recreational and cultural facilities and services the community needs'	p.27	NPPF
Proximity	'Mayor's target for 80 percent of all journeys to be made by walking, cycling and public transport'	p.15	London Plan
	'support active travel'	p.114	London Plan
	'Social infrastructure should be easily accessible by walking, cycling and public transport'	p.218	London Plan
	'improving street environments to make walking and cycling safe and more attractive'	p.402	London Plan
	'reduce car dominance'	p.402	London Plan
	'use of attractive, well-designed, clear and legible pedestrian and cycle routes'	p.27	NPPF
Digitalisation	'Fast, reliable digital connectivity is essential'	p.362	London Plan
	'support the expansion of electronic communications networks'	p.33	NPPF
Population Density	'Density measures are related to the residential population will be relevant for infrastructure provision'	p.116	London Plan

Table 3.2 Liveability Index domains, services and benefits

Domain	***Service***	***Benefit***
Diversity	Diversity of Commerce	Enhanced variety of commerce-related amenities and activities in neighbourhoods
	Diversity of Education	Enhanced variety of education-related amenities and activities in neighbourhoods
	Diversity of Entertainment	Enhanced variety of entertainment-related amenities and activities in neighbourhoods
	Diversity of Living	Enhanced variety of living-related amenities and activities in neighbourhoods
	Diversity of Healthcare	Enhanced variety of healthcare-related amenities and activities in neighbourhoods
Proximity	Proximity to Commerce	Improved proximity to commerce-related amenities and activities
	Proximity to Education	Improved proximity to education-related amenities and activities
	Proximity to Entertainment	Improved proximity to entertainment-related amenities and activities
	Proximity to Living	Improved proximity to living-related amenities and activities
	Proximity to Healthcare	Improved proximity to healthcare-related amenities and activities
Population Density	Population density per km^2	Optimal population density to sustain urban functions and resource consumptions

Table 3.2 incorporates the quotations from Table 3.1 and organises them into 3 domains encompassing 11 urban services and their corresponding benefits. The digitalisation pillar has been incorporated into this research by utilising various digital data. Each service accounts for distinctive dimensions present within the respective domain, facilitating a comprehensive presentation of liveability profiles. Specifically, in the diversity domain services, neighbourhoods with high values signify an abundance of amenities and activities related to a specific diversity service, whilst low values indicate scarcity. Conversely, the proximity domain operates oppositely. Lower values indicate proximity to amenities, whereas higher values denote greater distance.

It is important to clarify that the Liveability Index does not intend to measure the extent to which one neighbourhood is more liveable than another. Instead, it employs an area-based relative comparison method to offer a holistic portrayal of the liveability profiles of London's

neighbourhoods. This approach ensures a broader understanding of the overall liveability landscape.

3.3 Neighbourhood Construction

The significance of amenity diversity and convenient walkable access to these facilities is underscored as crucial in shaping lively and healthy neighbourhoods. Jane Jacobs, a notable urban advocate, emphasised the importance of creating diverse and vibrant urban neighbourhoods that promote organic interactions among residents, encourage mixed land uses, ensure walkability, and prioritise human-centred development (Jacobs, 1961). As administrative boundaries are not universally defined for neighbourhoods, their construction can adopt a bottom-up approach that prioritises diversity and proximity.

3.3.1 Data

OpenStreetMap

OpenStreetMap (OSM) is a dynamic collaborative mapping platform, enabling global users to both contribute to and access geospatial data. Renowned for its frequent updates, the data stands as a rich repository, distinguished by its quality and quantity. This abundance ensures a precise representation of urban areas concerning infrastructure, amenities, and more.

The amenities within neighbourhoods, also known as Point of Interest (POI), serve as a key attraction for residents. The querying of POIs from OSM concentrated on three distinct categories: amenity, shop, and tourism. These categories are chosen for their relevance and significance in fostering vibrant and diverse neighbourhoods. Consequently, there are 597 different types of POIs, and they are categorised into five essential urban services based on Moreno's urban function classification (see Appendix A). Alongside POIs data, road data has also been extracted. This data will later be used to construct road network and subsequently projecting POIs onto it.

Mobility Data

The mobility data spans the period from 1st to the 28th of February 2023. This dataset encompasses three key attributes: a distinctive hexagon identifier, the normalised footfall score and movement modality. Each hexagon is uniquely identified and corresponds to the granular level of uber h3 level 10. The footfall score assesses the probability of encountering a user within a specific geographical area during a designated time period. The score is computed daily for each individual hexagon grid. The footfall score values are initially normalised by the data provider. This normalisation process entails dividing each footfall score by the maximum value within the dataset and then multiplying by 100. Consequently, the normalised footfall scores for every hexagon grid are averaged over the 28-day period. This

aggregation yields an 'average normalised footfall score' for each hexagon. Additionally, the dataset includes three different types of movement modality. To investigate the variation in active travel patterns among neighbourhoods with varying liveability scores, the analysis exclusively focuses on pedestrian data. Figure 3.1 shows the distribution of average normalised footfall scores. Notably, the majority of footfall scores remain below 1, with only approximately 10% of hexagons exhibiting scores exceeding 1.

This hexagon-centred representation offers dual benefits, in terms of the capacity to store data at a granular-level and the ease of data projection onto spatial units with irregular shapes. The consistent hexagon size plays a crucial role in enabling effective comparisons of normalised footfall data across neighbourhoods, despite the inherent variations in their boundaries. This approach becomes especially pertinent in deciphering travel patterns among different neighbourhoods.

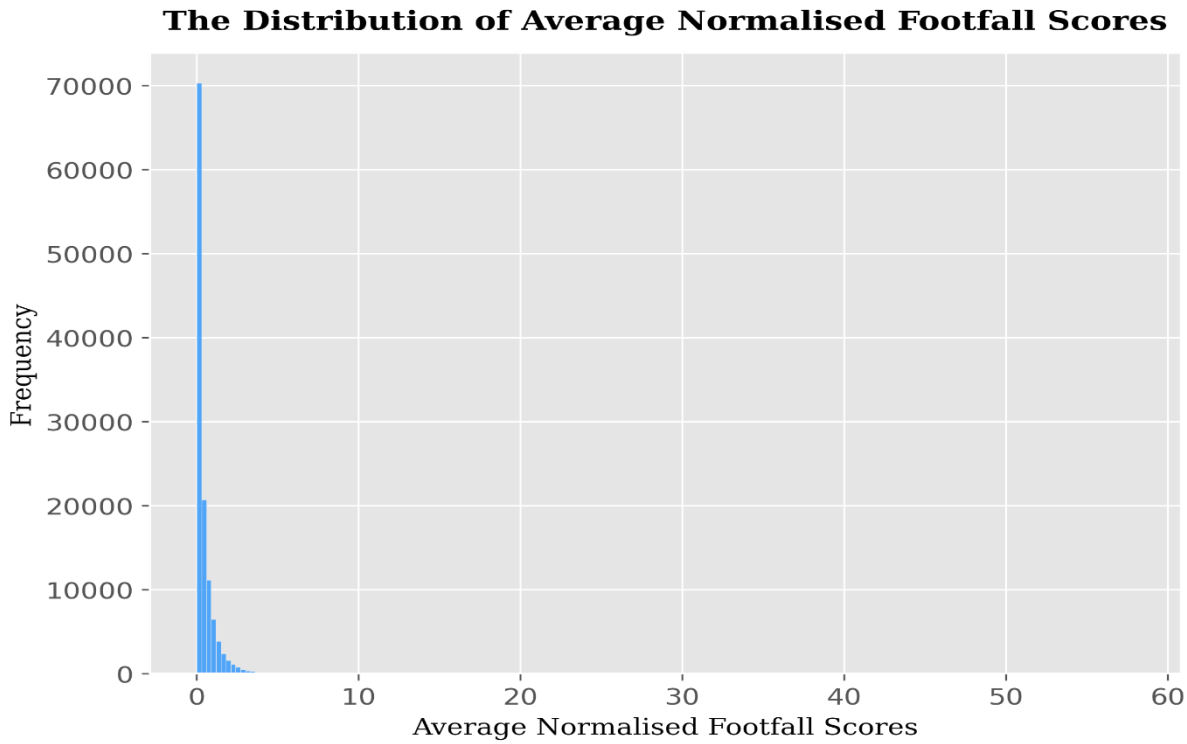

Figure 3.1 Distribution of average normalised footfall scores

3.3.2 Method

Isodistance

An isodistance delineates areas reachable from a specific point within a consistent travel distance, considering the actual road network. This aids in visualising accessibility and comprehending travel patterns. Amenity entropy can be computed based on isodistances, allowing amenities to mirror the diversity of their surrounding environment. Additionally, within the scope of neighbourhood construction, the integration of isodistances with

amenity's entropy enables the identification of local maximum entropy points. This will be further explained in **3.3.3 neighbourhood formation**. Using the cppRouting package in R (Larmet, 2022), isodistance for every POI was calculated.

Entropy

The diversity of urban environment can be quantitatively explained using Shannon's entropy (Shannon, 1948). Numerous literature have attempted to measure the diversity of amenities. Barbosa *et al.* (2021) utilised Shannon's entropy to compare the diversity of sub-areas within US and Brazilian cities based on the economic status of residents. The diversity of accessible amenities per resident was assessed using Shannon's entropy (Graells-Garrido *et al.*, 2021). The application of Shannon's entropy is not solely limited to explaining the diversity of amenities. For instance, TV, Aithal and Sanna (2012) employed Shannon's entropy as a measure of dispersion in urban growth patterns, which enabled to quantify and characterise the level and direction of urbanisation in different areas of Bangalore over time. Fan *et al.* (2023) applied Shannon's entropy to measure the diversity and evenness of time spent by different income groups on specific street segments.

The entropy is computed for each individual amenity point by considering other amenities within a t-metre walking distance from the specific amenity. The formula for Shannon's entropy is as follows:

$$S_i = -\sum_{j}^{N_c} P_{ij} * \ln P_{ij} \tag{3.1}$$

where S_I represents the entropy of amenity i, N_c denotes the number of amenity types, and P_{ij} signifies the ratios of amenities in category j to the total count of amenities within a t-metre walking radius from amenity i. In essence, S_i characterises the entropy of the space, as it sums all the entropy values of each category amenities. Moreover, it also incorporates the quantity of amenities within a certain radius. This is reflected in the formula where the ratios of amenities in each category are used. As the quantity of different amenity types changes, it affects the values of P_{ij}, thus influencing entropy calculation. Furthermore, the entropy is influenced by the number of amenity types which serves as an upper limit to the entropy value. The maximum entropy $S_{max} = \ln N_c \, (N_c = 597)$ equals 6.39, achieved when all amenity categories coexist within the radius. The minimum entropy $S_{min} = 0$ occurs when only one amenity type exists at the location.

Figure 3.2 illustrates the entropy of amenities within a 500m isodistance in London. The colour gradient, from darker to lighter shades of green, signifies the range of entropy values. Notably, a pronounced concentration of high entropy values in Inner London is evident, denoting a rich diversity of amenities. However, the visualisation also reveals scattered instances of elevated entropy values in Outer London. This observation underscores that whilst high entropy values

predominantly cluster in the city centre, they are also observable in the dispersed context of Outer London.

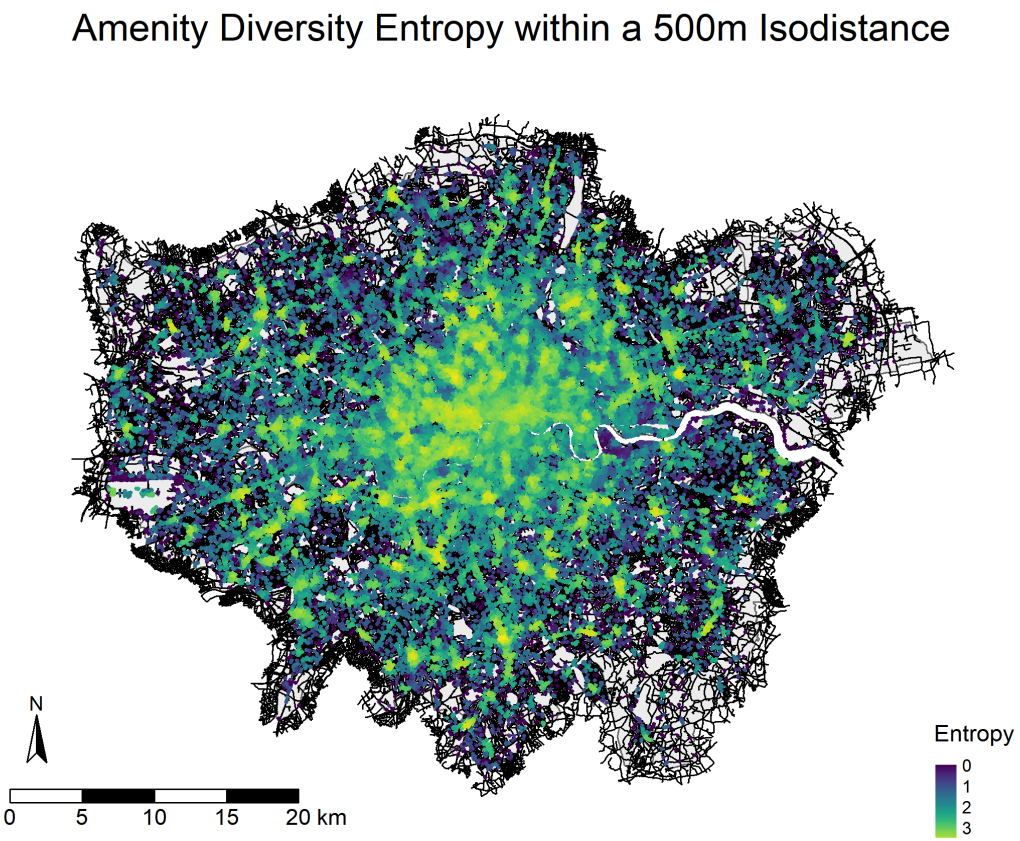

Figure 3.2 Amenity's entropy map with a 500m isodistance

3.3.3 Neighbourhood Formation

Approach

Drawing inspiration from Hidalgo, Castañer and Sevtsuk (2020), this study employs a methodology emphasising the influence of amenity agglomeration in shaping neighbourhoods. Central to this approach is the concept of "local maximum entropy", signifying pivotal zones within neighbourhoods where the diversity and distribution of amenities are at their highest compared to the surrounding areas. Linking amenities to these entropy-rich points offers a valuable approach for detecting potential centres within each neighbourhood, thereby contributing to the organic formation of neighbourhoods. Furthermore, the identification and cultivation of local maximum entropy areas hold the potential to create well-rounded, liveable, and sustainable neighbourhoods.

The algorithm follows a sequential process in which it begins with a specific amenity. It looks for the peak entropy within a predetermined walking distance limit. This process continues iteratively until the highest entropy matches with the original amenity itself. Ultimately, the

initial amenity that initiated the step-by-step process is linked to the identified local maximum. This approach relies on the assumption that the entropy function exhibits a certain degree of smoothness, enabling the algorithm to ascend along its gradient through this iterative process. This algorithm facilitates the assignment of each amenity to its respective local maximum, contributing to the establishment of neighbourhoods. Through iterative process, 1612 neighbourhoods were initially identified. However, only neighbourhoods containing a minimum of 5 amenities were retained, resulting in 1209 neighbourhoods.

Results

The predefined walking distance limit can have significant implications for the size of neighbourhoods. A larger distance value would lead to a greater agglomeration of amenities within neighbourhoods. Therefore, it is crucial to analyse the impact of different isodistance values on neighbourhood size. To explore this, various isodistance values were tested.

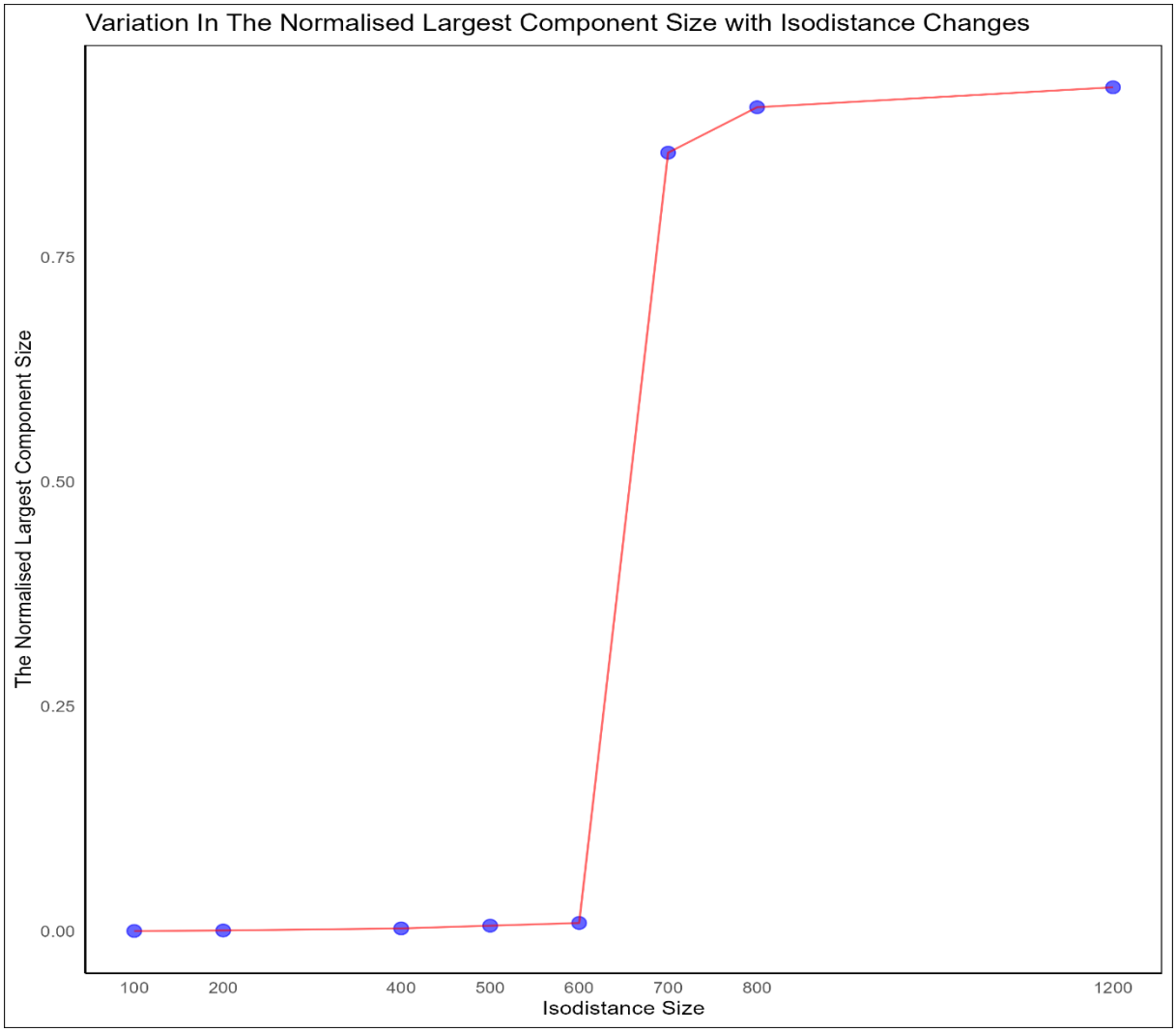

Figure 3.3 Variations in the normalised largest neighbourhood component size with isodistance changes.

Figure 3.3 displays the normalised largest neighbourhood size in relation to varying isodistance values. The normalisation involved dividing the largest neighbourhood size by the total area of London. The graph clearly illustrates that increasing the isodistance value results in a higher normalised size for the largest neighbourhood. Notably, a significant jump in the normalised largest neighbourhood size occurs after the isodistance reaches 600m. This suggests that beyond this point, the potential for amenity agglomeration and the subsequent creation of abnormally extensive neighbourhoods is enhanced. Thus, an isodistance value prior to this substantial jump appears reasonable. Existing literature provides guidance in determining an appropriate isodistance value. For instance, Sevtsuk (2014) discovered that a considerable number of trips within in neighbourhoods fall within a 10-minute walking radius. Furthermore, Hidalgo, Castañer and Sevtsuk (2020) observed that an amenity's impact on neighbourhoods diminishes by half approximately every 62.5m and becomes minimal at a distance of roughly 500m. Hence, an isodistance value of 500m appears a well-founded for constructing neighbourhoods.

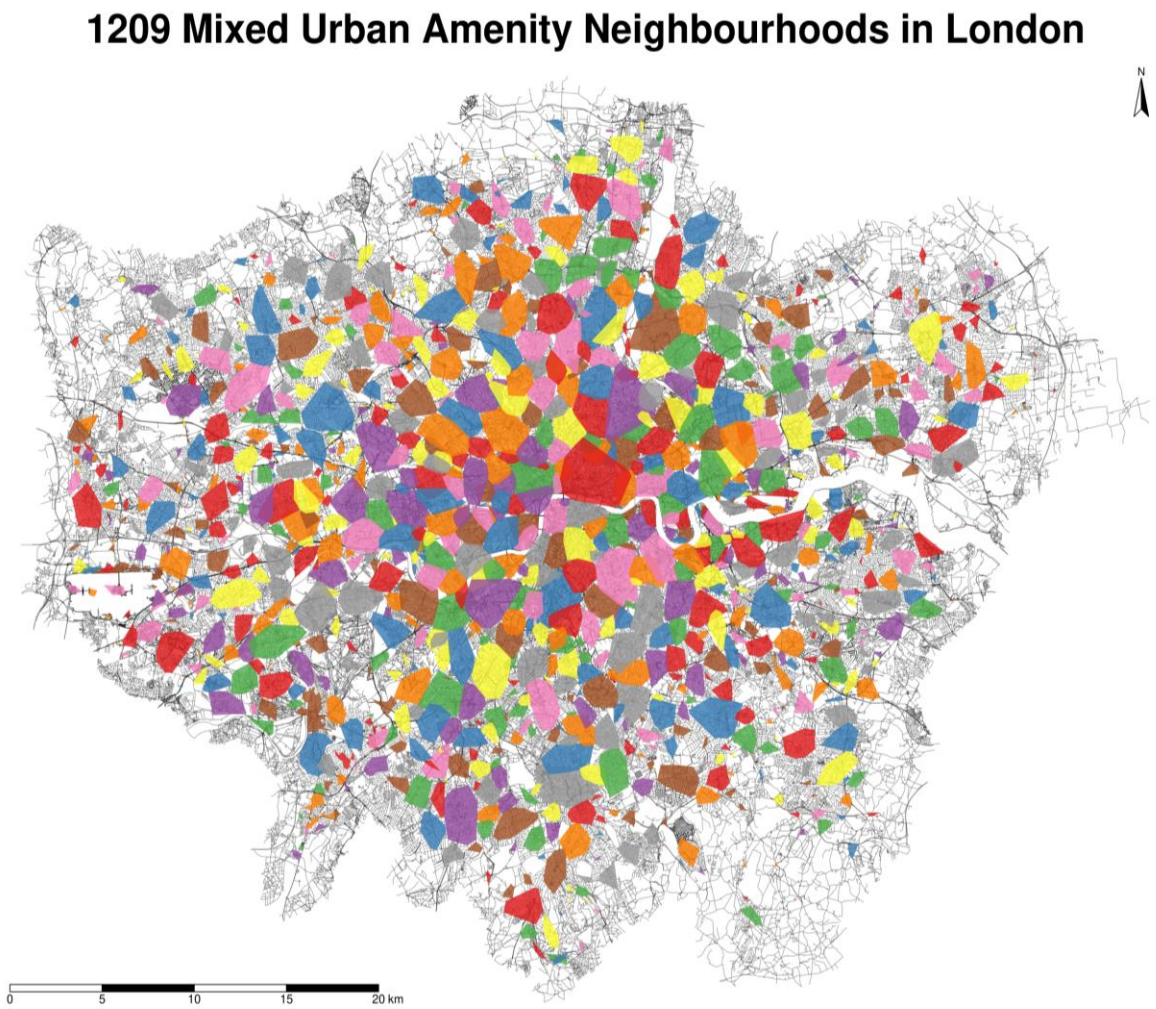

Figure 3.4 Neighbourhoods revealed through the investigation of amenity entropy of space. Isodistance of 500m is used and each polygon represents different neighbourhoods.

Figure 3.4 visually displays 1209 neighbourhoods in London, uncovered through the analysis of amenity entropy of space. Each polygon corresponds to distinct neighbourhoods. The neighbourhoods constructed with an isodistance value of 500m align well with the city's geographical features.

3.4 Data Selection and Imputation

This section focuses on the acquisition of neighbourhood-level indicator data, consisting of 11 metrics as outlined in Table 3.2. The process of obtaining these indicators for each neighbourhood is detailed below.

3.4.1 Diversity

To assess the diversity of distinct urban services within neighbourhoods, Shannon's entropy is employed. The POI data is organised by unique neighbourhood IDs and urban service categories. For every urban service type in each neighbourhood, the total count of POIs is computed, along with the probabilities of individual POI counts within their respective categories. Shannon's entropy is then calculated to quantify the diversity of urban services within each neighbourhood. For instance, the diversity of living services can be computed as follows:

$$D_{lk} = -\sum_{j}^{N_l} P_{kj} * \ln P_{kj} \tag{3.2}$$

where D_{lk} represents the diversity of living services for neighbourhood k, N_l is the number of living-related amenities, and j represents the amenity type within the living service category. The remaining diversity indicators can be derived using the same methodology.

3.4.2 Proximity

The measurement of proximity to urban services employs a fundamental physical concept. Considering that each urban service amenity is dispersed throughout the neighbourhood space, each urban service possesses its own centre of mass. This approach enables the calculation of the average Euclidean distance between the neighbourhood's centroid and the centre of mass of each urban service. By adopting this method, the analysis takes into account the overall distribution pattern of specific urban service-related amenities within the neighbourhood. Furthermore, this holistic perspective accounts for their collective proximity to the centre of neighbourhood and simplifies the distance calculation process.

However, it is important to note that the aforementioned approach assumes the presence of

all urban services within a given neighbourhood. In cases where a neighbourhood lacks any of the five urban services, a hybrid approach combining Euclidean and network distance was employed. For urban services available within a neighbourhood, the average Euclidean distance was utilised. Conversely, for absent urban services, the network distance came into play. This entails computing the distance from the neighbourhood's centroid to the nearest centre of mass of the missing urban service within neighbouring neighbourhoods. This nuanced calculation takes into consideration the likelihood of residents traveling to other neighbourhoods to access amenities not available in their own area.

The computation of the average Euclidean distance was facilitated using the sf package in R (Pebesma, 2018). However, the calculation of network distance necessitated additional steps. This involves the projection of POIs onto the road network. To achieve this, a road network was constructed utilising the cppRouting package in R (Larmet, 2022). Subsequently, the centroids of the neighbourhoods and the centre of mass for each urban service were projected onto nodes within the road network. This enabled the accurate computation of the network distance between these points.

3.4.3 Population Density

The population data is derived at the granularity of Lower-layer Super Output Area (LSOAs). Given the misalignment of neighbourhood boundaries with administrative boundaries, a direct projection of population data from LSOAs to neighbourhood levels could introduce inconsistencies in data interpretation. To address this, the utilisation of hexagon grids at a granular uber h3 level 10 as an intermediary level offers a consistent foundation for aggregation. This approach ensures more dependable comparisons between neighbourhoods.

In the process of projecting population data, the weighted sum approach was employed. This methodology entails the summation of population values, whereby each value is proportionately multiplied by its corresponding intersection ratios, representing its weighted contribution. This process effectively accounts for the influence of each LSOA's spatial coverage on a specific hexagon grid cell. The weighted sum approach aligns effectively with population counts, which exhibit an inherently additive nature. Once population data is projected onto the hexagon grid-level, the subsequent step involves additional aggregation to the neighbourhood-level. This step culminates in the calculation of population density per square kilometre.

3.4.4 Imputation

Table 3.3 presents the summary statistics for all indicators. It is immediately evident that there are missing values in the diversity indicators. These values primarily arise from neighbourhoods lacking amenities in specific urban service categories. It is crucial to handle these values thoughtfully, distinguishing them from diversity scores of 0 that result from

neighbourhoods with just one amenity type for a particular urban service category.

Given that the research's goal is to holistically illustrate the liveability profiles of all neighbourhoods in London. Omitting certain neighbourhoods due to the absence of specific amenity types could potentially result in a skewed representation.

To address this, an entropy value of -1 is assigned to neighbourhoods without amenities in certain urban services. This assignment can effectively differentiate these neighbourhoods from those containing only a single type of amenity for a given urban service category, which is indicated by an entropy value of 0. This will be particularly useful when employing the exponential transformation as neighbourhoods with an entropy value of -1 will be situated in the lowest bound of the exponential distribution.

However, it is important to note that the lowest entropy value that one can get is 0, and the inclusion of an entropy value of -1 is to retain all neighbourhoods to portray their liveability profiles.

Table 3.3 Summary statistics of data

Domain	*Indicator*	*Data type*	*Count*	*Null values*	*Mean*	*Std*	*Min*	*Median*	*Max*
Diversity	Diversity of Commerce	Float64	1209	276	1.74	1.08	0.00	1.76	3.88
Diversity	Diversity of Education	Float64	1209	379	0.44	0.46	0.00	0.45	1.80
Diversity	Diversity of Entertainment	Float64	1209	239	1.06	0.73	0.00	1.21	2.57
Diversity	Diversity of Living	Float64	1209	4	1.26	0.53	0.00	1.33	2.47
Diversity	Diversity of Healthcare	Float64	1209	461	0.98	0.72	0.00	1.10	2.23
Proximity	Proximity to Commerce	Float64	1209	0	387.06	492.30	0.00	186.40	5309.79
Proximity	Proximity to Education	Float64	1209	0	546.92	644.72	5.69	268.58	5568.92
Proximity	Proximity to Entertainment	Float64	1209	0	327.69	395.43	0.00	179.14	4330.85
Proximity	Proximity to Living	Float64	1209	0	32.90	56.01	0.00	16.46	1113.50
Proximity	Proximity to Healthcare	Float64	1209	0	596.40	656.72	0.67	282.25	5754.62
Population Density	Population Density per km^2	Float64	1209	0	6225.85	4324.29	122.83	5571.90	25080.49

3.5 Multivariate Analysis

The assessment of data structure plays a pivotal role in building a Liveability Index that accurately represents the inherent data distribution. Since a Liveability Index is constructed from a diverse set of indicators, this exploratory data analysis allows to uncover correlations between indicators and make informed methodological decisions. This process involves the examination of data distributions, correlation map, and Principal Component Analysis (PCA).

3.5.1 Distribution of Data

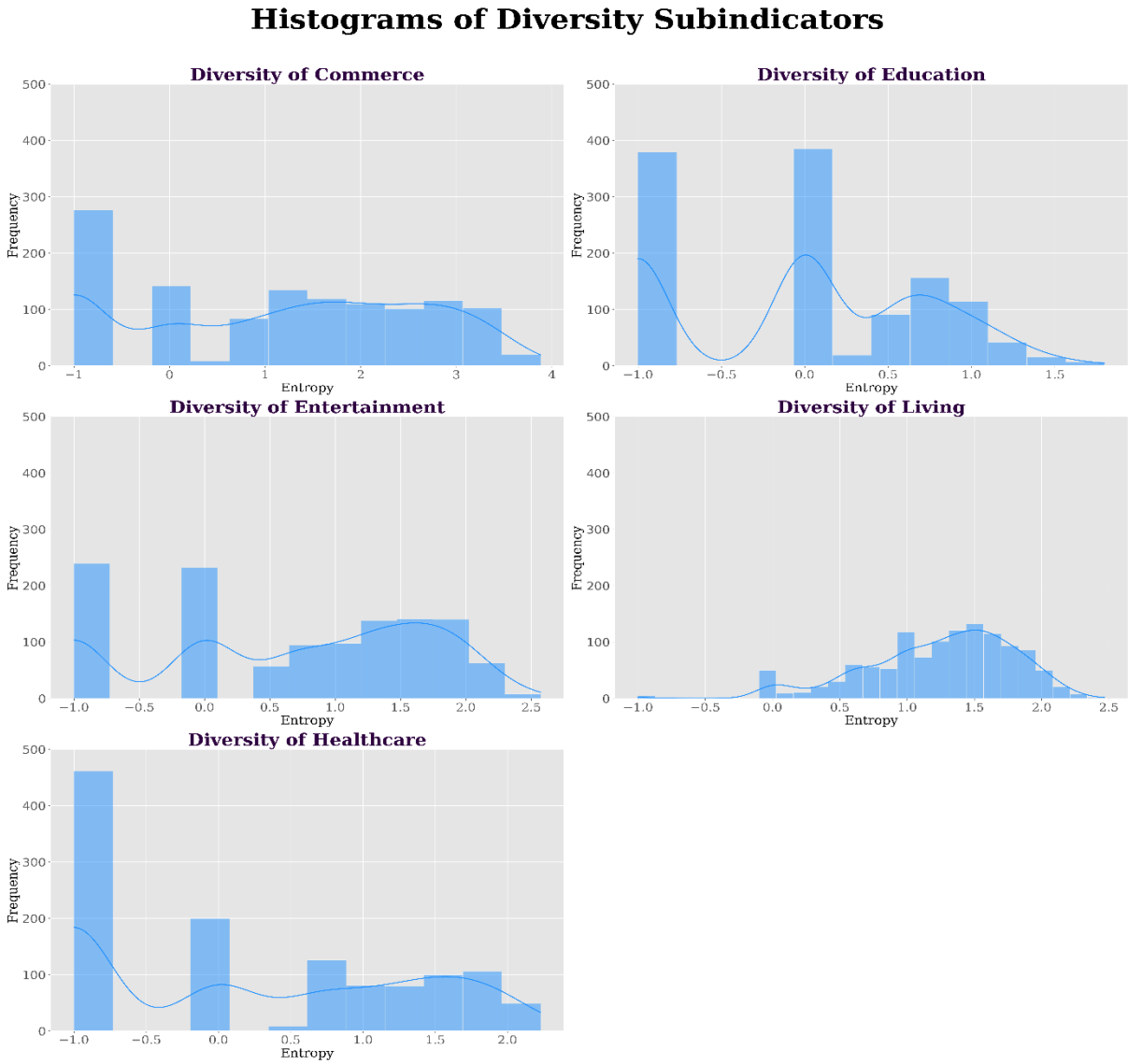

Figure 3.5 Distribution of diversity domain data. The entropy value of -1 is assigned to neighbourhoods lacking an amenity for a certain urban service category.

Figure 3.5 depicts the distribution of diversity domain indicators. A quick observation reveals

that numerous neighbourhoods either lack any amenity or possess only a single type of amenity for specific urban services, indicated by entropy value of -1 and 0, respectively. Interestingly, around one-third of neighbourhoods lacks healthcare and education-related amenities. The distribution of most indicators, with the exception of the diversity of living, deviates from a normal distribution.

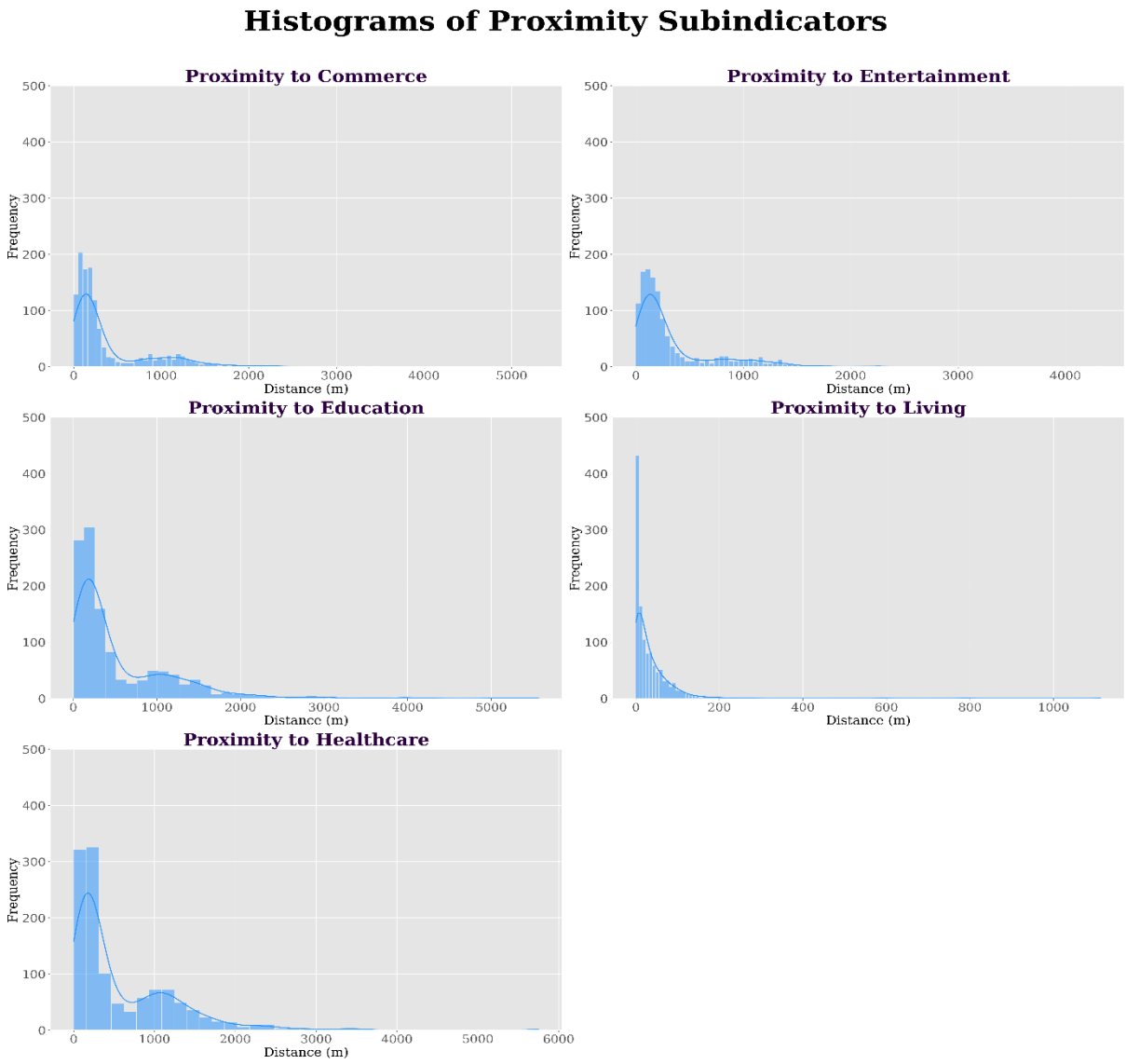

Figure 3.6 Distribution of proximity domain data

In Figure 3.6, it becomes apparent that the distribution of all proximity indicators is positively skewed. Notably, the majority of neighbourhoods exhibit close proximity to living-related amenities. Conversely, longer travel distances are expected for healthcare and education-related services in certain neighbourhoods. This phenomenon can be attributed to the limited availability of such urban services within neighbourhoods, necessitating longer travel

distances for residents to access them.

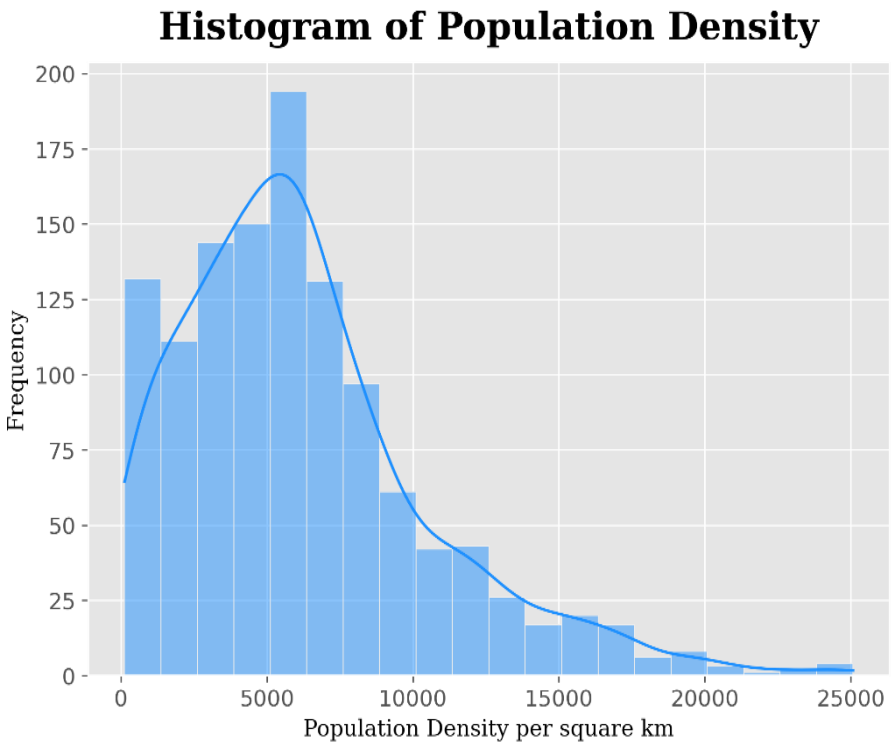

Figure 3.7 Distribution of population density domain data

Figure 3.7 illustrates the distribution of population density per square kilometre. The distribution is positively skewed, resembling the pattern observed in proximity indicators.

Overall, all indicators show distinct distribution patterns. The presence of various distribution shapes will not be a problem, as these variations will be addressed during the normalisation process. The key objective of this procedure is to ensure that each dataset provides scores that can enable comparisons among neighbourhoods, regardless of the initial distribution of the data.

3.5.2 Correlation Map

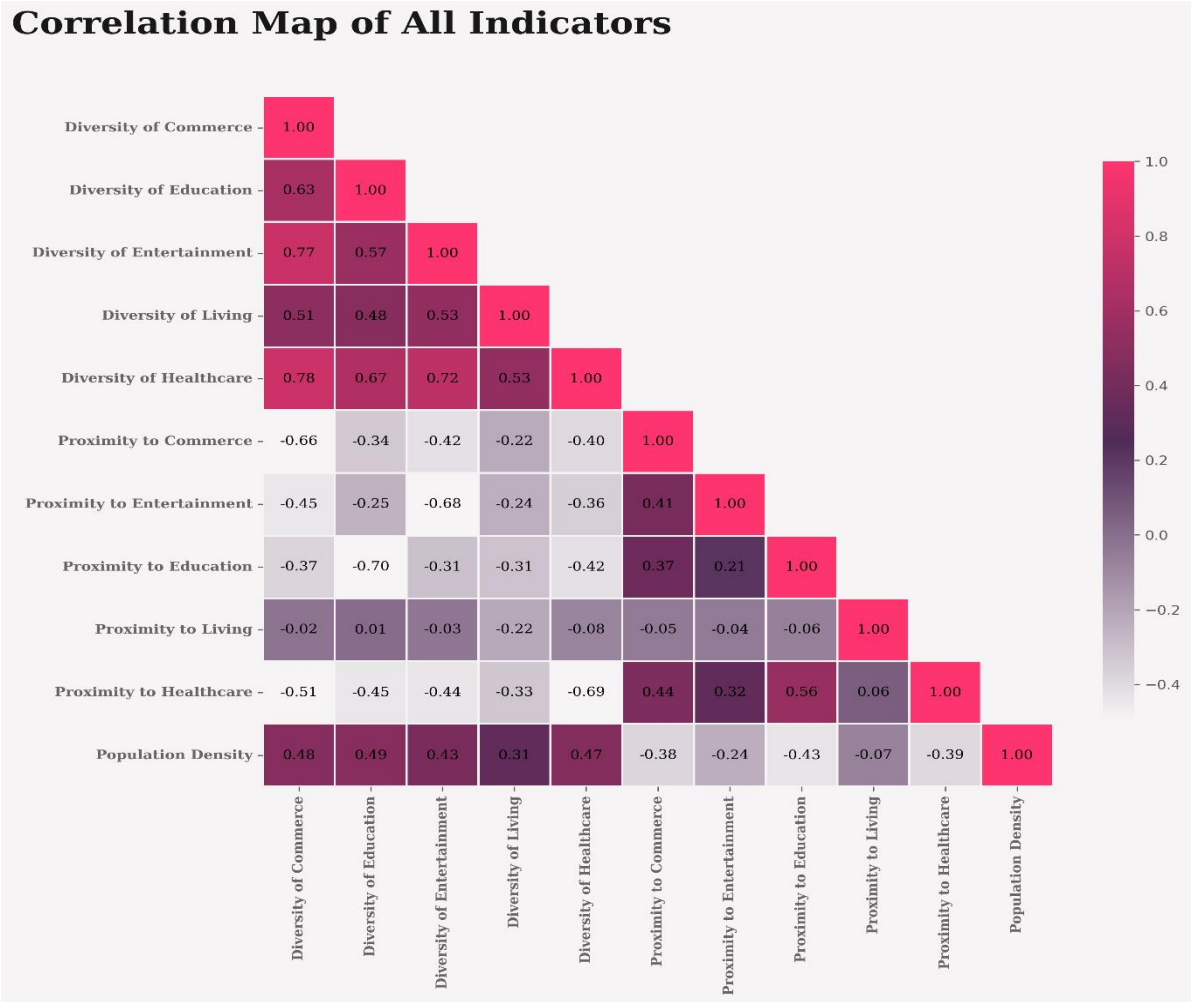

Figure 3.8 Correlation map of 11 indicators

Figure 3.8 presents a visual representation of the correlations between various indicators. Within the diversity domain, indicators exhibit a strong positive correlation among themselves. Notably, the diversity of healthcare and commerce indicators stand out with a substantial correlation coefficient of 0.78. The pronounced correlation between all diversity indicators implies the phenomenon of amenity agglomeration, where diverse, vibrant and mixed urban amenity neighbourhoods tend to attract and cluster a wide range of amenity types.

Of particular interest is the diverse range of negative correlations found between diversity and proximity domain indicators, spanning from -0.7 to 0.01. This intriguing observation suggests a potential trade-off between the closeness of urban services and the diversity of services available across different neighbourhoods. For instance, certain areas might exhibit a concentration of specific urban services, such as commercial centres, healthcare facilities or educational institutions, that serve multiple neighbourhoods in close proximity. Consequently, these neighbourhoods may experience a reduced variety of available services because their

reliance on the concentrated amenities in their vicinity might potentially discourage the development and availability of a wide range of services.

Furthermore, it is important to highlight that not all proximity indicators exhibit positive correlations. The proximity to living shows negative correlations with proximity to commerce, entertainment and education. The rationale behind this could be attributed to insights from urban economic models that explain how a city's spatial organisation is influenced by the interplay of economic agents – retail, firms and households - (Alonso, 1964). For example, commercial or entertainment districts often attract a large number of visitors, potentially driving up property values and living costs in those areas. As a result, residents may opt to reside further away from these areas in search of affordable housing options. Amidst these patterns, a strong positive correlation between proximity to healthcare and education stands out as an interesting contrast.

3.5.3 PCA

The challenge of addressing correlations between indicators often arises for CI designers due to concerns about potential double counting when assigning weights. In this context, PCA can offer valuable insights. PCA is a statistical method employed to decrease the dimensionality of a dataset whilst retaining as much meaningful information as possible. This reduction is achieved by linearly transforming the data using the covariance matrix of standardised dataset, which is equivalent to correlation matrix (Jolliffe and Cadima, 2016). The transformation results in a set of uncorrelated components, known as principal components.

The principal components are comprised of variables. The term 'PCA loadings' refers to the correlation coefficients existing between these components and the variables (Nardo *et al.*, 2005). These loadings quantify the extent to which the variance of a variable can be explained by a specific principal component. Importantly, the PCA loadings can provide a means to allocate weights to input variables during the process of building an index (Chao and Wu, 2017).

Table 3.4 PCA results for diversity domain data

Variable	*Principal Component Loadings*				
	PC1	*PC2*	*PC3*	*PC4*	*PC5*
Diversity of Commerce	0.478	-0.272	0.251	0.123	**0.787**
Diversity of Education	0.426	-0.132	**-0.847**	-0.288	0.011
Diversity of Entertainment	0.464	-0.145	0.466	**-0.633**	-0.382
Diversity of Living	0.381	**0.920**	0.032	0.051	0.069
Diversity of Healthcare	0.478	-0.203	0.026	**0.706**	-0.480
Eigenvalue	3.499	0.579	0.463	0.258	0.201
Proportion of Variance (%)	70.0%	11.6%	9.3%	5.1%	4.0%

Note. PCA loadings exceeding 0.5 (in absolute value) are highlighted

Table 3.4 displays the PCA loadings and eigenvalues derived from the correlation matrix of diversity indicators. It should be noted that the sum of the eigenvalues should match to the number of indicators. When determining the number of components, there are various 'stopping rules' to consider, and opting for a number of components that explain more than 90% of the total variance is a common approach (Joint Research Centre-European Commission, 2008). In Table 3.4, the first three components account for 90.9% of the overall variance.

The component loadings reveal a captivating pattern. Each indicator is distinctively associated with particular principal components. For instance, diversity of living strongly correlates with PC2 (0.920), diversity of education links with PC3 (-0.847), diversity of entertainment and healthcare associates with PC4 (-0.633 and 0.706, respectively), and diversity of commerce corresponds with PC5 (0.787). This underscores that different indicators contribute uniquely to specific dimensions captured by the principal components. As a result, this insight presents a compelling rationale for maintaining the original indicators without undergoing dimensionality reduction. Furthermore, considering the equal importance of each indicator in the Liveability Index, retaining all indicators appears to be better. This will ensure that the Liveability Index accurately encompasses the nuanced contributions of each diversity indicators.

Table 3.5 PCA results for proximity domain data

Variable	*Principal Component Loadings*				
	PC1	*PC2*	*PC3*	*PC4*	*PC5*
Proximity to Commerce	**0.517**	-0.059	-0.255	**0.809**	-0.101
Proximity to Entertainment	0.424	-0.112	**-0.721**	**-0.522**	-0.124
Proximity to Education	**0.502**	0.014	**0.560**	-0.221	**-0.621**
Proximity to Living	-0.037	**0.973**	-0.162	0.023	-0.162
Proximity to Healthcare	**0.547**	0.195	0.275	-0.155	**0.750**
Eigenvalue	2.171	1.019	0.849	0.546	0.415
Proportion of Variance (%)	43.4%	20.4%	17.0%	10.9%	8.3%

Note. PCA loadings exceeding 0.5 (in absolute value) are highlighted

Table 3.5 presents the PCA loadings and eigenvalues obtained from the correlation matrix of proximity indicators. The PCA analysis reveals that the initial four components explain over 90% of the total variance. An intriguing observation is that, apart from proximity to living, all other proximity indicators exhibit correlations with more than two components. Moreover, it is noteworthy that the highest PCA loadings for each indicator are not on the first component. This implies that the indicators' information and variance are spread across diverse dimensions. The distributed pattern of loadings underscores the inherently multidimensional nature of the data. Consequently, it seems reasonable to retain all indicators without dimensionality reduction.

3.6 Normalisation and Aggregation

In the construction of a CI, the role of normalisation is paramount in aligning diverse indicators, often expressed in varying scales and units, to a common and comparable metric. Whilst the literature often dissects normalisation and aggregation as distinct steps, the issue of compensability garners significance when consolidating the normalised values. Consequently, it becomes pertinent to discuss aggregation in conjunction with normalisation.

Central to CI construction is the contemplation of the degree of substitutability among the constituent indicators (Mazziotta and Pareto, 2016). This pertains to whether a low value in one indicator should be counterbalanced by a high value in another. This decision rests with the CI designer. Given that the research aims to comprehensively delineate the liveability profile of each neighbourhood, with the emphasis on comparing one neighbourhood's liveability score to another, a non-compensatory aggregation approach seems appropriate.

The Ministry of Housing, Communities and Local Government adopted a non-compensatory approach in formulating the Index of Multiple Deprivation (henceforth, IMD). The IMD employed the exponential transformation, grounded in a weighted cumulative model, to mitigate the occurrence of cancellation effects (McLennan *et al.*, 2019). The procedure commences with ranking areas based on indicator scores, which are then rescaled to a range of 0 and 1. The area with the lowest indicator score corresponds to $\mathrm{R} = 1/\mathrm{N}$, whilst the area with the highest indicator score corresponds to $\mathrm{R} = \mathrm{N}/\mathrm{N}$ ($\mathrm{R} = 1$). In our case, N signifies the total count of neighbourhoods (1209) in London. Subsequently, these ranking are translated to an exponential distribution using the following equation:

$$\mathrm{X} = -23 \ln(1 - R(1 - exp^{-100/23})) \tag{3.3}$$

where X denotes the exponentially transformed indicator score.

The value of the scaling constant, 23, yields an approximate 10% of cancellation effect (ibid.). The scaling constant helps adjust the rankings in a way that reflects a moderate level of cancellation, ultimately contributing to a more accurate representation of overall liveability. The exponential transformation culminates in score distribution spanning from 0 to 100.

In essence, the exponential transformation aids in aligning indicator scores on a common scale for normalisation and contribute to refining the aggregation process by allowing a controlled level of cancellation effects. This balance between normalisation and aggregation helps in constructing a CI that accurately represents the underlying dimensions whilst considering their interactions. Furthermore, the exponential transformation serves to accentuate the differences between neighbourhoods with no amenities (imputed as entropy value of -1) and those with only one amenity type (entropy value of 0).

As the index encompasses multiple indicators and domains, the exponential transformation

will only be performed after determining the final scores for each level of indicators and domains within the Liveability Index.

3.7 Weighting

Weighting constitutes the process of assigning relative significance to individual indicators during their combination. This enables each indicator to contribute proportionally to the overall index. Whilst the issue of compensability during the aggregation stage has been handled through the application of exponential transformation, another key aspect is determining the weights assigned to each individual indicator. The allocation of weights varies across different CIs due to their distinct objectives. However, this decision can be informed by comprehending the intrinsic characteristics of the data and carefully considering the overarching purpose of the CI.

As previously discussed, the PCA loadings serve as correlation coefficients indicating the relationships between indicators and principal components. These loadings illuminate the distinct influence of each indicator on various dimensions. Given that the highest loadings of each indicator are distributed across multiple components, assigning equal weights to all indicators ensures that no specific dimension or aspect is unduly emphasised. Moreover, equal weighting is a prevalent practice in the majority of CIs, driven by the principal that each variable holds an equivalent importance within the CI (Joint Research Centre-European Commission, 2008). Furthermore, each selected indicator within this study uniquely captures specific facets of a Liveability Index. Nardo *et al.* (2005) highlighted that equal weighting can be particularly useful when correlated indicators within a CI are not redundant but rather provide different valuable perspectives on the overall concept being measured. It is true that some indicators show correlations. Considering the overarching objective of this research to holistically depict the comprehensive liveability landscape of neighbourhoods, however, the adoption of equal weights for each indicator resonates with the research's fundamental purpose. Hence, the decision to employ equal weighting in this research is informed by the insights derived from PCA and harmonises with the ultimate goal of this study.

Figure 3.9 illustrates the workflow of the Liveability Index construction process.

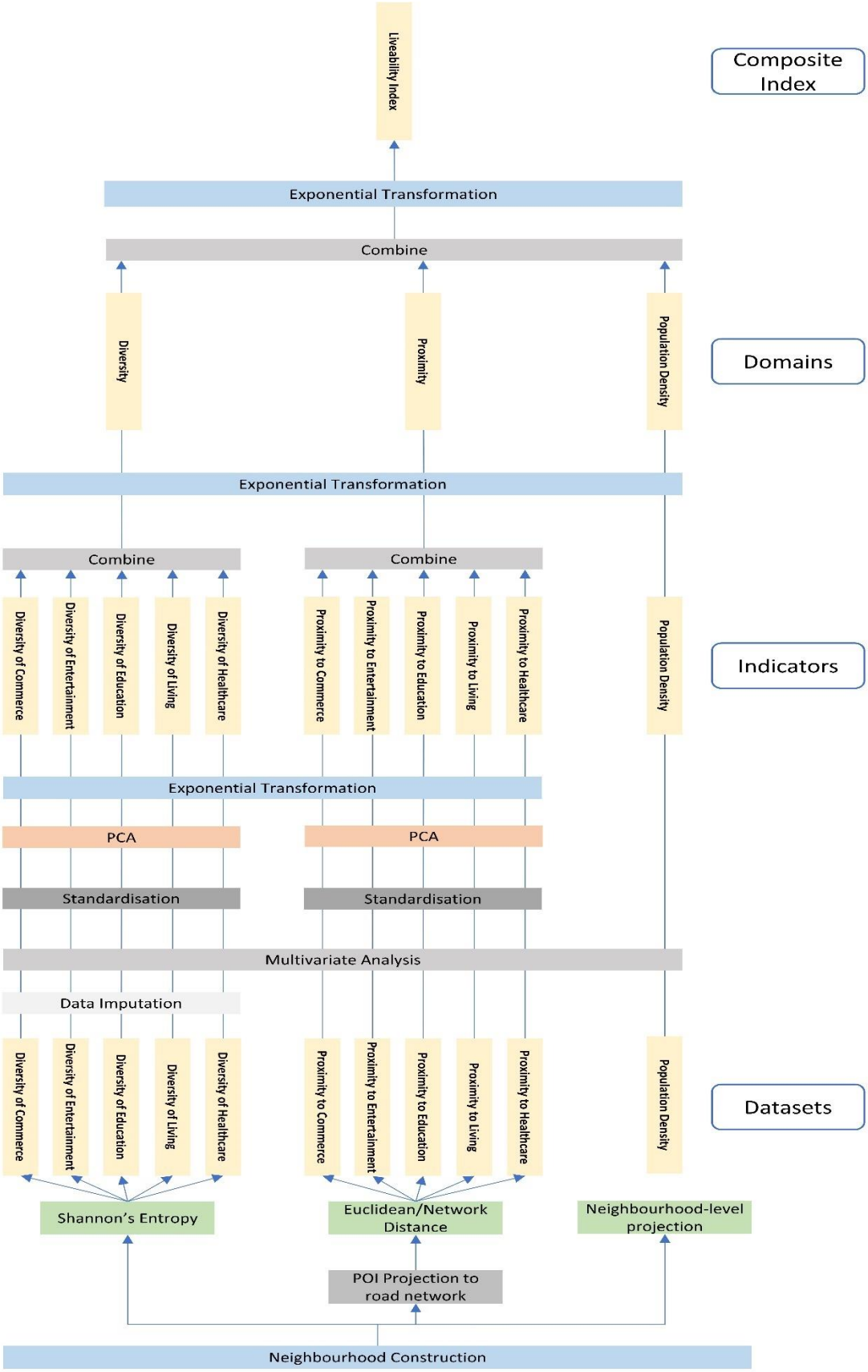

Figure 3.9 Flowchart of Liveability Index construction process

3.8 Robustness Test

3.8.1 Uncertainty Analysis

The development of a CI involves critical phases that require subjective decision-making. These instances of subjective judgement can introduce potential uncertainties that could impact the final outcome. Conducting a robustness test serves as a valuable mechanism to assess the resilience of the CI and enhance its level of transparency (Greco *et al.*, 2019). The OECD guidelines outlined potential sources of uncertainty that may arise during the CI construction process, encompassing aspects such as data selection, normalisation methods, and choices of weighting strategies and values (Joint Research Centre-European Commission, 2008). In addressing such uncertainty, uncertainty analysis (UA) steps forward.

UA is concerned with examining how uncertainty present in input factors diffuse through the structure of the CI, ultimately influencing the outputs of the CI (Nardo *et al.*, 2005). To scrutinise the robustness of the CI, Saisana, Saltelli and Tarantola (2005) suggested taking the Monte Carlo approach. This approach entails conducting multiple evaluations of a model by randomly selecting input factors X_i, $i = 1, \ldots, k$, to analyse the uncertainty's impact on a CI. The procedure comprises assigning probability density functions (PDFs) to input factors, generating various combinations of these factors, and subsequently computing the output values for each combination.

In this section, a simplified form of UA will be implemented, concentrating on pivotal input factors of the Liveability Index (LI) model – namely, data selection and normalisation methods. The focus will be on exploring how combinations of these input factors influence the model's final output.

Table 3.6 presents a number of input factors utilised in the simulations, along with concise descriptions. The simulations involve running the model for N distinct combinations of input factors, denoted as $\mathbf{X}^l$, where l ranges from 1 to N (N = 288). Each of these combinations is referred to as a sample or a set, represented as $\mathbf{X}^l = X_1^l, \ldots, X_k^l$, where k is the total number of input factors. The final LI score and ranking of each neighbourhood will be recorded in every simulation.

Table 3.6 Input factors of the uncertainty analysis

Input Factor	*Name*	*Interpretation*	*Range*	*Values*
X1	Diversity Indicators	Evaluate the impacts of excluding each individual indicator in the Diversity domain	[1, 6]	1 = All Diversity domain indicators included 2 = Diversity of Commerce excluded 3 = Diversity of Education excluded 4 = Diversity of Entertainment excluded 5 = Diversity of Living excluded 6 = Diversity of Healthcare excluded
X2	Proximity Indicators	Evaluate the impacts of excluding each individual indicator in the Proximity domain	[1, 6]	1 = All Proximity domain indicators included 2 = Proximity to Commerce excluded 3 = Proximity to Entertainment excluded 4 = Proximity to Education excluded 5 = Proximity to Living excluded 6 = Proximity to Healthcare excluded
X3	Population Density Indicator	Evaluate the impacts of excluding the Population Density domain	[1, 2]	1 = Population Density included 2 = Population Density excluded
X4	Normalisation Methods	Perform different normalisation methods	[1, 4]	1 = Exponential transformation used 2 = MinMax normalisation used 3 = Robust normalisation used 4 = Standardisation used

Suppose CI as the index value for area n, $n = 1, 2, \ldots, M$. The OECD guidelines suggest assessing an area's ranking of the CI and the average shift in area's ranking because the uncertainties in input factors are translated into affecting these results (Joint Research Centre-European Commission, 2008). The average change in area's ranking can be calculated by averaging the absolute discrepancies in the ranks of areas concerning a reference ranking across the total count of M areas:

$$\bar{R}_s = \frac{1}{M} \sum_{n=1}^{M} | Rank_{ref}(CI_n) - Rank(CI_n) | \tag{3.4}$$

The reference ranking pertains to the initial ranking assigned to an area according to the original index. The configuration of reference model is $X1 = 1$, $X2 = 1$, $X3 = 1$, $X4 = 1$, and all indicators and domains are aggregated using equal weights. Thus, exploring $Rank(CI_n)$ and $\bar{R}_s$ constitutes the focal point of the UA.

3.8.2 Ranking

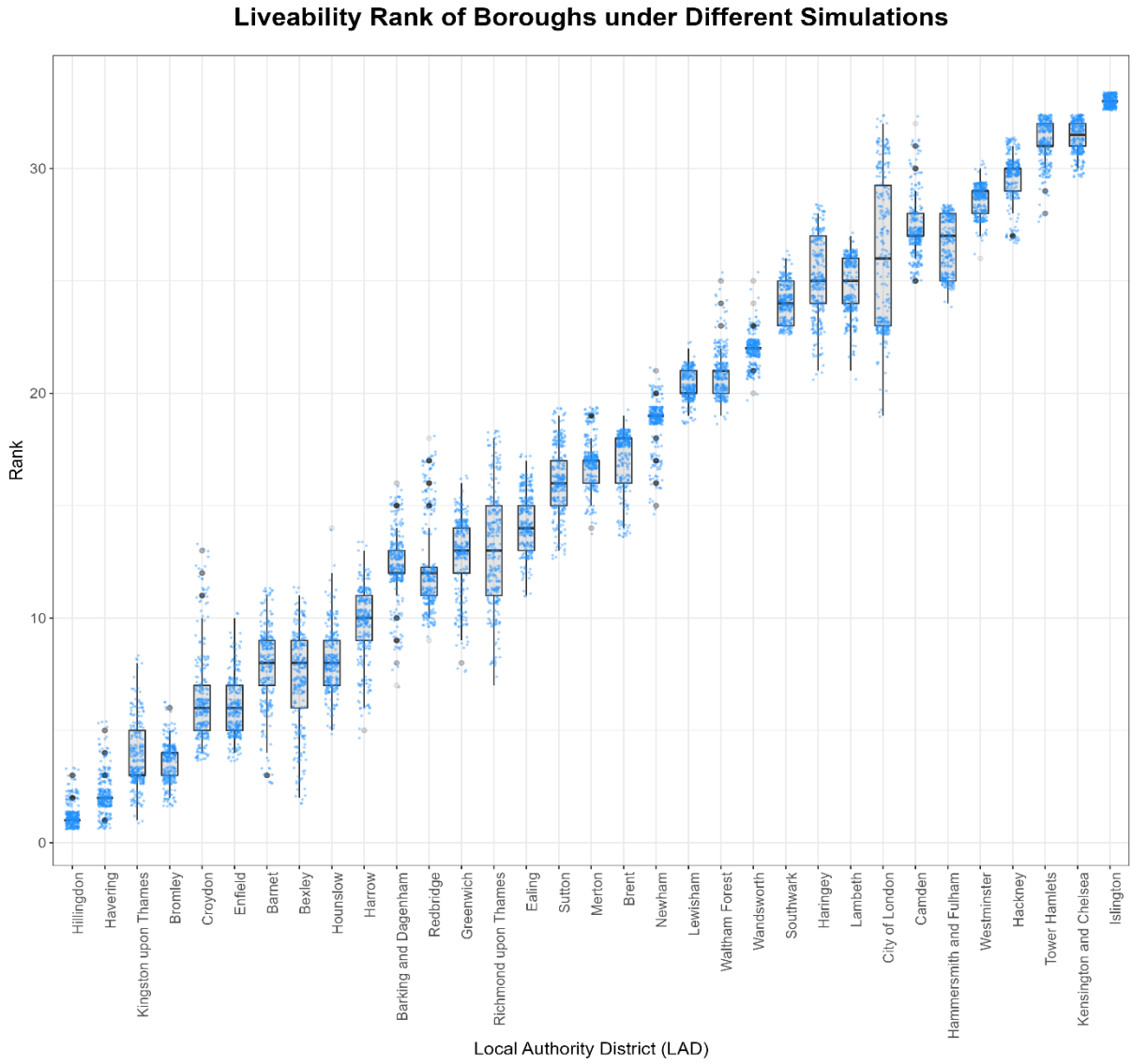

Figure 3.10 Final liveability rankings of boroughs across various simulations. The rankings range from 33, representing the highest liveability ranking, to 1, indicating the lowest.

To simplify interpretation, the dataset encompassing 1209 neighbourhoods has been aggregated into 33 Local Authority Districts (LADs). Due to the discrepancies between neighbourhoods and administrative boundaries, neighbourhoods have been allocated to the LAD that shares the largest intersection area. Subsequently, neighbourhoods are grouped within their respective LADs, and the average liveability score for each simulation configuration has been calculated. Each data point in Figure 3.10 corresponds to the ranking of a specific borough resulting from distinct test configurations involving all four different input factors.

Overall, varying by the test condition, the considerable degree of variation in borough rankings

can be identified across all boroughs. The variance is more pronounced among the boroughs in the middle range of rankings, whilst the boroughs at the extreme ends show comparatively lower variance. This difference could be attributed to the similarity in liveability characteristics among neighbourhoods in the mid-range of rankings, making differentiation challenging. On the contrary, at the extremes, there might be more significant disparities between neighbourhoods, leading to clearer distinctions in their rankings. The observed variance may also be influenced by the exponential transformation used for normalisation. Exponential transformation can magnify the differences between values. In the mid-range, where neighbourhoods may have similar indicator scores, the transformation can amplify even slight variations, resulting in a broader spread of rankings compared to the extreme ends.

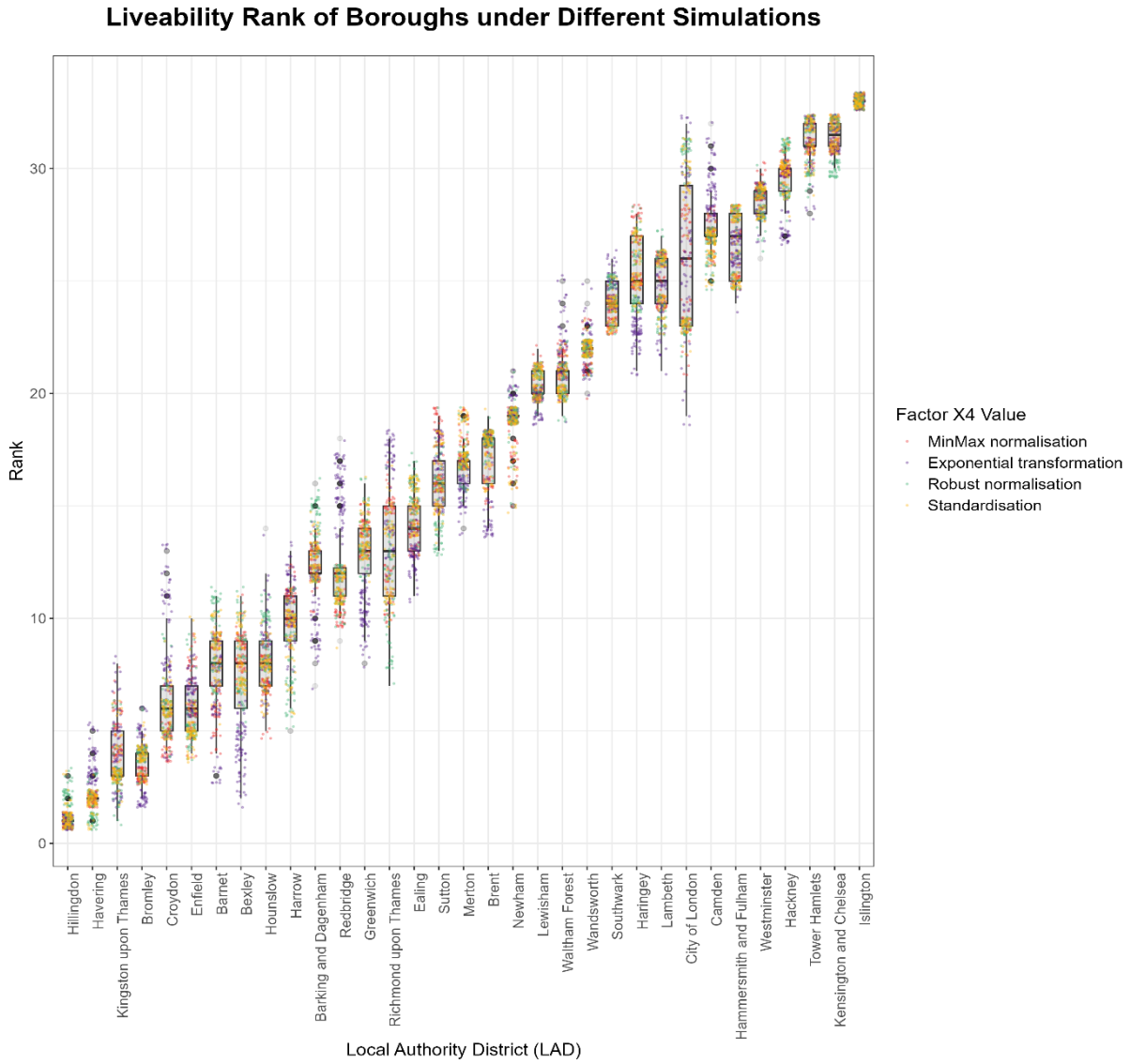

Figure 3.11 Final liveability ranking of boroughs across various simulations, with colour differentiation based on the X4 input factor

Figure 3.11 differentiates the colours of each data point based on the values of input factor X4. Two patterns can be clearly seen in Figure 3.11: dispersion and clustering of data points. The exponential transformation, represented in purple, notably makes distinction in boroughs of the mid-range. This differentiation is evident as data points in mid-range boroughs are dispersed across a wide range of rankings. This pattern weakens and transitions to a clustering effect in the extreme ends. This observation aligns with the previously discussed higher variance in mid-range rankings. Furthermore, it is interesting to note the clustering effect is generally present across all boroughs when other normalisation methods are applied. This effect might be a result of how these methods scale and centre the data, leading to a different pattern from that observed with exponential transformation.

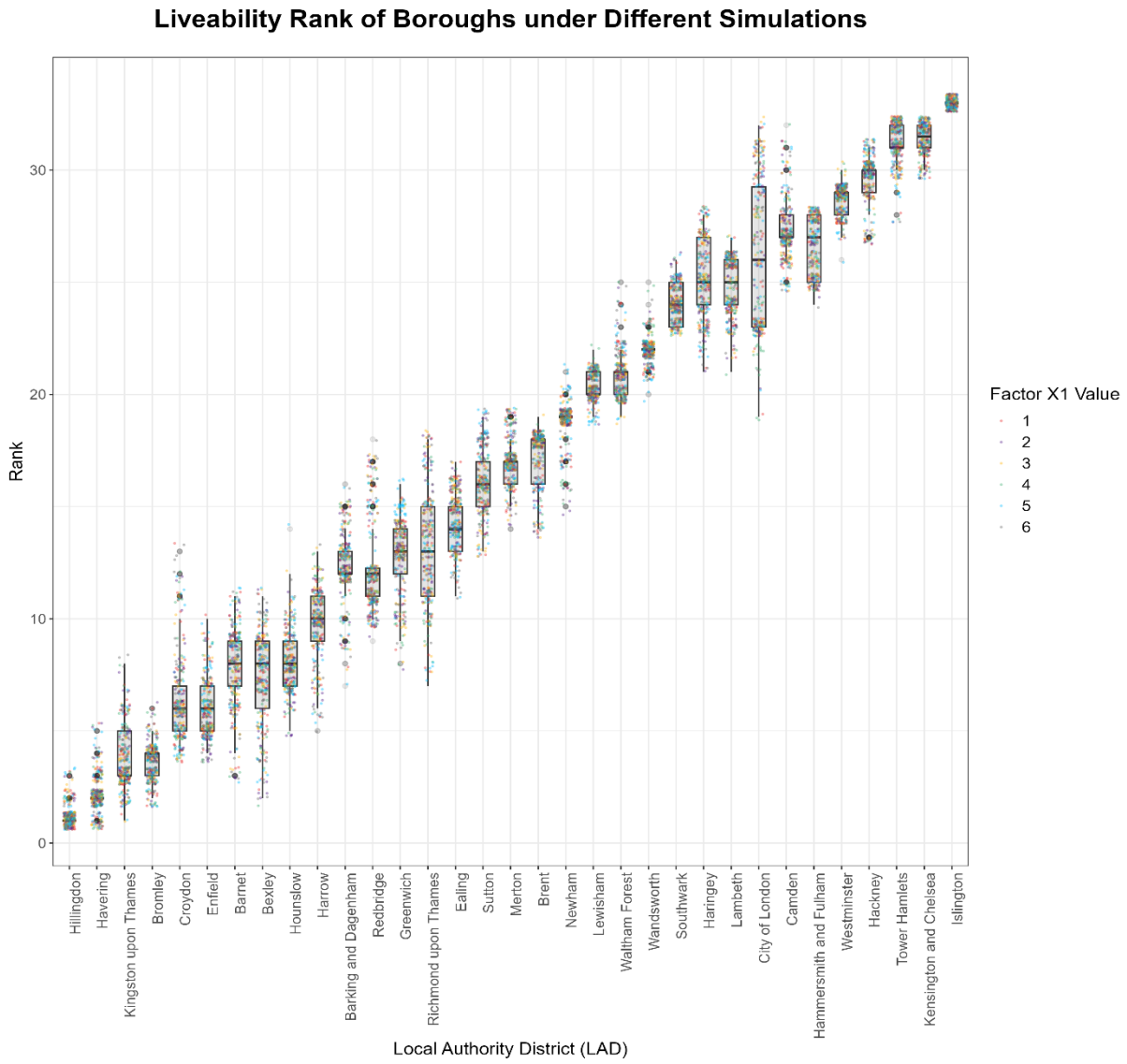

Figure 3.12 Final liveability ranking of boroughs across various simulations, with colour differentiation based on the X1 input factor

In Figure 3.12, data points are coloured based on the values of input factor X1. Unlike the observation in Figure 3.11, each value of factor X1 shows relatively uniform distribution across the range of ranking outcomes. This indicates that certain input factors exert a greater influence on the final output compared to others.

3.8.3 Average shift in Ranking

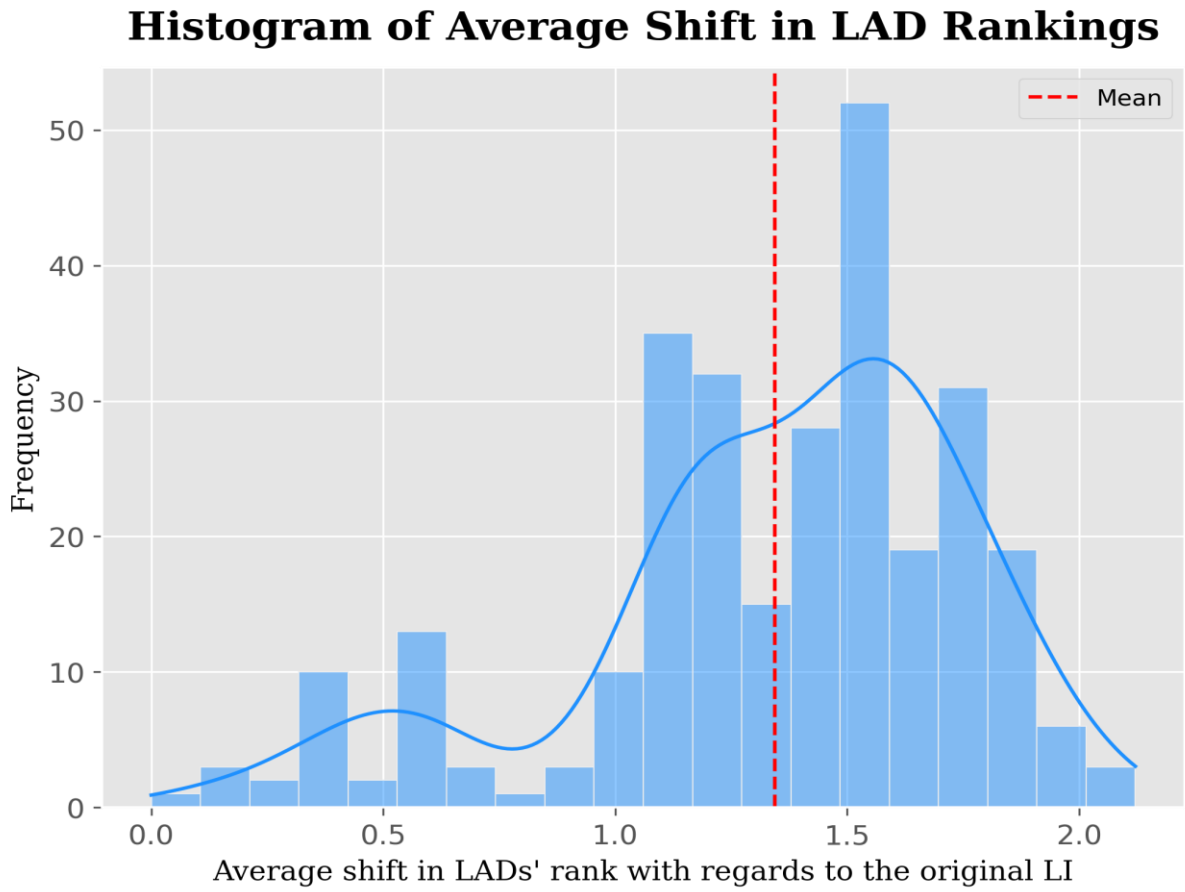

Figure 3.13 The average shift in boroughs' rank with regards to the original LI. Uncertainty input factors are inclusion-exclusion of a sub-indicator and a domain indicator, and normalisation method.

Figure 3.13 illustrates a histogram depicting the distribution of the average shift in output variable's rank, as defined in equation (3.4), in relation to the original LI rank. The calculated mean value of the average shift in a borough's rank is 1.344. This suggests that, on average, the ranks of LAD change by approximately 1.344 positions due to the consideration of uncertainty input factors. The standard deviation of 0.415 indicates that the variations around this average shift are relatively moderate, with most LADs experiencing shifts within this range. In other words, the ranks of LADs are not drastically altered by the uncertainty in input factors, but there is some variability in how much they change.

3.8.4 Quantifying Input Factors' Impact

The quantification of each input factor's influence on the final ranking outcome can be accomplished through the utilisation of the standard deviation of mean ranks across neighbourhoods. This measure involves a systematic process:

1. Calculation of mean ranks: For each input factor, the mean rank is computed for every neighbourhood across different values of that input factor. For instance, considering the first input factor $X1$, the mean rank is calculated for each neighbourhood at different $X1$ values. Given that there are 288 simulations, each with 48 distinct test results, this yields the mean rank for each neighbourhood across these 48 results for a specific value of $X1$.
2. Standard deviation of mean ranks: Following the calculation of mean ranks for different values of an input factor, the standard deviation in mean ranks is determined for each neighbourhood. This measurement captures the variability in neighbourhood rankings as the input factor value changes.
3. Iterative process: The described process is iterated for all input factors. For each factor, the mean ranks and standard deviation of mean ranks are computed across all neighbourhoods, thereby encompassing the full range of inpupt factor values.

This methodology offers deeper insights into how changes in individual factors contribute to fluctuations in neighbourhood rankings.

Figure 3.14 Spread of standard deviation in average neighbourhood rankings across different input factor values

Figure 3.14 provides a clear explanation for the uneven distribution of final rankings resulting from input factor $X4$ compared to input factor $X1$. The variance caused by changes in the normalisation input factor is greater compared to other input factors. Conversely, the variance resulting from proximity and diversity input factors is small, suggesting the model's robustness against variations in these factors.

3.9 Validation

The validation against an established index or recognised phenomenon provides an external and objective verification process, bolstering the credibility, reliability, and applicability of the newly constructed CI. This validation ensures that the CI serves as a robust instrument for decision-making and policy shaping.

The English Indices of Deprivation 2019 comprises seven distinct indices, each addressing a specific facet of deprivation (McLennan *et al.*, 2019). Among these, the 'Barriers to Housing and Services Domain' includes two sub-domains: the 'Geographical Barriers Sub-domain

(henceforth, GBS)' and the 'Wider Barriers Sub-domain'. The GBS refers to the physical closeness to local services, where lower scores signify improved proximity to such services.

3.9.1 Approach

The methodology employed in this context bears resemblance to the projection of population data. When projecting GBS scores, the weighted mean approach was harnessed. The inherent non-additive characteristics of GBS scores were taken into consideration. Even with the integration of weights, represented by the proportion of intersecting areas, a simple summation of GBS scores would yield inflated values, distorting the true representation. In contrast, in the weighted mean approach, each value is multiplied by its corresponding weight, and then the sum is divided by the sum of the weights. Consequently, this methodology ensures a more balanced and accurate representation of the overall situation. Once the GBS scores are projected to a hexagon grid-level, they are further aggregated to a neighbourhood-level.

3.9.2 Results

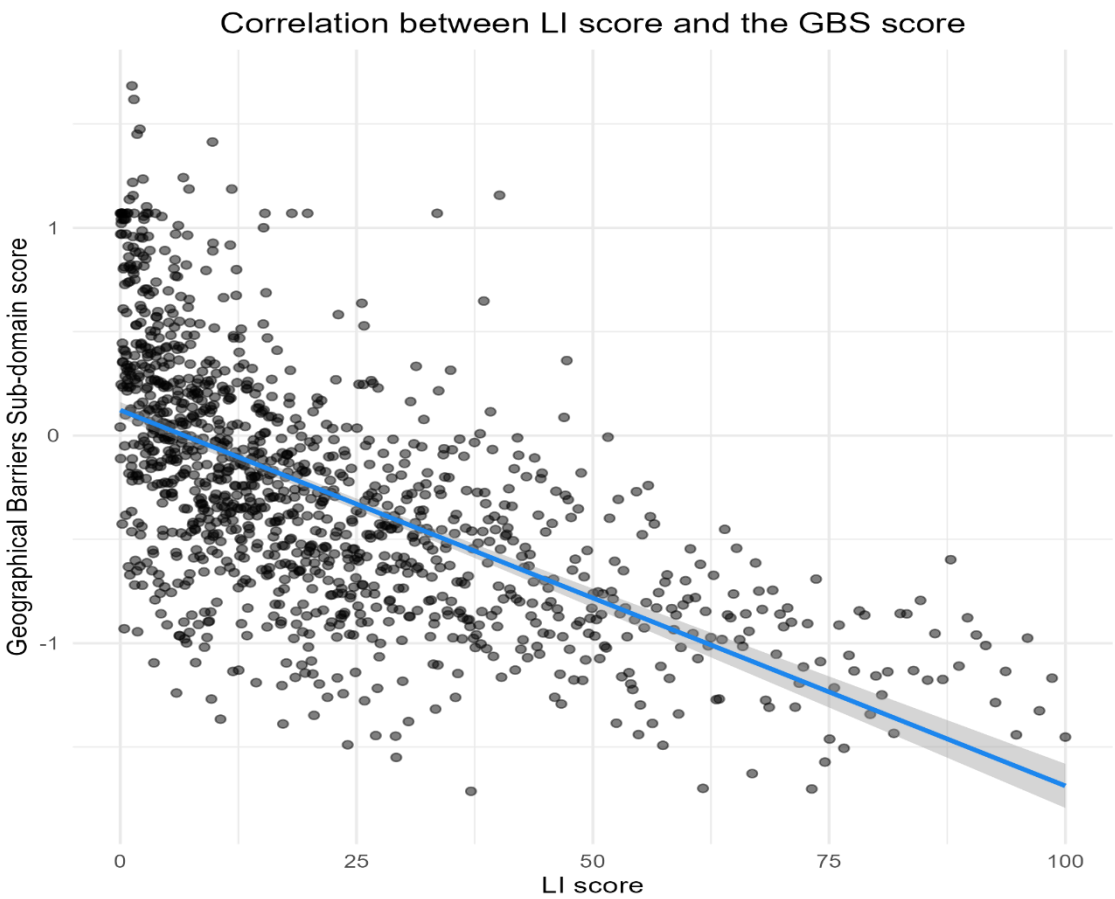

Figure 3.15 The correlation between Liveability Index (LI) score and the Geographical Barriers Sub-domains (GBS) score at a neighbourhood-level. The correlation deviates from zero at a significance level of 1%, and the adjusted r-squared and RMSE values between LI score and the GBS score are 0.38 and 29.94, respectively.

Figure 3.15 displays the outcomes of correlation analysis between LI and GBS score. Notably, the adjusted r-squared value of 0.38 sheds light on the interplay between these scores. This signifies that approximately 38% of the variance in the GBS score can be accounted by variations in the LI score. Furthermore, a consistent descending pattern between the LI score and the GBS score suggests that higher LI scores are associated with lower GBS scores. This association can be interpreted as higher liveability being positively linked to better proximity.

The correlation analysis demonstrates the similarity in variations between two scores. However, it is crucial to note that the correlation does not imply a causal relationship, where changes in one score directly lead to changes in the other. Correlation merely signifies that there are resemblances in the variations of two datasets. A change in the GBS score does not necessarily result in a corresponding change in the LI score, and vice versa. Other factors and interactions might be at play, contributing to the observed correlation.

4. Results

4.1 Overview

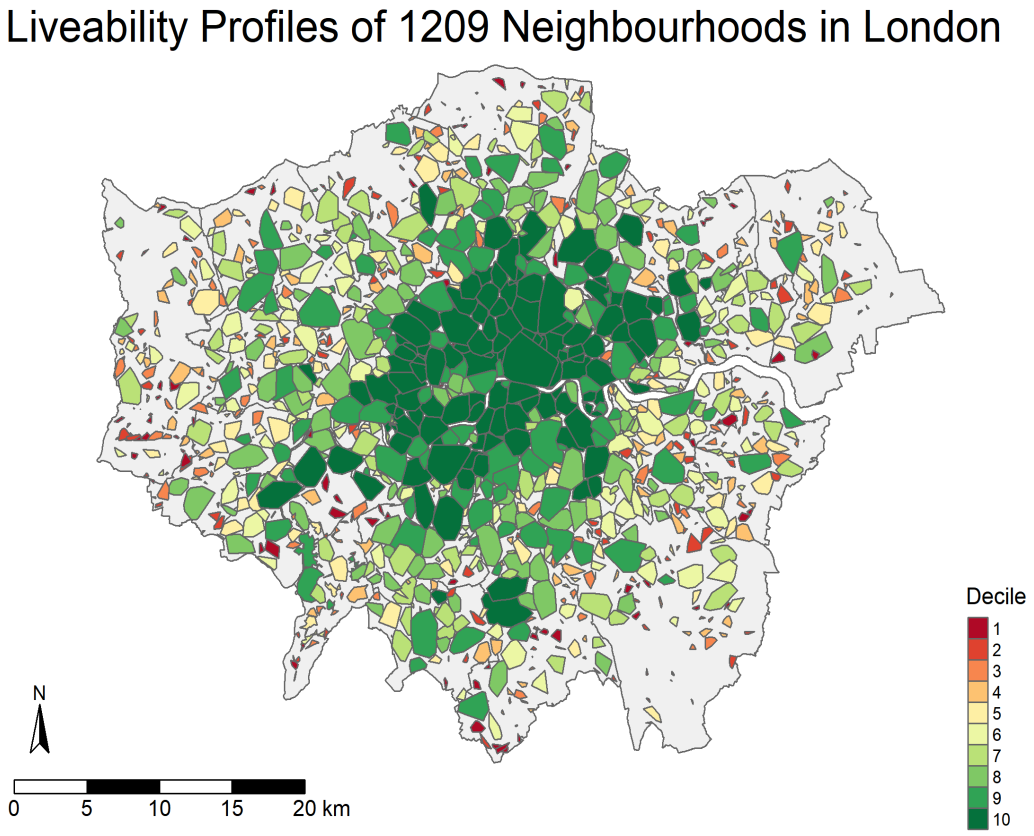

Figure 4.1 Deciles of liveability profiles of London's neighbourhoods. 1 denotes the lowest liveability and 10 being the highest liveability.

Figure 4.1 shows the overall liveability profiles of London's neighbourhoods. The amalgamation of the three domains reveals that neighbourhoods in Inner London exhibit higher liveability compared to neighbourhoods in Outer London. Whilst this assertion could invite discussion, it is crucial to recognise that the unveiled liveability profiles have been constructed from the perspective of the built environment.

This prominent contrast can be elucidated by considering the interaction of density, diversity and proximity within the framework of agglomeration economies. Inner London is known to accommodate a substantial population. The concentration of inhabitants in this area signifies a pronounced demand for urban services, fostering the emergence of various types of amenities to meet the demand. Consequently, individuals residing in these neighbourhoods have convenient access and proximity to essential urban services. The intricate interplay among the three domains culminates in the high liveability in neighbourhoods in Inner London.

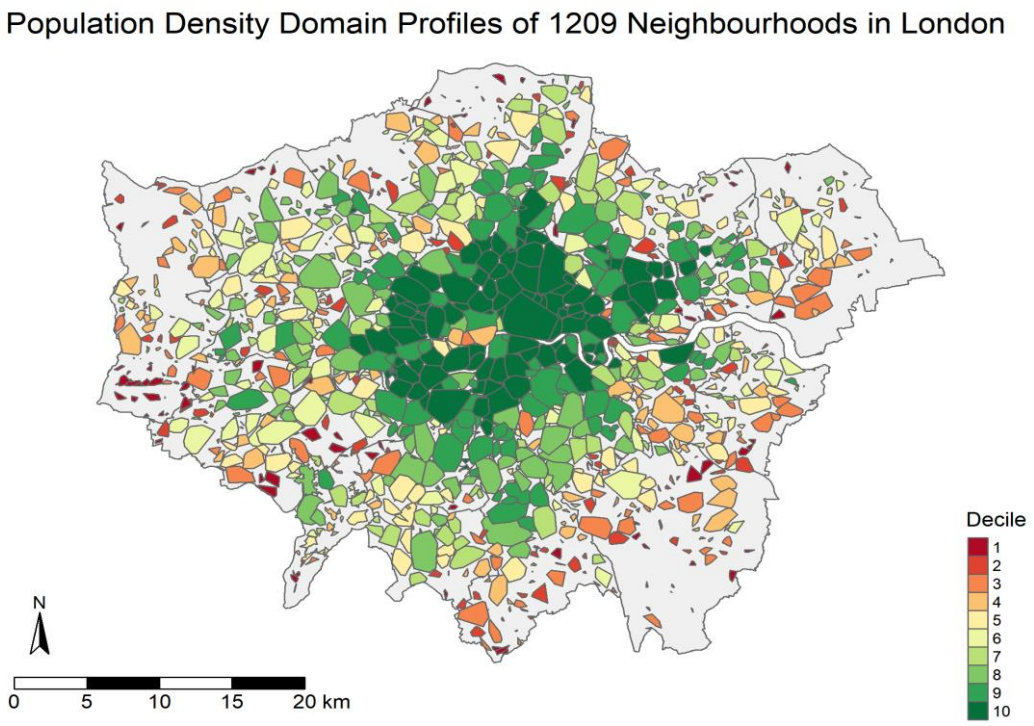

Figure 4.2 Deciles of population density domain profiles of London's neighbourhoods. 1 denotes the lowest density and 10 being the highest.

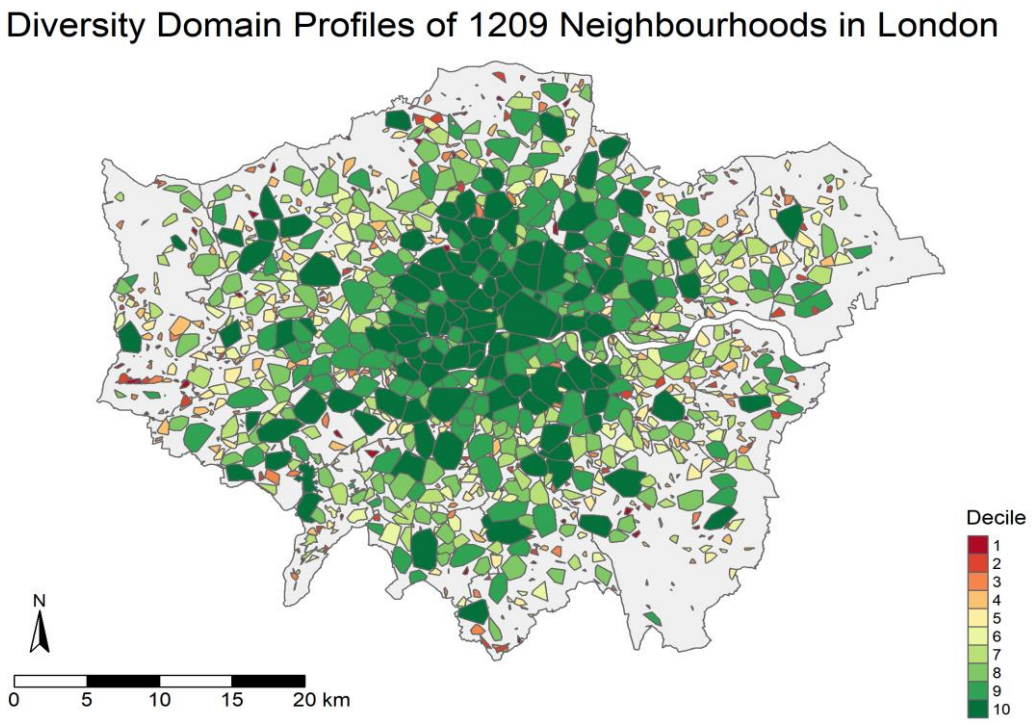

Figure 4.3 Deciles of diversity domain profiles of London's neighbourhoods. 1 denotes the

lowest diversity in amenities and 10 being the highest.

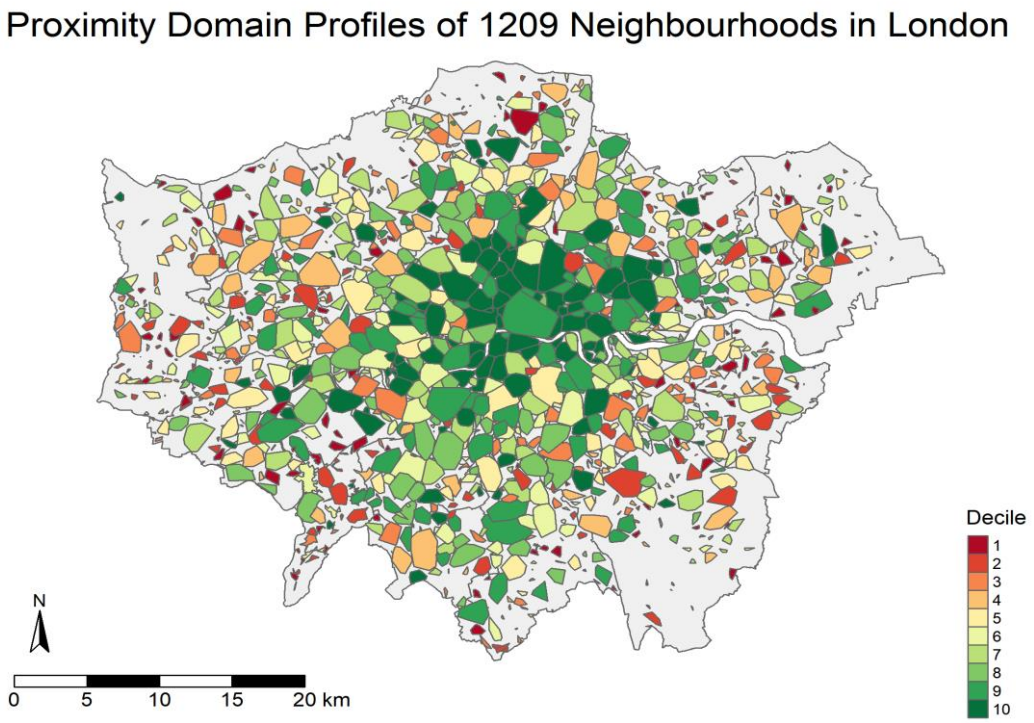

Figure 4.4 Deciles of proximity domain profiles of London's neighbourhoods. 1 denotes the lowest proximity to amenities and 10 being the highest.

Figure 4.2 illustrates the population density distribution across London's neighbourhoods. Higher population concentrations are evident in Inner London, whilst Outer London experiences lower densities. Figure 4.3 presents the diversity of amenities in the city's neighbourhoods, revealing spatial patterns akin to those seen in Figure 4.2. Diverse amenities are centred in Inner London; however, it is important to remember that the diversity domain comprises five distinct diversity services. Neighbourhoods being in decile 10 does not equate to perfect diversity nor the presence of all five distinct urban services. Instead, it indicates a high diversity of amenities related to any of these five services. In other words, decile 10 neighbourhoods are characterised by a significant level of diversity in amenities from any of the five urban service categories.

Figure 4.4 demonstrates proximity profiles, unveiling different spatial trends. Although Inner London generally enjoys good proximity to urban services, the prevalence of decile 10 concentrations is not as dominant as in Figure 4.2 and Figure 4.3. This can be attributed to variations in neighbourhood size and the absence of specific urban service-related amenities in some areas. As depicted on the map, each neighbourhood varies in size. This could have resulted in a longer travel distance between a neighbourhood's centroid and the centre of mass of an urban service, particularly in larger neighbourhoods. Additionally, some neighbourhoods ranking in the upper deciles (8-10) for the diversity domain might lack certain

urban services. Meeting residents' needs in these areas necessitates travel along the road network, which significantly impacts travel distance. Consequently, these factors could have engendered different spatial patterns in the proximity domain.

4.2 De-construction of Liveability Index

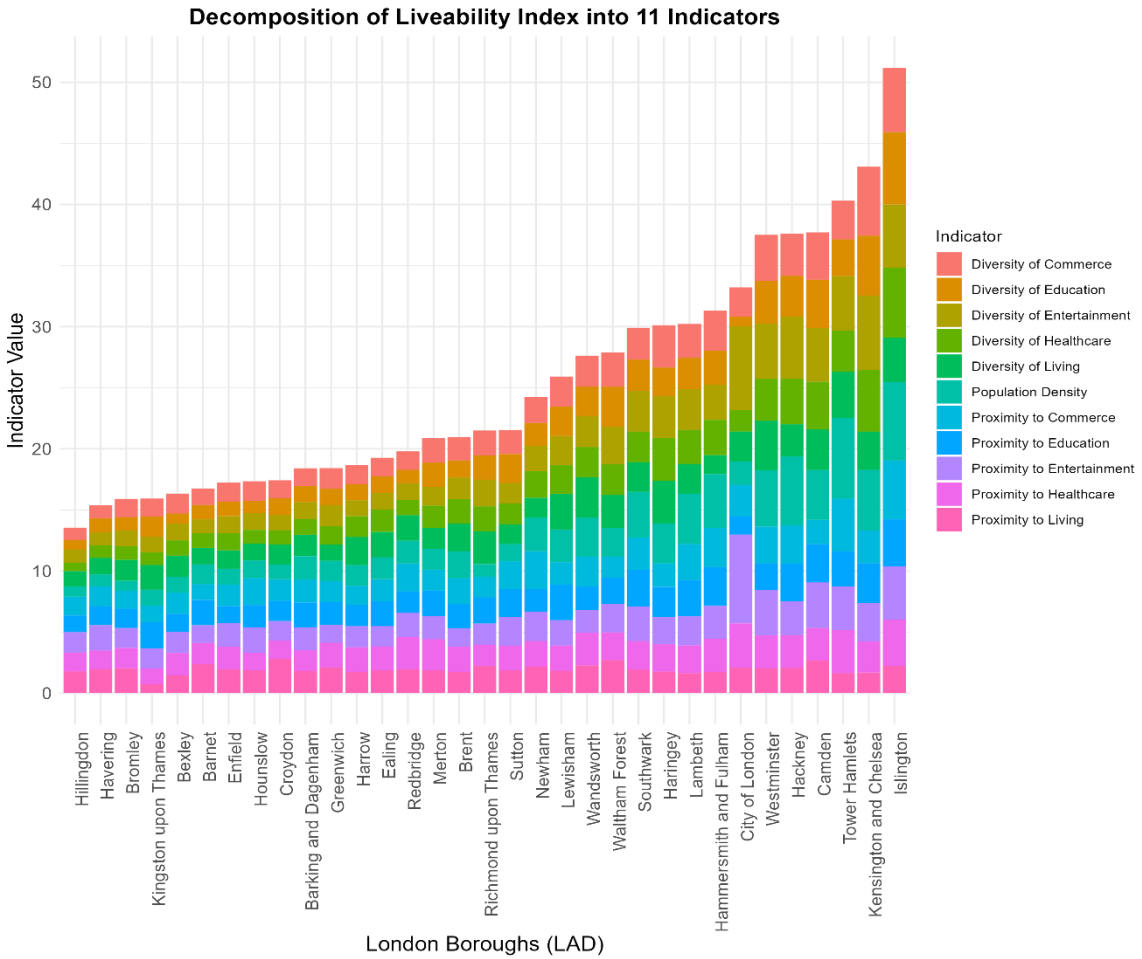

Figure 4.5 Mean Liveability Index scores by Boroughs, with deconstructed indicator scores

The deconstruction of the CI into individual indicators provides insights into the comprehensive performance assessment of a given subject (Joint Research Centre-European Commission, 2008). This approach is particularly valuable as it facilitates a deeper comprehension of both the strengths and weaknesses within each neighbourhood.

Figure 4.5 clearly illustrates that the 9 highest-ranked boroughs are all situated within Inner London. Among these, Islington leads the ranking with the sole LI score exceeding 50, followed

by Kensington and Chelsea and Tower Hamlets. Notably, the diversity domain is the most prominent contributor to the LI score in these leading boroughs. Conversely, this trend is inverted in the lowest-ranked boroughs, where the proximity domain takes precedence in influencing LI score. Furthermore, it is worth noting that the contribution of population density to the LI score remains consistent at around 10% across both high and mid-ranking boroughs. However, this contribution markedly diminishes in significance among the bottom-ranked boroughs.

Figure 4.6 and Figure 4.7 provide a comprehensive view of each borough's individual indicator contribution. Each indicator's score has been normalised by dividing it by the maximum score of that indicator across all boroughs. This normalisation process brings the scores to a common scale for comparison. This makes it easier to compare the performance of different boroughs across multiple indicators, even if the absolute values of the scores vary significantly between indicators.

As depicted in Figure 4.6, in the top-ranked boroughs, the influence of the diversity domain is more pronounced compared to the other two domains. Whilst the impact of the diversity domain appears less distinct in Tower Hamlets, it is more evident in Islington and Kensington and Chelsea.

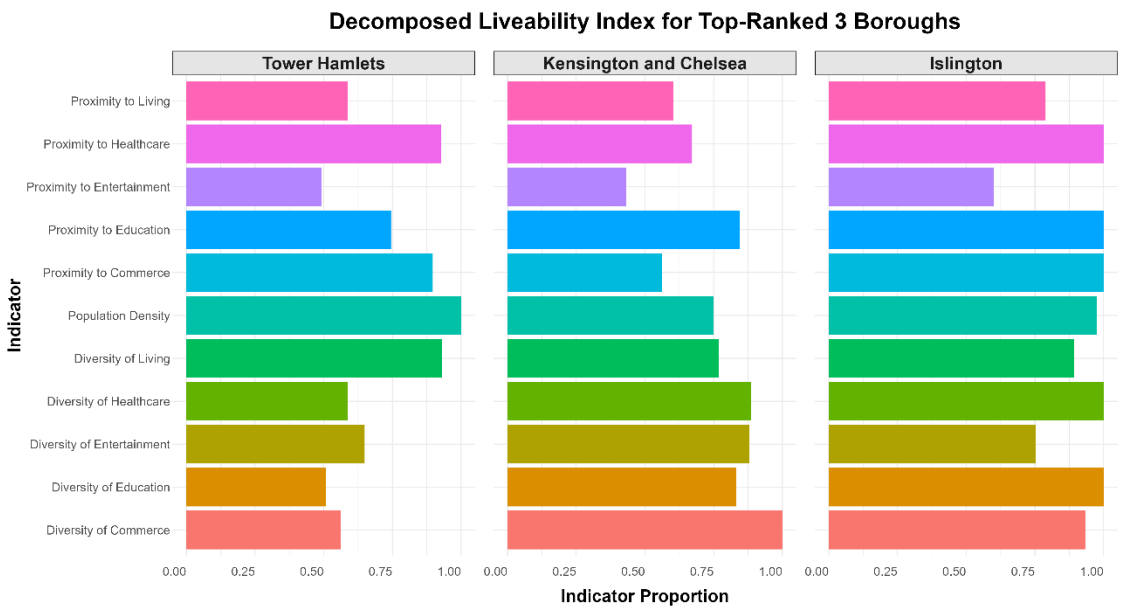

Figure 4.6 Deconstruced indicator scores for three highest boroughs

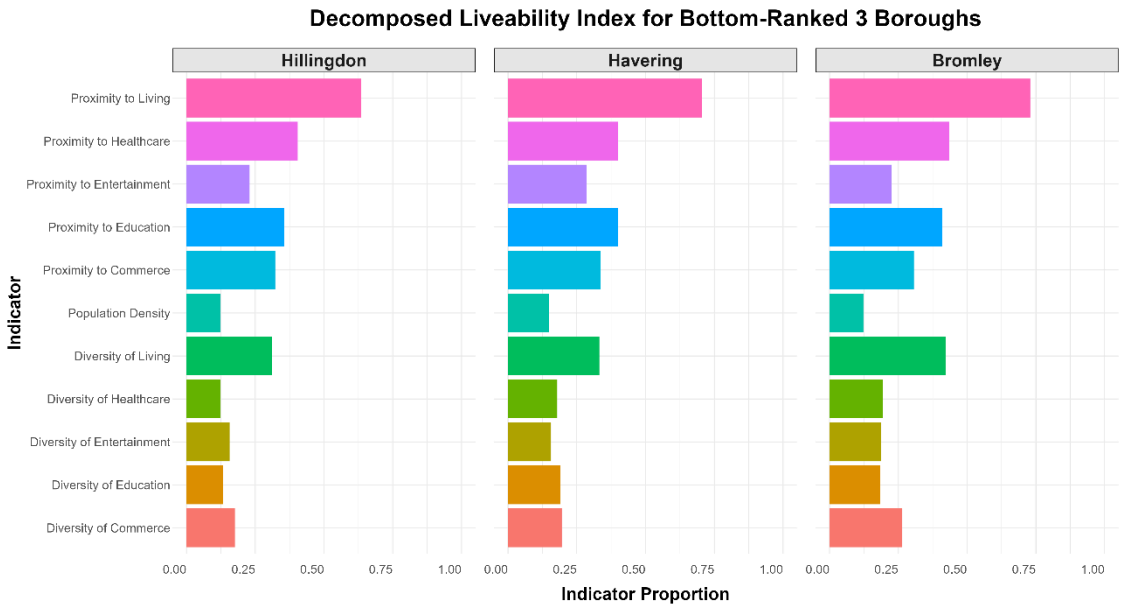

Figure 4.7 Deconstructed indicator scores for three lowest boroughs

On the other hand, as shown in Figure 4.7, amongst the three lowest-ranked boroughs, the contribution of the proximity domain is notably significant compared to the other domains. Particularly, the proximity to living amenities holds the highest contribution. Additionally, the influence of population density appears to be the least influential on the LI score.

4.3 Variations in Active Travel Patterns

Considering the non-additive characteristics of the footfall score, the average normalised footfall scores at a hexagon-level are projected to a neighbourhood-level utilising a weighted mean approach.

4.3.1 Hypotheses

The following hypotheses were formulated to investigate the potential variation in active travel patterns between neighbourhoods with differing liveability scores:

H_0 : There is no statistically significant difference in active travel patterns between neighbourhoods with high and low liveability scores. $(\alpha = 0.05)$

H_1 : A statistically significant difference exists in active travel patterns between neighbourhoods with high and low liveability scores. $(\alpha = 0.05)$

4.3.2 Approach

The neighbourhoods were categorised based on the median liveability scores. Those surpassing the median were classified as "High Liveability" group (605 neighbourhoods), whilst the remaining were designated as "Low Liveability" group (604 neighbourhoods). Figure 4.8 portrays the distribution of normalised footfall scores by liveability groups. The observations suggest that there are differences in the distribution of footfall scores between the two categories, with 'High Liveability Neighbourhoods' generally exhibiting higher scores. The vertical dotted lines represent the median values of normalised footfall scores for each group. Specifically, the median values are 0.63 for 'High Liveability Neighbourhoods' and 0.35 for 'Low Liveability Neighbourhoods'. Nevertheless, the presence of an overlapping area and the occurrence of extreme values indicate potential complexities in the distribution of normalised footfall scores. These visual insights will be further explored through the Shapiro-Wilk test to assess the normality assumption.

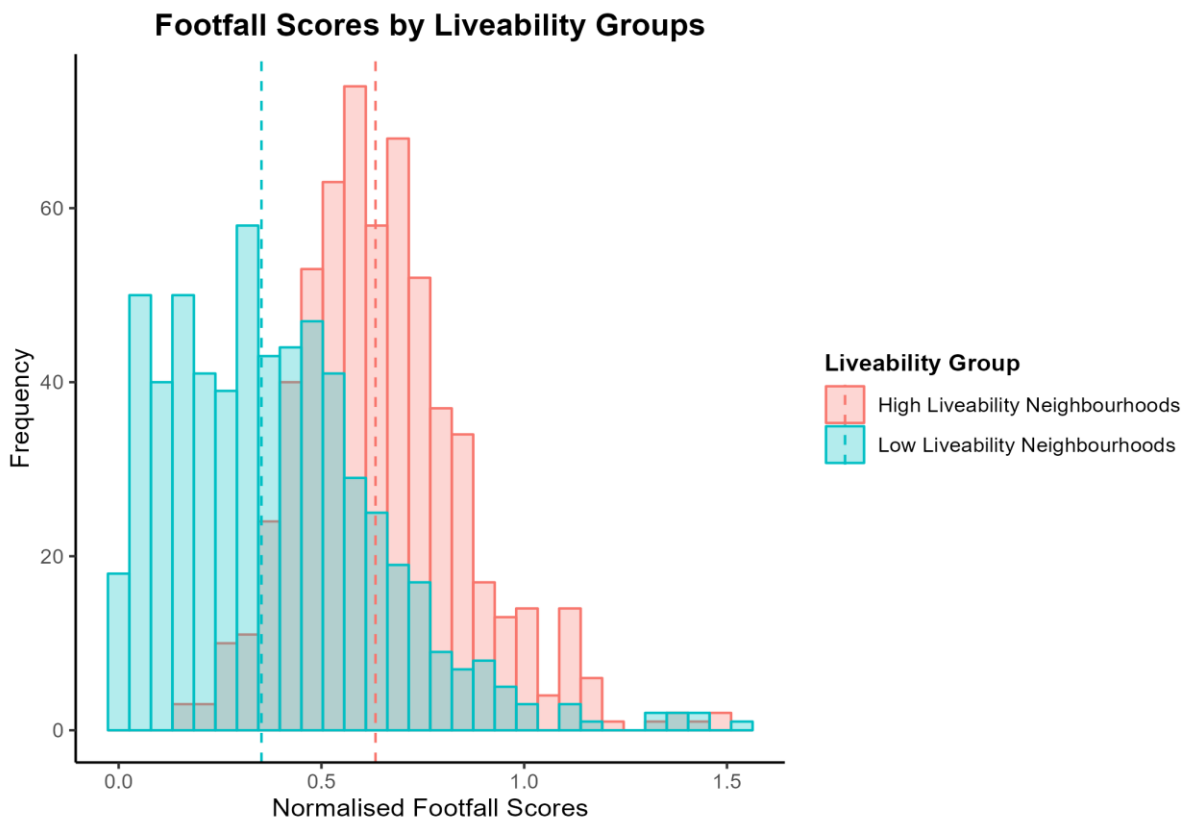

Figure 4.8 Distribution of the normalised footfall scores by different liveability groups. The vertical dotted lines represent median values of normalised footfall scores for each group.

4.3.3 Results

Table 4.1 Results of the Shapiro-Wilk test

Group	*Test Statistic (W)*	*P-value*
High Liveability Neighbourhoods	0.97	8.657e-10
Low Liveability Neighbourhoods	0.94	3.691e-15

Note. The significance level is set at 0.05.

Table 4.1 presents the results of the Shapiro-Wilk test, which was applied to the two specified neighbourhood categories. Both groups showed non-normal distributions, evidenced by the extremely low p-values. Consequently, the comparison of normalised footfall scores between the two groups was executed through the Mann-Whitney U test.

Table 4.2 Results of the Mann-Whitney U test

Test Statistic (U)	*P-value*
71019	2.2e-16

Note. The significance level is set at 0.05.

The outcome of the Mann-Whitney U test is outlined in Table 4.2. The computed test statistic, denoted as U, stands at 71019. This statistic signifies the sum of ranks for one group compared to the other. The range of U statistic varies between 0 and 365420. It is worth noting that the U statistic reaches its lowest value of 0 when the distributions of the two groups are entirely dissimilar. This contrasts with its highest value, 365420, which signifies perfect similarity and is achieved by multiplying the number of observations in both groups.

The notably miniscule p-value underlines the improbability of observing such extreme disparities in footfall scores between the two groups if their distributions were indeed identical. The p-value, significantly lower than the predetermined significance level of 0.05, presents compelling evidence to reject the null hypothesis. Therefore, with a p-value close to zero, it can be concluded that a substantial discrepancy in active travel patterns prevails between neighbourhoods characterised by high and low liveability scores.

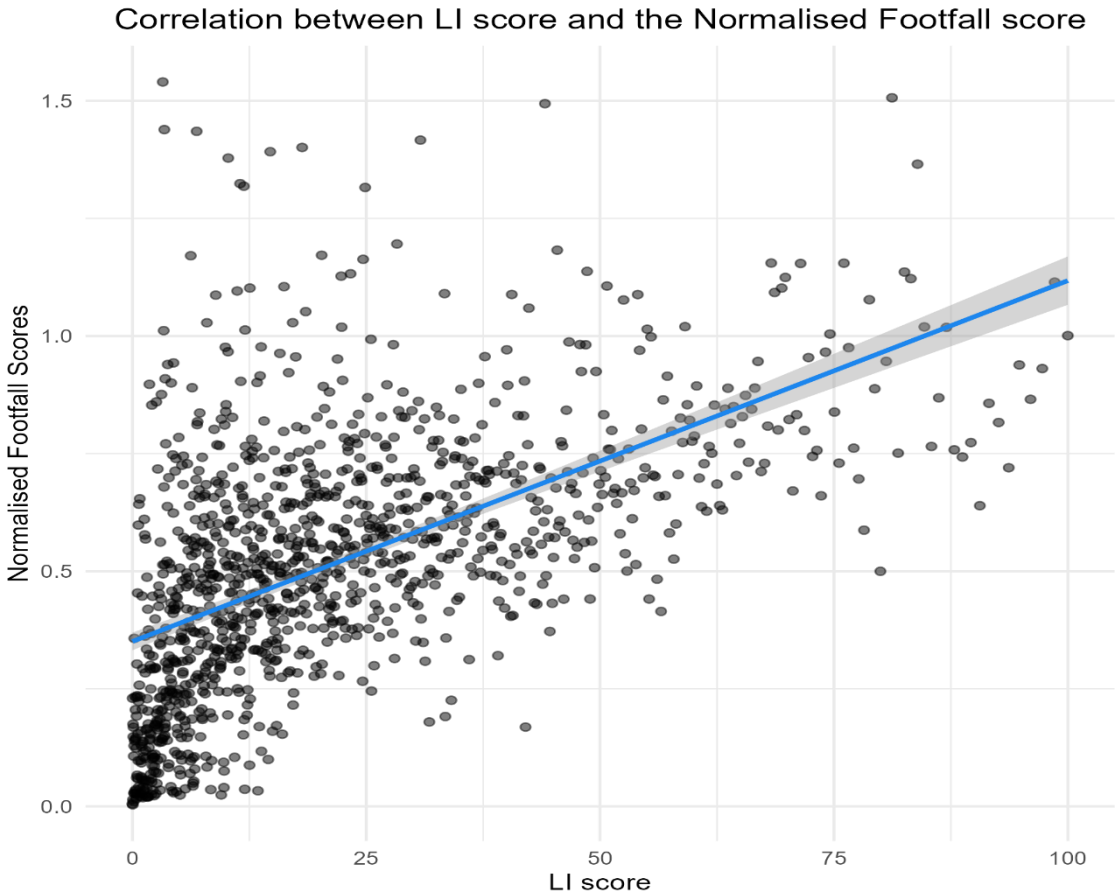

Figure 4.9 Correlation between Liveability Index (LI) score and the Normalised Footfall score at a neighbourhood-level. The correlation deviates from zero at a significance level of 1%, and the adjusted r-squared and RMSE values between LI score and the footfall score are 0.31 and 29.01, respectively.

In addition to the Mann-Whitney U test results, a correlation analysis was performed to assess the link between the Liveability Index (LI) score and the normalised footfall score at a neighbourhood-level. Figure 4.9 illustrates a clear positive correlation between the LI score and the footfall score. The adjusted r-square value of 0.31 suggests that approximately 31% of the variance in the footfall score can be explained by the variations in the LI score. Whilst this correlation may not be exceptionally strong, it provides further evidence to support the study's findings concerning noticeable disparities in footfall scores among neighbourhoods with varying liveability scores. The positive correlation signifies that neighbourhoods with higher LI scores tend to exhibit higher footfall scores. However, it is important to note that correlation does not imply causation.

5. Discussion

At the outset, this study was driven by a fundamental curiosity: what constitutes the liveable neighbourhood envisioned by Jane Jacobs? Given the variability of definitions surrounding liveability and neighbourhoods across disciplines, the investigation was structured into three distinct parts: construction of neighbourhoods and Liveability Index, and active travel comparison.

5.1 Neighbourhoods Through a Bottom-Up Approach

The research sets out to construct London's neighbourhoods using a bottom-up methodology. The agglomeration of amenities, taking into account pedestrian accessibility, facilitated the identification of a range of diverse and walkable neighbourhoods in London, which align with Jane Jacob's description of neighbourhoods. The local maximum entropy points, serving as local hubs, along with proximate amenities within reasonable walking distances from these entropy-rich hubs, led to the formation of vibrant and walkable neighbourhoods. 1209 neighbourhoods identified in the study strongly support to the existing body of research indicating that urban systems shift from monocentric to polycentric organisation (Louf and Barthelemy, 2013, 2014), as well as confirming London's polycentric urban structures (Roth et al., 2011).

Exploring changes in the normalised largest neighbourhood size by varying isodistance values adds a deeper dimension to the discussion. The notable surge in normalised largest neighbourhood size beyond the 600m isodistance indicates that London's geographical features no longer play a diminishing influence on shaping the boundaries or size of London's neighbourhoods. Thus, values exceeding this threshold might lead to abnormal increase in the normalised largest neighbourhood size. Discovering this threshold not only aids in determining the optimal walkable distance for constructing diverse and walkable neighbourhoods within London's context, but also unravel the extent to which London's artificial and geographical attributes exert influence over London's neighbourhood size. Nevertheless, it is essential to acknowledge that the leap in normalised largest neighbourhood size after the 600m isodistance may vary across global cities due to distinct road networks, artificial constructs, and geographical traits specific to each urban context. The bottom-up neighbourhood formation approach employed in this study exhibits scalability and adaptability, rendering it transferrable to other urban contexts.

5.2 Liveability Profiles of London's Neighbourhoods

The foundation of the Liveability Index is grounded in the principles of the 15-minute city paradigm. The three essential domains – diversity, proximity and density – are seamlessly integrated into the index, each holding equal importance. This integration allows for a holistic

depiction of the liveability profiles of London's neighbourhoods. The fourth dimension, digitalisation, was woven into the research through publicly available data, facilitating the incorporation of the three domains into the index (Moreno et al., 2021).

Whilst the Liveability Index provides an overview of each neighbourhood's liveability profile, breaking down the liveability scores into individual indicators could provide further insights. The deconstruction allows for the identification of each borough's strengths and weakness that contribute to the overall liveability and providing policymakers with data-informed guidance. Notably, the boroughs with the three lowest liveability scores – Hillingdon, Havering and Bromley (as depicted in Figure 4.7) - could particularly benefit from integrating the research findings into their local planning.

Taking Hillingdon as a focal example, Figure 4.7 underscores the challenges it faces regarding low diversity in healthcare and education, which are also acknowledged in Hillingdon's local planning reports. In terms of education, the borough experiences an increasing demand for primary and secondary schools, along with specialised education facilities catering to special needs (Hillingdon Council, 2017). Moreover, Hillingdon Council (2012) notes that only around a quarter of its residents possesses a university degree, significantly lower than the London average of 36.9%.

Turning to healthcare, the borough's localised health needs patterns between its northern and southern regions, coupled with Hillingdon's average ratio of 44 GPs per 100,000 weighted populations falling significantly below London's average of 52 GPs per 100,000, signify healthcare challenges within the borough (Hillingdon Council, 2017).

These instances clearly demonstrate the potential of the Liveability Index as a diagnostic tool for shaping evidence-based policy formulation. Furthermore, the index's utility extends to monitoring policy implementation progress. For example, 'Policy CI1: Community Infrastructure Provision' aims to enhance education quality through additional educational establishments like schools and libraries, whilst also ensuring accessible healthcare facilities tailored to resident needs (Hillingdon Council, 2012). By tracking changes in diversity of education indicator scores, policy effectiveness can be evaluated. Moreover, as resident participation gains importance in sculpting vibrant and walkable neighbourhoods, the index's user-friendly interpretation offers added advantage. It enables resident to comprehend local challenges, encouraging their active engagement in the urban planning process.

5.3 Difference in Active Travel Patterns

The outcomes of this study reveal a statistically significant difference in active travel patterns among neighbourhoods characterised by varying levels of liveability. This observation holds significant implications for understanding the relationship between neighbourhood attributes and travel behaviour. Whilst the Mann-Whitney U test does not inherently pinpoint which specific neighbourhood group exhibits higher active travel patterns, the positive correlation

identified between LI score and the footfall score, coupled with the notably higher median value of normalised footfall scores in 'High Liveability Neighbourhoods', hints at a propensity for heightened active travel engagement within these localities. These findings underscore the potential influence of liveability of urban settings on people's choice of active travel modes. These findings resonate with existing research, notably the work of Hooper et al. (2015), emphasising that urban designs prioritising people's needs and accessibility are instrumental in fostering increased physical activity. Additionally, the positive correlation between liveability and active travel frequencies, as supported by Higgs et al. (2019), aligns with this study's outcome.

However, it is crucial to acknowledge the multifaceted nature of active travel behaviour. The decision to opt for active travel modes can be subject to an intricate interplay of factors. Whilst neighbourhood liveability certainly holds significance, the choice of active travel can be influenced by factors ranging from the quality of transport infrastructure and road networks to socio-economic conditions and individual preferences.

5.4 Limitations

In the computation of isodistance or network distance, POI data were projected onto the nearest nodes within the road network. A key drawback of this snapping method is its potential inability to accurately represent the true proximity of the POI points. Furthermore, the likelihood of different POI data points being assigned to the same network node raises concerns about accuracy. Due to memory limitations, the 'blending' technique could not be employed in this study; however, future analyses have the potential to harness it. This algorithm projects POI data onto the closest network edges, checking for a match with existing nodes; if matched, POI's information integrates, otherwise a new node is created, merging the information (der Meer et al., 2023).

Moreover, aggregating neighbourhoods to boroughs could inadvertently lead to misrepresentations of liveability characteristics for both neighbourhoods and boroughs. Due to memory limitations, neighbourhoods intersecting multiple boroughs are allocated to a borough with the largest overlap. However, since neighbourhoods do not align perfectly with administrative boundaries, this aggregation method might have led to an overestimation or underestimation of some boroughs' liveability profiles.

Additionally, it is crucial to highlight the imputation of an entropy value of -1 for neighbourhoods lacking amenities in specific urban services. This imputation was carried out to ensure a comprehensive portrayal of all neighbourhoods' urban service diversity. Whilst the imputation does not alter data distribution by placing neighbourhoods with missing amenities at the lowest bound, it is important to note that the lowest entropy value remains 0. Future research could explore alternative methodologies for measuring diversity.

Lastly, the inclusion of qualitative context with quantitative approaches could further enrich

this study. Integrating survey and workshop analyses into the indicator weighting process, for instance, could offer a more nuanced representation of each indicator's significance within London's context. As Norouzian-Maleki et al. (2015) noted, the importance of indicators contributing to liveability may vary across cities due to their unique contexts. Moreover, the application of mixed methods could offer a profound understanding of disparities in active travel patterns, whilst also delving deeper into the complex dynamics that shape neighbourhood liveability.

6. Conclusion

The escalating significance of a city's role in addressing climate crisis and shift towards human-centric urban planning have propelled the concept of 'liveable neighbourhood' to the forefront. However, the diverse definitions of neighbourhoods and the multifaceted nature of liveability have posed challenges for urban planners to define and assess liveable neighbourhoods.

In response to these challenges, this study embarked on the task of constructing a comprehensive Liveability Index. Grounded in the theoretical framework of the 15-minute city concept, this index aimed to holistically illustrate liveability profiles of London's diverse and walkable neighbourhoods through a singular metric. Structured into three main parts, the research ranges from the creation of vibrant and walkable neighbourhoods akin to Jane Jacobs' vision within London's context, the construction of Liveability Index to offer an all-encompassing depiction of neighbourhood liveability, and to culminating in the exploration of active travel disparities among neighbourhoods with varying liveability profiles. Through these processes, the research was able to answer to its research questions.

The neighbourhood construction through a bottom-up process sheds light on the potential utility of entropy-based approach in constructing neighbourhoods. The variation in isodistance values offers insights into the optimal threshold for walkable neighbourhoods and understanding the extent to which a city's geographical features plays a role in limiting neighbourhood size and boundaries.

The research endeavours to transparently share the whole Liveability Index construction process. Despite a relatively modest number of simulations, the Liveability index demonstrated resilience to alterations in proximity and diversity indicators, whilst also revealing sensitivity to changes in normalisation method and the complete removal of population density. The Liveability Index's outcomes underscored that high liveability neighbourhoods generally cluster in Inner London. This phenomenon can be attributed to the intricate interaction between diversity, proximity and population density. Elevated population levels spur heightened demand for urban services, thereby attracting a concentration of amenities to the area. This clustering effect results in a convenient access and close proximity to essential urban services. Moreover, the decomposed LI scores yield indicator-specific insights, suggesting their potential for evaluating and monitoring local government's planning policies and projects. With resident participation gaining prominence in local-based planning, the Liveability Index's user-friendly interpretability could empower local residents to better understand their neighbourhoods, thus fostering proactive community engagement in shaping their neighbourhoods. Furthermore, the study's findings illuminate discernible distinctions in active travel patterns across neighbourhoods characterised by varying liveability levels. This observation enriches our understanding of the relationship between neighbourhood liveability and travel behaviours.

In conclusion, this study navigated the complexities of liveability assessment, contributing

valuable insights to local urban planning endeavours and enhancing our understanding of neighbourhood dynamics.

7. References

Abbiasov, T. *et al.* (2022) 'The 15-Minute city quantified using mobility data'.

Allam, Z. *et al.* (2022) 'The 15-minute city offers a new framework for sustainability, liveability, and health', *The Lancet Planetary Health*, 6(3), pp. e181–e183.

Alonso, W. (1964) *Location and land use: toward a general theory of land rent*. Harvard university press.

Aras, R.L., Ouellette, N.T. and Jain, R.K. (2021) 'Automated identification of urban substructure for comparative analysis', *Plos one*, 16(1), p. e0245067.

Barbosa, H. *et al.* (2021) 'Uncovering the socioeconomic facets of human mobility', *Scientific Reports*, 11(1), p. 8616. Available at: https://doi.org/10.1038/s41598-021-87407-4.

Chao, Y.-S. and Wu, C.-J. (2017) 'Principal component-based weighted indices and a framework to evaluate indices: Results from the Medical Expenditure Panel Survey 1996 to 2011.', *PloS one*, 12(9), p. e0183997. Available at: https://doi.org/10.1371/journal.pone.0183997.

Congress for the New Urbanism (2000) 'Charter of the new urbanism', *Bulletin of Science, Technology & Society*, 20(4), pp. 339–341.

Davies, S. (2020) *How COVID-19 could change urban infrastructure planning*. Available at: https://www.weforum.org/agenda/2020/05/coronavirus-change-cities-infrastructure/ (Accessed: 15 August 2023).

Economist Intelligence Unit (2023) *The Global Liveability Index 2023*. Available at: https://www.eiu.com/n/campaigns/global-liveability-index-2023/ (Accessed: 18 August 2023).

Eurofound (2022) *The rise in telework: Impact on working conditions and regulations*. Publications Office of the European Union, Luxembourg.

Fan, Z. *et al.* (2023) 'Diversity beyond density: Experienced social mixing of urban streets', *PNAS nexus*, 2(4), p. pgad077.

Gehl, J. (2013) *Cities for people*. Island press.

Glaeser, E. (2021) 'The 15-minute city is a dead end—cities must be places of opportunity for everyone', *LSE COVID-19 Blog* [Preprint].

Gongadze, S. and Maassen, A. (2023) 'Paris' Vision for a "15-Minute City" Sparks a Global Movement', 25 January. Available at: https://www.wri.org/insights/paris-15-minute-city (Accessed: 17 August 2023).

González, M.C., Hidalgo, C.A. and Barabási, A.-L. (2008) 'Understanding individual human mobility patterns', *Nature*, 453(7196), pp. 779–782. Available at:

https://doi.org/10.1038/nature06958.

Graells-Garrido, E. *et al.* (2021) 'A city of cities: Measuring how 15-minutes urban accessibility shapes human mobility in Barcelona', *PloS one*, 16(5), p. e0250080.

Greater London Authority (2021) *The London Plan: The Spatial Development Strategy For Greater London*. Available at: https://www.london.gov.uk/programmes-strategies/planning/london-plan/new-london-plan/london-plan-2021 (Accessed: 24 August 2023).

Greco, S. *et al.* (2019) 'On the Methodological Framework of Composite Indices: A Review of the Issues of Weighting, Aggregation, and Robustness', *Social Indicators Research*, 141(1), pp. 61–94. Available at: https://doi.org/10.1007/s11205-017-1832-9.

Hidalgo, C.A., Castañer, E. and Sevtsuk, A. (2020) 'The amenity mix of urban neighborhoods', *Habitat International*, 106, p. 102205. Available at: https://doi.org/10.1016/j.habitatint.2020.102205.

Higgs, C. *et al.* (2019) 'The Urban Liveability Index: developing a policy-relevant urban liveability composite measure and evaluating associations with transport mode choice', *International Journal of Health Geographics*, 18(1), p. 14. Available at: https://doi.org/10.1186/s12942-019-0178-8.

Hillingdon Council (2012) *Local Plan: Part1 -Strategic Policies*. Available at: https://www.hillingdon.gov.uk/local-plan (Accessed: 20 August 2023).

Hillingdon Council (2017) *London Borough of Hillingdon Strategic Infrastructure Plan (SIP)*. Available at: https://www.hillingdon.gov.uk/infrastructure-planning#:~:text=The%20Strategic%20Infrastructure%20Plan%20assesses,latest%20SIP%20in%20May%202017. (Accessed: 21 August 2023).

Hooper, P. *et al.* (2015) 'The building blocks of a "Liveable Neighbourhood": Identifying the key performance indicators for walking of an operational planning policy in Perth, Western Australia', *Health & Place*, 36, pp. 173–183. Available at: https://doi.org/10.1016/j.healthplace.2015.10.005.

IPCC (2023) *Climate Change 2023: Synthesis Report*. First. A Report of the Intergovernmental Panel on Climate Change. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [Core Writing Team, H. Lee and J. Romero (eds.)]. IPCC, Geneva, Switzerland, (in press). Available at: https://doi.org/10.59327/IPCC/AR6-9789291691647.

Jacobs, J. (1961) *The death and life of great American cities*. Vintage Books, New York.

Joint Research Centre-European Commission (2008) *Handbook on constructing composite indicators: methodology and user guide*. OECD publishing.

Jolliffe, I.T. and Cadima, J. (2016) 'Principal component analysis: a review and recent

developments.', *Philosophical transactions. Series A, Mathematical, physical, and engineering sciences*, 374(2065), p. 20150202. Available at: https://doi.org/10.1098/rsta.2015.0202.

Larmet, V. (2022) *cppRouting: Algorithms for routing and solving the traffic assignment problem*. manual. Available at: https://CRAN.R-project.org/package=cppRouting.

Leby, J.L. and Hashim, A.H. (2010) 'Liveability dimensions and attributes: Their relative importance in the eyes of neighbourhood residents', *Journal of construction in developing countries*, 15(1), pp. 67–91.

Louf, R. and Barthelemy, M. (2013) 'Modeling the polycentric transition of cities', *Physical review letters*, 111(19), p. 198702.

Louf, R. and Barthelemy, M. (2014) 'How congestion shapes cities: from mobility patterns to scaling', *Scientific Reports*, 4(1), p. 5561. Available at: https://doi.org/10.1038/srep05561.

Lynch, K. (1964) *The image of the city*. MIT press.

Mazziotta, M. and Pareto, A. (2016) 'Methods for Constructing Non-Compensatory Composite Indices: A Comparative Study', *Forum for Social Economics*, 45(2–3), pp. 213–229. Available at: https://doi.org/10.1080/07360932.2014.996912.

McLennan, D. *et al.* (2019) *The English Indices of Deprivation 2019: Technical report*. Ministry of Housing, Communities and Local Government. Available at: http://www.gov.uk/mhclg.

der Meer, L. van *et al.* (2023) *sfnetworks: Tidy geospatial networks*. manual.

Ministry of Housing, Communities & Local Government (2021) *National Planning Policy Framework*. Available at: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/1005759/NPPF_July_2021.pdf (Accessed: 24 August 2023).

Moreno, C. *et al.* (2021) 'Introducing the "15-Minute City": Sustainability, resilience and place identity in future post-pandemic cities', *Smart Cities*, 4(1), pp. 93–111.

Nardo, M. *et al.* (2005) 'Tools for composite indicators building', *European Comission, Ispra*, 15(1), pp. 19–20.

Niemelä, J. *et al.* (2010) 'Using the ecosystem services approach for better planning and conservation of urban green spaces: a Finland case study', *Biodiversity and Conservation*, 19(11), pp. 3225–3243. Available at: https://doi.org/10.1007/s10531-010-9888-8.

Nold, C. (2009) 'Emotional cartography: Technologies of the self'.

Norouzian-Maleki, S. *et al.* (2015) 'Developing and testing a framework for the assessment of neighbourhood liveability in two contrasting countries: Iran and Estonia', *Ecological Indicators*, 48, pp. 263–271. Available at: https://doi.org/10.1016/j.ecolind.2014.07.033.

O'Sullivan, F. (2021) 'Where the "15-Minute City" Falls Short', *Bloomberg.com*, 2 March. Available at: https://www.bloomberg.com/news/articles/2021-03-02/the-downsides-of-a-15-minute-city (Accessed: 17 August 2023).

Pebesma, E. (2018) 'Simple features for R: Standardized support for spatial vector data', *The R Journal*, 10(1), pp. 439–446. Available at: https://doi.org/10.32614/RJ-2018-009.

Postaria, R. (2021) 'Superblock (Superilla) Barcelona—a city redefined. Public Realm', *citiesforum.org*, 31 May. Available at: https://www.citiesforum.org/news/superblock-superilla-barcelona-a-city-redefined/ (Accessed: 17 August 2023).

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

Rotem-Mindali, O. (2012) 'Retail fragmentation vs. urban livability: Applying ecological methods in urban geography research', *Applied Geography*, 35(1), pp. 292–299. Available at: https://doi.org/10.1016/j.apgeog.2012.08.003.

Roth, C. *et al.* (2011) 'Structure of urban movements: polycentric activity and entangled hierarchical flows', *PloS one*, 6(1), p. e15923.

Saisana, M., Saltelli, A. and Tarantola, S. (2005) 'Uncertainty and sensitivity analysis techniques as tools for the quality assessment of composite indicators', *Journal of the Royal Statistical Society Series A: Statistics in Society*, 168(2), pp. 307–323.

Saltelli, A. (2007) 'Composite indicators between analysis and advocacy', *Social indicators research*, 81, pp. 65–77.

Sevtsuk, A. (2014) 'Location and agglomeration: The distribution of retail and food businesses in dense urban environments', *Journal of Planning Education and Research*, 34(4), pp. 374–393. Available at: https://doi.org/10.1177/0739456X14550401.

Shamsuddin, S., Hassan, N.R.A. and Bilyamin, S.F.I. (2012) 'Walkable Environment in Increasing the Liveability of a City', *AcE-Bs 2012 Bangkok, Sukosol Hotel, Bangkok, Thailand, 16-18 July, 2012*, 50, pp. 167–178. Available at: https://doi.org/10.1016/j.sbspro.2012.08.025.

Shannon, C.E. (1948) 'A mathematical theory of communication', *The Bell system technical journal*, 27(3), pp. 379–423.

Sheppard, E. (2015) 'Thinking Geographically: Globalizing Capitalism and Beyond', *Annals of the Association of American Geographers*, 105(6), pp. 1113–1134. Available at: https://doi.org/10.1080/00045608.2015.1064513.

Tian, Y., Jim, C.Y. and Wang, H. (2014) 'Assessing the landscape and ecological quality of urban green spaces in a compact city', *Landscape and Urban Planning*, 121, pp. 97–108. Available at: https://doi.org/10.1016/j.landurbplan.2013.10.001.

TV, R., Aithal, B.H. and Sanna, D.D. (2012) 'Insights to urban dynamics through landscape

spatial pattern analysis', *International Journal of Applied Earth Observation and Geoinformation*, 18, pp. 329–343. Available at: https://doi.org/10.1016/j.jag.2012.03.005.

UN-Habitat (2022) *World Cities Report 2022: Envisaging the Future of Cities*.

Victoria State Government (2017) *Plan Melbourne 2017-2050 Summary*. Planning. Available at: https://www.planning.vic.gov.au/guides-and-resources/strategies-and-initiatives/plan-melbourne/the-plan (Accessed: 17 August 2023).

Whyte, W.H. (1980) 'The social life of small urban spaces'.

World Bank (2023) *Urban Development*. Available at: https://www.worldbank.org/en/topic/urbandevelopment/overview#1 (Accessed: 14 August 2023).

Appendix A

Table A1. OSM amenities categorised by the 15-minute city concept

Urban Service	*Amenity*
Living	post_box, post_office, recycling, parking, telephone, public_building, waste_basket, toilets, community_centre, place_of_worship, grit_bin, bench, taxi, vending_machine, bus_station, bicycle_repair_station, clock, ferry_terminal, drinking_water, locker, fire_station, social_facility, police, grave_yard, bus_garage, dressing_room, townhall, courthouse, newsagent, funeral, charity, guest_house, information_centre, hotel, apartment, bus_stop, Housing Office, animal_boarding, public_hall, scout_hut, ticket_validator, wedding_venue, conference_centre, chalet, Childrens Centre, hall, church_hall, community_hall, shower, compressed_air, trolley_bay, courtyard, waste_transfer_station, social_centre, car_garage, hostel, social, bbq, smoking_area, prison, crematorium, lifeboat_station, mobile_phone_mast, gate, sanitary_dump_station, retirement_home, device_charging_station, lift, monastery, narrow_gauge_railway, scout_hall, pet_waste_basket, vicarage, building, motel, delivery_office, hunting_stand, village_hall, Housing_Office, bicycle_pump, coworking_space, Waterloo&City Line, waiting_room, parking_meter, local_government, reception_desk, ranger_station, notice_board, public_display_screen, youth_project, mortuary, refuse_incinerator, bin_store, register_office, collection_point, parcel, lifeboat, buggy_parking, table, student, taxi_point, cabinet, visa, polling_station, weapon_bin, traffic_camera, livery_hall, newspaper_distribution_bin
Commerce	atm, rental, bank, fuel, photo_booth, bureau_de_change, garden, car_wash, marketplace, bicycle, convenience_store, doityourself, car_repair, department_store, supermarket, hairdresser, general, books, clothes, carpet, craft, trade, outdoor, car_parts, grocery, hardware, curtain, estate_agent, butcher, printer_ink, electronics, kiosk, ticket_office, mobile_phone, shoes, sports, travel_agency, camera, storage, wine, bookmaker, laundry, bed, copyshop, car, paint, variety_store, florist, tattoo, cosmetics, hifi, kitchen, interior_design, tobacco, boutique, jewelry, video_games, collector, furniture, party, mall, surveyor, antiques, gift, photography, shoe_repair, frozen_food, houseware, flooring, tool_hire, tailor, seafood, frame, motorcycle, pyrotechnics, lighting, erotic, motorcycle_repair, studio, food_court, advice_bureau, money_transfer, locksmith, pet_grooming, tile, games, sewing, baby_goods, wholesale, glass, security, hearing_aids, computer, printing, computer_repair, health_food, stationery, toys, signs, balloon, fishing, tyres, cake_decorations, cctv, doors,

pawnbroker, perfumery, building_materials, window_blind, furnishing, accessories, hairdresser_supply, candles, money_lender, appliance, fabric, bag, catalogue, beverages, musical_instrument, party_goods, video, money, nails, garden_furniture, cash_and_carry, weapons, vehicle_inspection, comic, linen, employment_agency, finance, piercing, media, computer_games, arts_and_crafts, second_hand, charity;second_hand;clothes, plumbing, legal, heating, office, fireworks, shop_indian, radiotechnics, wigs, electrical, Local, metal recycling, tools, wheelchair, medical_supply, weighbridge, window_service, repair, job_centre, brazilian_store, golf, watch, nutrition_supplements, cheese, nuts, model, airsoft, garage_door_supplier, tattoo_remover, farm, design, military_surplus, wool, photo_studio, vat_refund, hobby, duty_free, ship_chandler, fashion, sunglasses, leather, monument, solicitor, food, business, communication, hat, cash, washing_machine, aerial, boat, auction_house, skylights, trophy, cobbler, lost_property, retail, credit_union, student_accommodation, puppet, catering, beauty_products, discount_shop, pottery, vacuum_cleaner, boat_storage, plant_hire, magic, accountant, delivery, reprographics, popup, fish, cannabis, architects, clockmaker, piano, rehearsal_studio, charity;furniture, toner-refill, pet_food, off_licence, new_age, electrical_supplies, clothing, roofing, upholstery, stall, plumbers_merchant, shops, boot_cleaner, Picture_Hanging_Systems, dance, office_supplies, pest_control, lottery, scooter, canteen, thrift_store, glazing, minicab, auction, carpenter, educational_supplies, furniture_repair, signwriter, dresswear_hire, iron_monger, telecommunication, loft_conversions, hydroponics, alarms, second_hand tools, binoculars, key_cutting, mobility_aids, brewery, stables, kitchenware, ballet, mirrors, sheltered_housing, art_supplies, lawyer, groundskeeping, fishmonger, post_production, textiles, hats, Hosiery, bridal, skate, sanitary_engineering, rugs, ceramic, Iron_Radiators, wallpapers, spices, ornament, maps, racing, stamps, caviar, travel_goods, crystal, mirror, spy_equipment, aromatic, shopping_centre, style, souvenir, videostudio, chinese_medicine, gold_buyer, check_in, student_union, frozen, street market, alteration, umbrella, customizing_cap_shop, watch_repair, 3d_shop, anime, masonic_regalia, workshop, bells, sign, taximeters, maintenance, translation_services, joinery, audio_video, taxidermist, misc, restaurant_supplies, sewing_machines, memorabilia, commercial, magazine shop, watch_supplies, heating_supplies, showroom, loan_shark, satellite_tv, design_agency, film, white_goods, var, spare_parts, internet, medicine, Arcade,_various_retailers, baby, commercial_equipment, credit, joiners, landscaping_design,

	composting, trade_school, entertainment, money_lender;mortgage, construction, stock_exchange, luxury, pens
Healthcare	pharmacy, veterinary, dentist, doctors, childcare, clinic, hospital, nursery, beauty_clinic, health, optician, massage, shelter, counselling, dojo, dentures, alternative_medicine, Care_Agency, medical_centre, gym, health_centre, animal_shelter, herbalist, tanning, meditation, herbal_medicine, therapists, medical, esoteric, residential_home, healthcare, chiropodist, Nutritionist, surgery, pole, hospital_department
Education	school, library, kindergarten, driving_school, university, college, public_bookcase, prep_school, motoring, flight_school, scuba_diving, language_school, dancing_school, driving_test_centre, training, research_institute, music_school, society, adult_education, archive, cookery_school, art_school, school_workshop
Entertainment	pub, fountain, fast_food, cafe, restaurant, bar, cinema, nightclub, biergarten, events_venue, theatre, bakery, alcohol, deli, confectionery, music, patisserie, sweets, artwork, museum, viewpoint, attraction, zoo, picnic_site, theme_park, gallery, aquarium, gambling, internet_cafe, stripclub, social_club, arts_centre, ice_cream, casino, sports_club, fireplace, art, tea, camp_site, stage, amusements, sandwich, chocolate, caravan_site, historical building, Shisha_Lounge, spa, lounge, miniature_railway, island, dairy, school_playground, function_hall, arena, hookah_lounge, swimming_pool, weathervane, paddling_pool, music_venue, dive_centre, leisure_centre, snooker_hall, concert_hall, camera_obscura, planetarium, cake, ball court, angling, psychic, water_sports, confectionary, clubhouse, villa, mounting_block, cultural_centre, private_club, sport, brothel, bandstand, street_performance, park, juice_bar, sculpture, exhibition_centre, square, venue, swingerclub

Appendix B

Table B1. Meeting log

Date	***Meeting Type***	***Discussion***
31.03.2023	Online	Explanation on overall dissertation submission process and literature review homework related to the research topic was given
13.04.2023	In-person	First one-on-one discussion on the 15-minute city project, and Elsa introduced potential data sources and project partners
21.04.2023	Online	Team meeting with the CEO of Locomizer and brief information on types of data available for this work
17.05.2023	In-person	Based on literature review, I suggested types of data that can be utilised to measure the three measures of the 15-minute city concept. Diversity - categorisation of OSM data Proximity - UK Survey Ordnance Road Network or Multimodal Spatial Network Analysis on Python Density - LSOA-level population data
10.06.2023	In-person	Presentation of initial results in front of colleagues. Discussion on what could be used as potential origin and destination point in measuring proximity of the 15-minute city concept. I received feedback on measuring distinctive distances to 5 different urban functions, instead of measuring one single proximity measure
23.06.2023	In-person	Presentation preparation for CASA mini conference Elsa recommended me to look for a document on how to build a composite index
05.07.2023	In-person	I presented the overall structure of the Liveability Index construction process during the CASA mini conference
12.07.2023	In-person	I showed the initial result of entropy of amenities considering isodistance and gave an overall summary for how I am going to construct neighbourhoods and measure diversity and proximity of the paradigm
20.07.2023	In-person	I showed the constructed neighbourhoods by using local maximum entropy and isodistance, and presented the equations for calculating diversity and proximity measures
15.08.2023	Online	Elsa gave feedback on the draft and asked some clarification on some plots

Appendix C

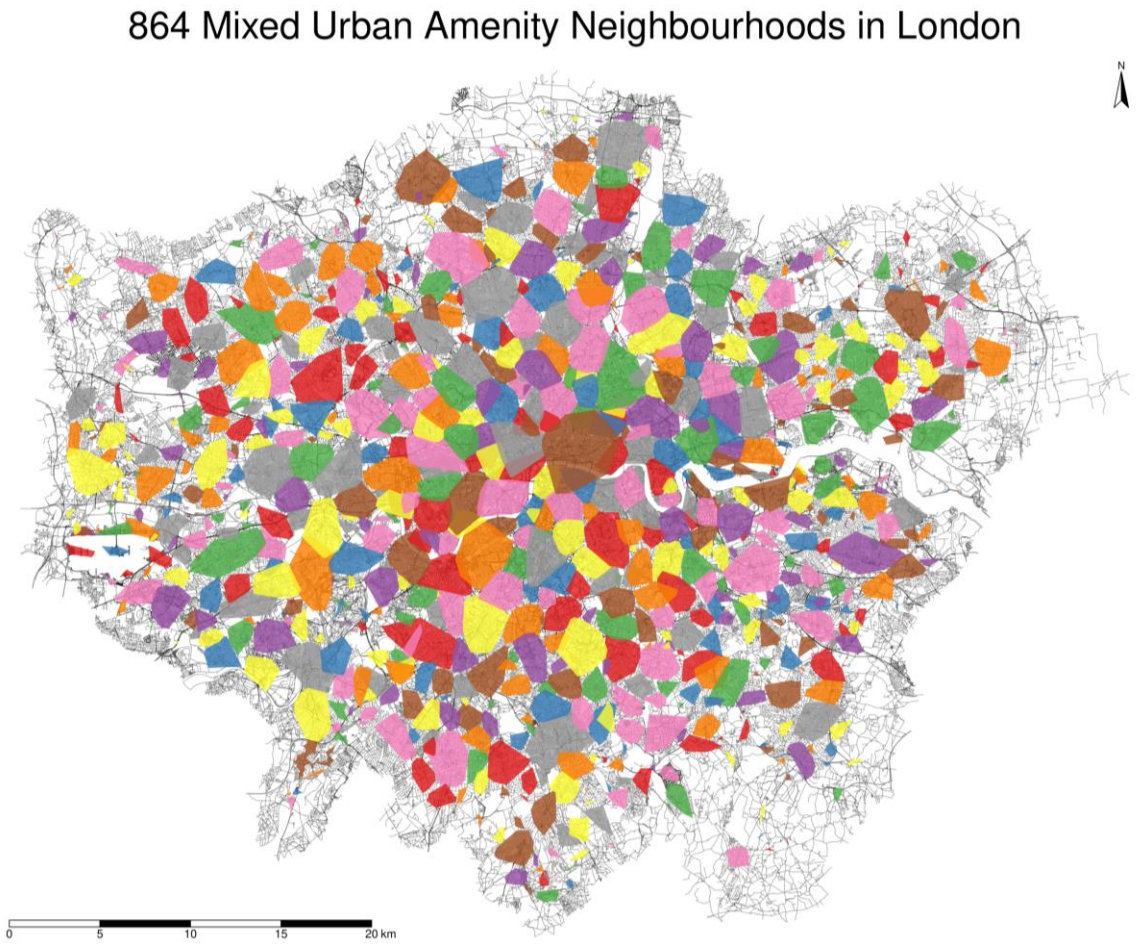

Figure C1. 864 Neighbourhoods revealed through the investigation of amenity entropy of space. Isodistance of 600m is used and each polygon represents different neighbourhoods.