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Evaluating quality of life in the Porto Metropolitan Area: an integrated approach

Maria Mortágua Nadais

M

2026



U.PORTO
FEP FACULDADE DE ECONOMIA
UNIVERSIDADE DO PORTO

EVALUATING QUALITY OF LIFE IN THE PORTO METROPOLITAN AREA: AN INTEGRATED APPROACH

Maria Mortágua Nadais

Internship report
Master in management

Supervised by
Pedro José Ramos Moreira de Campos, PhD

2026

Acknowledgements

This report would not have been possible without the support of many people, to whom I would like to express my sincere gratitude.

First, I would like to thank my academic supervisor, Professor Pedro Campos, for the guidance and feedback throughout this process. His availability and genuine interest in this work were deeply appreciated at every stage. Working under his guidance was both a privilege and a learning experience.

I am also grateful to Patrícia Serrão, my internship supervisor at the Porto City Council, for welcoming me into the team and for the trust shown from the very first day. A special thank you also goes to my fellow interns for their support. The good moments we shared made this experience truly rewarding.

I would like to extend my gratitude to Sérgio Bacelar, for generously dedicating his time to meet with me and discuss the methodological approach of this study. His expertise in quality of life measurement was incredibly valuable and his insights helped me navigate some of the most complex aspects of this work.

I would also like to thank my closest friends, *As Engenheiras*, whose presence and support throughout this period meant a great deal to me. Their friendship and ability to make me think about something other than composite indicators when I most needed it were more helpful than they probably realise.

Finally, and above all, I would like to thank my mom, my dad, my brother and Tiago. Their love, patience and unwavering support carried me through every challenge this journey brought. They believed in me even when I struggled to believe in myself, and for that I will always be grateful. This achievement is as much theirs as it is mine.

Abstract

Quality of life is widely recognised as a multidimensional concept influenced by both material conditions and personal perceptions. Although open data portals have become essential tools for monitoring urban dynamics, a benchmarking analysis of 27 platforms showed that most of them, including Leme Porto, lack the structured frameworks necessary for systematically assessing quality of life. Existing initiatives also tend to present individual datasets instead of combining them into comprehensive indicators, thus limiting the understanding of urban well-being. To address this gap, this study develops a multidimensional framework to assess quality of life in the municipalities of the Porto Metropolitan Area. This approach combines objective municipal indicators with subjective evaluations collected through a resident survey of 245 respondents. Principal component analysis identified seven quality of life dimensions, which were subsequently validated using partial least squares structural equation modelling. The dimensions were then aggregated into composite indicators using the goal-based composite indicator with multiple constraints method. The optimisation indicated that perceived economic security and place attachment contributed most strongly to variations in the composite indicators. The results also revealed a clear centre-to-periphery pattern, with Porto achieving the highest quality of life composite score. This was mainly driven by the city's above-average objective conditions and high levels of place attachment and satisfaction with essential services. However, Porto performed below the metropolitan average in terms of perceived social cohesion and environmental quality, highlighting that economic and infrastructural advantages do not necessarily translate into positive residential experiences in all areas. Valongo presented the most concerning profile, with the lowest scores on all subjective dimensions. Overall, the proposed framework offers a robust and policy-relevant approach for monitoring territorial disparities in quality of life and supporting urban planning in the Porto Metropolitan Area.

Keywords: Quality of life; Life satisfaction; Open data portals; Composite indicator; Porto Metropolitan Area; Urban benchmarking; Structural equation modelling; Principal component analysis

Resumo

A qualidade de vida é reconhecida como um conceito multidimensional, influenciado por condições materiais e perceções subjetivas. Embora os portais de dados abertos sejam ferramentas essenciais para monitorizar o ambiente urbano, uma análise de 27 plataformas revelou que a maioria, incluindo o Leme Porto, carece das estruturas adequadas para avaliar a qualidade de vida. As iniciativas existentes tendem a apresentar dados individuais, em vez de os integrar em indicadores abrangentes, limitando a compreensão do bem-estar urbano. Este estudo procura colmatar esta lacuna através de uma abordagem multidimensional para avaliar a qualidade de vida nos municípios da Área Metropolitana do Porto. A metodologia combina indicadores objetivos com avaliações subjetivas recolhidas através de um inquérito a 245 residentes. A análise de componentes principais identificou sete dimensões de qualidade de vida, validadas através de um modelo de equações estruturais de mínimos quadrados parciais. Estas dimensões foram agregadas em indicadores compósitos utilizando o método do indicador composto baseado em objetivos com restrições múltiplas. A otimização revelou que a segurança económica percebida e o apego ao lugar foram as dimensões que mais contribuíram para a variação dos indicadores compósitos. Os resultados indicaram também um padrão centro-periferia, tendo o Porto registado o maior valor compósito de bem-estar. Este desempenho foi impulsionado pelas condições objetivas acima da média e pelos elevados níveis de apego ao lugar e satisfação com serviços essenciais. Contudo, o município apresentou um desempenho abaixo da média metropolitana nas perceções de coesão social e qualidade ambiental, mostrando que vantagens económicas e estruturais nem sempre se traduzem em experiências residenciais positivas em todas as áreas. Valongo evidenciou o perfil mais preocupante, registando as menores pontuações em todas as dimensões subjetivas. Globalmente, a metodologia proposta constitui uma abordagem relevante para a monitorização das disparidades territoriais de qualidade de vida na Área Metropolitana do Porto.

Palavras-chave: Qualidade de vida; Satisfação com a vida; Portais de dados abertos; Indicador composto; Área Metropolitana do Porto; Benchmarking urbano; Modelação de equações estruturais; Análise de componentes principais

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List of Acronyms and Abbreviations

QoL – quality of life

ODPs – open data portals

OGD – open government data

CMP – *Câmara Municipal do Porto*, Porto City Council

OECD – Organisation for Economic Cooperation and Development

INE – *Instituto Nacional de Estatística*

AMP – Porto Metropolitan Area

PCA – principal component analysis

SEM – structural equation modelling

PLS-SEM – partial least squares structural equation model

GB-CI-MC – goal-based composite indicator with multiple constraints

CI – composite indicator

KMO – Kaiser-Meyer-Olkin

AVE – average variance extracted

HTMT – heterotrait-monotrait ratio

SRMR – standardised root mean square residual

VIF – variance inflation factor

1. Introduction

Monitoring quality of life (QoL) in cities, which are home to an increasing share of the world's population, has become an essential part of sustainable urban management (Engin et al., 2020). Open data portals (ODPs) support this process by making public information more accessible and transparent, reflecting the increasing importance of open data as a tool for public management (Janssen et al., 2012).

Over the past two decades, the number of ODPs worldwide has grown significantly, following early initiatives such as the United States administration's data.gov portal (Neves et al., 2020). Subsequently, governments across the globe adopted open data practices at national, regional, and local levels (Barns, 2018; Lnenicka & Nikiforova, 2021). At the urban scale, cities such as Chicago, Helsinki, Amsterdam, Dublin and Barcelona have become leading examples of the implementation of open government data (OGD) initiatives (Neves et al., 2020).

OGD is defined as "non-privacy-restricted and non-confidential data [...] produced with public money and made available without any restrictions on its usage or distribution" (Janssen et al., 2012). ODPs constitute the infrastructure through which such data is published, allowing governments, researchers, businesses and citizens to access and reuse public sector information (Janssen et al., 2012; Lnenicka & Nikiforova, 2021). This reuse supports decision-making, policy development and the creation of innovative solutions to collective problems, while also fostering government accountability (Anderson & Whitford, 2018; Kitchin et al., 2015; Lnenicka et al., 2024).

Within this broader international context, this report was developed as part of a curricular internship at the Office of Data and Strategic Research of the Porto City Council (*Câmara Municipal do Porto*), with the aim of supporting the development of the second phase of *Leme* Porto[1], an ODP that aggregates socioeconomic information about the city. Despite its strategic relevance within the Porto City Council, *Leme* currently lacks an analytical framework capable of monitoring QoL. This gap was identified through an internal analysis and confirmed by the benchmarking of international urban ODPs, conducted as part of the internship.

[1] https://leme.porto.pt/pt

Therefore, the present report adopts an exploratory approach to develop and test an integrated multidimensional framework for assessing QoL in the Porto Metropolitan Area. As such, the central research questions guiding this report are:

How can subjective perceptions and objective conditions be integrated to create multidimensional QoL composite indicators for the municipalities of the Porto Metropolitan Area? What can these indicators reveal about QoL disparities between municipalities?

To answer these questions, subjective and objective data were collected and analysed using a principal component analysis to identify the main QoL dimensions. These dimensions were subsequently validated through a partial least squares structural equation model, and their latent scores were aggregated into composite indicators using a weighting approach inspired by Libório et al. (2026).

The work done during the curricular internship makes three main contributions. Empirically, it develops and tests an integrated QoL assessment framework for the Porto Metropolitan Area, providing a foundation for well-being monitoring on the *Leme* platform. Methodologically, it presents the first application of Libório et al.'s (2026) composite indicator framework to urban QoL assessment, extending it to a European metropolitan context and incorporating subjective survey-based dimensions. Practically, it identifies perceived economic security and place attachment as the dimensions most strongly associated with QoL variation across the metropolitan area, informing the prioritisation of urban interventions aimed at improving residents' well-being.

The remainder of this report is structured as follows. Chapter 2 provides an overview of the Porto City Council, its organisational structure and the activities developed during the internship. Chapter 3 reviews the relevant literature on open data portals and the conceptualisation and measurement of QoL. It also presents a benchmarking analysis and an overview of the *Leme* platform. Chapter 4 describes the methodological approach adopted for data collection and multidimensional QoL assessment. Chapter 5 presents the study's main findings, and Chapter 6 discusses the results in light of the relevant literature. Finally, Chapter 7 concludes the report by summarising the research's main findings, contributions and limitations. This section also includes a brief critical reflection on internship activities.

2. The Porto City Council and internship activities

2.1. Institution overview

This report was produced as part of a curricular internship at the Municipal Department of Economy of the Porto City Council (hereinafter, CMP), carried out between February and July 2026. As the governing authority of the city of Porto, CMP is responsible for the design and implementation of municipal policies across various domains. To do that, the administration is guided by a mission to promote citizens' well-being through transparent public management and sustainable economic, social and cultural development, placing particular emphasis on values such as transparency, participation and innovation (Barbosa & Fonseca, 2025).

The organisational structure of CMP is characterised by a hierarchical governance model, encompassing the President and Vice-president, municipal portfolios (*pelouros*), departments, divisions and offices, with progressively higher levels of functional specialisation[2]. The Municipal Department of Economy plays a central role within this structure, being responsible for designing Porto's economic development policies that go from investment attraction to entrepreneurship and local commerce[3]. The Department is organised into the divisions of InvestPorto, Entrepreneurship, Commercial Activity, and Local Accommodation, and the Office of Data and Strategic Research.

Specifically, the internship took place within the Office of Data and Strategic Research, which supports evidence-based policymaking through the production and analysis of socioeconomic information relevant to the municipality and its stakeholders. Its core activities include the development of empirical studies, the monitoring of economic and social trends, and the support of policy design and planning processes[4]. As part of its activity, the Office manages several strategic outputs, including the sustainable development report, the *Boletim Económico do Porto* and *Leme* Porto, CMP's socioeconomic ODP.

2.2. Internship activities

The internship focused primarily on data analysis and strategic reporting activities, encompassing five main tasks. The first task involved identifying and mapping new indicators for integration into the *Leme* platform as part of its second development phase, with the aim

[2] https://www.cm-porto.pt/estrutura-organica
[3] https://diariodarepublica.pt/dr/detalhe/despacho/6088-2026-1119817856
[4] https://www.cm-porto.pt/economia/estudos-estrategicos

of expanding and restructuring its existing set of indicators. This required establishing data gaps relative to international benchmarks and assessing which additional indicators could strengthen the platform's analytical scope while also being relevant to municipal policy priorities.

A second central activity was the elaboration of the *Boletim Económico do Porto* for the final quarter of 2025 and the first quarter of 2026. This included the collection and interpretation of official statistical indicators to characterise Porto's recent economic trends. The activity culminated in analytical reports published on CMP's website, one of which also received media coverage in *Jornal de Notícias* and *ECO*.

Additional analytical work was carried out to update the *Pulsar* cluster factsheets. *Pulsar* is Porto's economic development strategy and has the goal of promoting the city's competitiveness and sustainable economic growth by identifying eight priority industry clusters[5]. The activity involved gathering and analysing cluster-specific data from multiple official sources, such as statistics on employment, turnover, gross value added, and exports, to produce updated sector profiles for the local retail, and real estate and construction clusters.

The internship also involved attending meetings with data and software providers, as well as with other municipal departments. This provided direct insights into the operational and strategic aspects of data governance within CMP, especially the processes behind the development and management of the *Leme* platform and other public data systems.

Finally, the most significant part of the internship and the primary focus of this report was the development of a multidimensional QoL assessment framework for the Porto Metropolitan Area. This involved conducting a resident survey, collecting objective municipal indicators from official sources and crowdsourced platforms, and constructing composite QoL indicators integrating both data types. The resulting framework is intended for future publication either through *Leme* or as part of the Office's strategic research output.

Overall, the internship provided direct participation in strategic data analysis and reporting processes, deepening the understanding of how data-driven approaches can support more responsive urban governance.

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[5] https://www.cm-porto.pt/files/uploads/cms/cmp/181/files/Pulsar_Estrategia_Desenvolvimento_Economico_Porto_Relatorio_Sumario_2022.pdf

3. Literature review

The growth of urban data and the associated multiplication of open data portals (ODPs) have created new opportunities for evidence-based municipal governance. More specifically, it has enabled cities to monitor socioeconomic dynamics, evaluate policy outcomes, and communicate information to their stakeholders (Engin et al., 2020; Kitchin et al., 2015). The use of statistical indicators is fundamental to this transformation, as they translate complex datasets into more accessible information that supports policymaking and, therefore, has the potential to improve the management of urban spaces (Anderson & Whitford, 2018; Kitchin et al., 2015). However, the interpretation of these indicators depends on the spatial scale at which they are produced (Prince, 2020). For instance, an unemployment rate measured at the city level can reflect local economic structures that cannot be interpreted in the same way as a national indicator. As such, indicators do not just describe urban reality, but they actively influence how issues are prioritised in public governance (Prince, 2020; Kitchin & Moore-Cherry, 2021).

3.1. Data governance and open government data (OGD)

As data becomes increasingly central to urban management, greater attention has been given to how it is collected, shared and managed (Engin et al., 2020). In this context, data governance refers to the institutional and political arrangements that determine how data is accessed, controlled, shared and used (Micheli et al., 2020). These arrangements influence what priorities are reflected in public information systems and how the value generated from data is distributed between stakeholders. Public administrations play a central role in this process as they are responsible for many of these governance arrangements. Therefore, their governance choices directly influence the access to public sector information and the regulatory frameworks that determine data quality and usability (Abraham et al., 2019; Micheli et al., 2020).

OGD, defined as publicly funded data made freely accessible and reusable, represents one of the clearest manifestations of data governance (Janssen et al., 2012). However, its value does not depend on publication alone but more so on the extent to which data can generate social, economic and operational benefits (Janssen et al., 2012). To maximise such value, governments increasingly rely on ODPs and visualisation dashboards to make information more accessible for both decision-makers and citizens (Kitchin et al., 2015).

The effectiveness of OGD initiatives also depends on the quality and relevance of the datasets published, as poorly structured or low-value datasets may damage transparency efforts and weaken public trust (Janssen et al., 2012). Furthermore, Chatfield and Reddick (2017) and Lnenicka et al. (2024) argue that wider political and socioeconomic conditions also influence their success. Continued investment in financial and human resources and institutional capacity are essential elements for maintaining OGD (Chatfield & Reddick, 2017). Consequently, municipalities with larger populations or greater economic resources are often in a better position to implement these policies effectively, meaning that open data may reinforce existing inequalities between cities (Chatfield & Reddick, 2017).

Smart city governance has also reinforced the strategic role of OGD in urban management. Smart cities are defined as urban environments where investments in human capital, social capital, and communication infrastructure drive sustainable economic growth and QoL (Caragliu et al., 2011). Within this framework, OGD is responsible for enabling the circulation and reuse of information among a large range of stakeholders, supporting shared forms of knowledge production and more inclusive urban governance (Anderson & Whitford, 2018). In turn, ODPs provide the digital infrastructure through which this information can be shared and reused, facilitating transparency and citizen engagement (Janssen et al., 2012). Knowing these relationships provides the basis for analysing how they are implemented in practice. Therefore, the following section examines how *Leme* Porto compares with other urban ODPs through a benchmarking analysis.

3.2. Benchmarking of open data portals

For the benchmarking analysis[6], 27 ODPs were selected from dataportals.org[7] to be as geographically representative as possible. Preference was given to portals available in English, Portuguese, or Spanish to minimise language barriers. For portals in other languages, Google's Translator feature was used to facilitate analysis.

Each portal was evaluated against eight predefined criteria. First, geographic granularity was assessed, identifying whether data was collected at the parish (or equivalent) level, municipality, or larger regional or national scale. Second, the portal type was classified using the Barns (2018) typology (see Annex 1). Third, data content was divided into nine categories: socioeconomic; industry; environment; health; public governance; infrastructure;

[6] The benchmarking analysis was conducted in October of 2025.

[7] https://dataportals.org/

mobility; culture; and crime and safety, based on common dataset types (see Annex 2). Fourth, update frequency was examined, while fifth, temporal coverage noted the years of the most and least recent data. Sixth, the existence of a city or region QoL indicator framework was checked. Seventh, the volume of information was measured by the total number of datasets or indicators available at the time of the analysis. Finally, the assessment recorded whether the portal included a dashboard containing socioeconomic information. Dashboards focused on transit, infrastructure, or other non-socioeconomic data were excluded. Annex 3 summarizes the most relevant benchmark criteria.

The benchmarking analysis revealed important differences in how ODPs publish urban data. According to Barns' (2018) typology, most analysed ODPs can be classified as either data marketplaces or data repositories. Data repositories mainly enhance transparency, presenting data in tables or simple visualisations with basic filtering tools, while data marketplaces promote data reuse and performance monitoring through advanced analytics and customisable visualisation options.

Leme represents a data showcase, a less common typology characterised by intuitive dashboards designed to improve data accessibility for non-specialist users and reduce information asymmetries between the municipality and its stakeholders (Barns, 2018; Lnenicka & Nikiforova, 2021). Although *Leme* contains fewer indicators than most ODPs, it offers a more contextualised dataset than comparable data showcase platforms, such as VanDashboard, reflecting an intentional emphasis on interpretability.

In terms of geographic granularity, most of *Leme's* indicators are available at municipal or regional level, with parish-level data limited mostly to the "Transactions" and "Real Estate" categories. This may reflect the pattern observed in the benchmark where socioeconomic data is generally produced at larger territorial scales and updated less frequently than infrastructure, mobility, or environmental data, for example. By contrast, these latter datasets are often available at higher granularity and updated daily or hourly, as shown by platforms such as the Barcelona Datastore.

This granularity constraint may also be influenced by institutional factors (Kitchin & Moore-Cherry, 2021). In Portugal, statistical production remains largely centralised at the national level, limiting municipalities capacity for more granular data production. Conversely, Spain's more decentralised statistical system enables greater territorial disaggregation, helping explain the higher geographic granularity observed in the Barcelona Datastore (Instituto Nacional de Estadistica, n.d.).

Finally, the benchmarking analysis showed that only a few advanced ODPs, such as London Datastore and Data South Australia, have developed QoL frameworks. As QoL measurement requires integrating multiple social, economic and environmental dimensions, it is conceptually and methodologically complex to implement (Stiglitz et al., 2009). Nevertheless, this gap is important given the growing policy interest in resident well-being as a metric of urban performance (Stiglitz et al., 2009) and highlights the relevance of exploring the conceptual and methodological foundations of QoL assessment.

3.3. QoL conceptualisation and measurement

3.3.1 Beyond gross domestic product: the emergence of QoL frameworks

Gross domestic product (GDP) has been used to represent societal progress for decades (Stiglitz et al., 2009). However, several authors have questioned its use as an indicator of QoL, arguing that GDP measures only economic output and, consequently, fails to capture a bigger range of QoL dimensions (Diener and Suh, 1997; Stiglitz et al., 2009). These concerns led to the European Commission's "Beyond GDP" initiative in 2007, which urged for the development of more comprehensive indicators that could capture societal progress beyond economic performance (Bleys, 2012). In addition, the 2008 financial crisis further exposed the gap between macroeconomic indicators and people's actual experiences, strengthening the demand for multidimensional QoL measurement tools (Instituto Nacional de Estatística [INE], n.d.).

In response to the growing awareness of GDP's limitations, several frameworks have been developed to comprehensively measure QoL. One of the earliest examples was the Human Development Index, introduced in 1990, that incorporates dimensions beyond economic measures of progress (Marsal-Llacuna et al., 2015). Since then, various frameworks have emerged at both national and international levels, including public initiatives such as the Organisation for Economic Cooperation and Development's (OECD) Better Life Index (2024) and INE's *Índice de Bem-estar* (2017), as well as private-sector measures created by organisations like Mercer and The Economist (Marsal-Llacuna et al., 2015).

3.3.2 Conceptualising QoL

Despite the growing interest in assessing QoL, there is still no globally accepted definition of the concept. Several authors highlight its theoretical ambiguity, noting that related terms, such as "quality of life", "well-being", "happiness", "life satisfaction" and "welfare", are often used inconsistently and interchangeably to describe fundamentally

different phenomena (Bleys, 2012; Bovkir et al., 2023; Cardoso et al., 2021). Following Bleys (2012), this report adopts a general understanding of QoL and well-being as a comprehensive evaluation of an individual's or group's life conditions.

QoL is conceptualised as a multidimensional latent construct that cannot be directly observed and must be deduced from indicators representing different life domains (Diener & Suh, 1997; Kuentz-Simonet et al., 2023). These domains are typically divided into objective and subjective dimensions. The objective dimension refers to observable physical and functional aspects of people's living environment, such as income, housing quality, public safety, and accessibility, and is often measured using statistical indicators at different geographical levels (Diener & Suh, 1997; Marsal-Llacuna et al., 2015). The subjective dimension captures peoples' perceptions of their own lives, typically through life satisfaction surveys (Bleys, 2012; Diener & Suh, 1997).

The relationship between objective and subjective dimensions of QoL is, however, not straightforward. Easterlin's Paradox argues that although wealthier countries report higher levels of happiness than poorer countries at a given moment, increases in absolute income over time do not necessarily result in proportional increases in happiness (Easterlin, 2006). This implies that improving functional or economic resources does not necessarily increase subjective well-being (Diener & Suh, 1997). Similarly, Petrovici et al. (2026) identified the "provision paradox" in Romania, showing larger cities with better infrastructure were associated with lower satisfaction. These findings suggest that objective conditions are linked to QoL, but their effects are filtered through residents' subjective perceptions (Nicolás-Martinez et al., 2024; Mouratidis, 2020).

According to Diener and Suh (1997) and Easterlin (2006), this disconnect can be partly explained by comparison and adaptation mechanisms, as individuals evaluate their conditions relative to personal expectations and others' circumstances. Other authors have suggested that this divide can also be related to resource concentration in larger cities, which can lead to negative externalities such as inequalities in accessibility to urban resources (Mouratidis, 2021; Petrovici et al., 2026). Therefore, overall life satisfaction should not be treated as equivalent to QoL itself, but rather as a subjective evaluation of more comprehensive living conditions and experiences (Diener & Suh, 1997; Stiglitz et al., 2009).

Nevertheless, objective conditions remain an essential component of QoL assessments, as the socioeconomic profile of cities provides important insights into subjective QoL perceptions (Kourtit et al., 2021). Research in Rotterdam supports this by

demonstrating that residents of low-income neighbourhoods report lower attachment to their place of residence, suggesting that material deprivation may be linked to connections with place (Kourtit et al., 2022). Adding to the evidence that objective conditions do not always translate into higher subjective well-being, these findings support integrating objective conditions and subjective evaluations as complementary dimensions of QoL (Diener & Suh, 1997; Stiglitz et al., 2009).

Another branch of subjective well-being research distinguishes between needs-based and place-based evaluations of QoL. Needs-based evaluations assume that people share universal needs regardless of location. In this perspective, QoL is assessed by the degree to which individuals' needs for protection, participation, identity, freedom and leisure are met (Cardoso et al., 2021). For instance, feelings of financial stability have been shown to mediate the relationship between objective income and life satisfaction due to their fulfilment of needs such as freedom and protection (Dolan et al., 2008).

In contrast, place-based evaluations focus on what Kourtit et al. (2021) name as the "soul" of a city, referring to a person's emotional connection to their physical surroundings. Here, QoL is viewed as relational, emphasising the extent to which a place fosters feelings of appreciation and attachment among its residents (Kourtit et al., 2022). In this context, place attachment is defined as the affective bond that individuals develop with a place over time, based on its material and social atmosphere and characterised by feelings of pride and satisfaction (Barreira et al., 2019; Kourtit et al., 2021).

Although distinct, these perspectives are closely connected. Cardoso et al. (2021) argue that even if basic human needs are universal, their "satisfiers" are contextual and depend on a time and a place. Cities can therefore be understood as spaces with a concentration of social and material resources able to fulfil universal needs (Cardoso et al., 2021). Where such resources (the city's "body") are available, residents tend to report stronger attachment to the city and are less likely to "vote with their feet" (Barreira et al., 2019; Kourtit et al., 2024). Therefore, place attachment plays an important role in overall QoL evaluations (Kourtit et al., 2021). This is consistent with Nicolás-Martinez et al. (2024), who found that more positive perceptions of the urban environment are associated with higher levels of life satisfaction.

3.3.3 Determinants of urban QoL

Several authors argue that QoL is better measured at scales below the country level, such as neighbourhoods or municipalities, where contextual differences are easier to identify

(Càrcaba et al., 2020; Marsal-Llacuna et al., 2015; Prince, 2020). Therefore, cities represent a particularly relevant scale for QoL analysis. In both academic literature and international frameworks, there is a general agreement on the main domains influencing QoL, namely housing, accessibility, environmental quality, economic conditions, healthcare, education, social relationships, safety, leisure, and public management (Càrcaba et al., 2020; Greater London Authority, 2023; INE, 2017; Kuentz-Simonet et al., 2023; Mouratidis, 2020; 2021; OECD, 2024). Among these, four dimensions are especially relevant for understanding how spatial conditions influence residents' QoL.

First, satisfaction with local services and amenities has often been linked to a greater place attachment (Kourtit et al., 2021). Services such as public transport and education influence how residents relate to their place of residence through their impact on peoples' everyday lives. However, Mouratidis (2020) shows that access alone does not create attachment unless residents perceive services as meeting their expectations. Similarly, Kourtit et al. (2021) argue that "city love" (i.e. residents' appreciation of their urban environment) is strongly associated with satisfaction with urban amenities. This suggests that residents satisfied with local services are more likely to develop a positive emotional connection with their place of residence.

Second, physical environment quality is a strong predictor of place attachment (Cardoso et al., 2021). Unlike local services, which influence residents through their functional characteristics, the physical environment impacts lived experiences of place. In this context, two aspects are especially relevant in the literature: built infrastructure, including building conditions (Cardoso et al., 2021; Kourtit et al., 2021), and environmental atmosphere, related to air quality, noise levels and cleanliness (Mouratidis, 2020). By influencing liveability, these features are related to residents' emotional bonds with place (Cardoso et al., 2021; Mouratidis, 2020). However, Petrovici et al. (2026) argue that for physical conditions to translate into place attachment, trust between residents and in local government must exist.

This links to social capital, which positively influences place attachment. According to Kourtit et al. (2022), social capital develops through both bonding and bridging mechanisms. The former refers to trust and support within socially similar groups, while the latter refers to connections across social groups. Together, these mechanisms strengthen residents' sense of belonging and emotional attachment to place (Kourtit et al., 2022). Research in Flanders further shows that weaker infrastructure in rural areas does not

necessarily reduce place attachment, suggesting that social networks can compensate for less favourable physical conditions (Kourtit et al., 2024). Nevertheless, Cardoso et al. (2021) note that in dense urban areas, strong place attachment can coexist with loneliness and isolation.

Finally, from a needs-based perspective, perceptions of economic stability are among the strongest predictors of overall life satisfaction (Dolan et al., 2008; Kuentz-Simonet et al., 2023). Objective economic resources can only contribute to well-being if they are perceived as meeting individual's needs for sustenance and protection (Cardoso et al., 2021). This perceived security also supports the development of place attachment by allowing residents to engage more with the social and symbolic aspects of urban life. Consequently, stronger emotional bonds with place are more likely to emerge, contributing to Kourtit et al.'s (2021) "city love".

Other than influencing individual well-being, these dimensions also help explain how QoL varies across urban space. Studies using frameworks such as the "15-min city" show that differences in access to essential amenities are associated with spatial variations in well-being (Dobrowolska & Kopczewska, 2024; Petrovici et al., 2026). This is evident in metropolitan regions, where central municipalities tend to accumulate advantages in economic activity, infrastructure and opportunities relative to peripheral areas (Cardoso et al., 2021; Kourtit et al., 2024). Consequently, higher levels of well-being are generally observed in the central areas of cities and metropolitan regions (Dobrowolska & Kopczewska, 2024; Kourtit et al., 2024; Yarahmadi et al., 2026). However, Mouratidis (2021) notes that these advantages may be counterbalanced by the negative externalities of urban density, such as noise and pollution.

3.4. The *Leme* platform and the QoL measurement gap

3.4.1 *Leme* and its role in Porto's data ecosystem

Because living conditions have been shown to impact a city's ability to attract skilled workers and capital, QoL monitoring has become an essential instrument for urban governance and policy design (Lambiri et al., 2007; Micheli et al., 2020). ODPs, such as *Leme*, play a key role in this context by publicising the results of such monitoring efforts, making them accessible to residents, researchers and other stakeholders (Kitchin et al., 2015).

Leme, launched in 2021, functions as a centralised ODP that aggregates statistical indicators from sources such as INE, Eurostat and the *Banco de Portugal*, as well as strategic studies produced internally. Unlike other Porto platforms, such as *Portal de Dados Abertos do*

Porto[8], which mainly focuses on the publication of raw municipal data, *Leme* prioritises curated socioeconomic indicators presented through simpler and more accessible dashboards. This user-oriented approach positions it as a tool that can inform decision-making for different types of stakeholders (Lnenicka & Nikiforova, 2021).

The platform's second development phase, focused on expanding its analytical capacity, creates a unique opportunity to integrate a QoL monitoring framework into Porto's urban data ecosystem. This objective is consistent with the municipality's institutional priorities, reflected in a statement by the president of CMP, Pedro Duarte, who noted that "a city like Porto must prioritise people's well-being and quality of life"[9].

3.4.2 Research gap

Despite including a broad range of socioeconomic indicators, *Leme* does not have an integrated framework for assessing urban QoL. Current municipal approaches to "well-being" are mostly focused on healthcare access, ignoring other important dimensions of the concept. This limitation is particularly relevant given that QoL is a multidimensional concept that cannot be evaluated through isolated indicators (Diener & Suh, 1997; Stiglitz et al., 2009).

Moreover, this gap contrasts with Porto's earlier analytical practices. Between 2001 and 2011, CMP published three reports that systematically monitored urban QoL across four domains: environmental conditions, collective material conditions, economic conditions, and society (Câmara Municipal do Porto, 2003). The discontinuation of this project suggests a shift from QoL monitoring, creating a disconnect between the municipality's stated commitment to citizens' well-being and the tools currently available to assess it.

This limitation is not unique to Porto but reflects a general tendency of ODPs to prioritise administrative data over multidimensional assessments of urban well-being. Although a few cities, such as London, have developed dedicated QoL frameworks, many still don't have systematic approaches to monitor how residents' living conditions and perceptions evolve over time. In Porto, this limits the municipality's ability to identify which dimensions of QoL require policy attention.

[8] https://opendata.porto.digital/

[9] https://eco.sapo.pt/2026/04/21/municipio-do-porto-aprova-transportes-gratuitos-pedro-duarte-antecipa-medida-para-julho/

4. Methodology

Building on the gap presented in the previous Chapter, this report aims to build a multidimensional framework for assessing urban QoL in the Porto Metropolitan Area (AMP) by integrating objective indicators and subjective perceptions of well-being. This approach attempts to reflect the understanding of QoL as a multidimensional construct (Diener & Suh, 1997) and provides a methodological foundation for future monitoring initiatives within CMP.

A wide range of methodologies has been proposed for this purpose, with most studies focusing on the construction of composite indicators. These indicators summarise complex concepts into a single measure that is easier for both policymakers and citizens to interpret, and they facilitate comparisons across geographical units and over time (Marsal-Llacuna et al., 2015; OECD, 2008). This supports benchmarking, helps identify areas with lower levels of urban performance and informs resource allocation (OECD, 2008). Kourtit et al. (2021) further argue that composite indicators can be integrated into urban dashboards to link long-term strategic objectives with monitoring tools, thus reinforcing their practical value for ODPs such as *Leme*.

Due to their extensive use, considerable attention has been given to the evaluation of different statistical techniques for building composite indicators. The most frequently discussed methods in the context of QoL measurement are data envelopment analysis (Càrcaba et al., 2020; Jimenez-Fernandez & Ruiz-Martos, 2020), the benefit of the doubt method (Jimenez-Fernandez & Ruiz-Martos, 2020), the Mazziotta-Pareto index (Jimenez-Fernandez & Ruiz-Martos, 2020), principal component analysis (Bovkir et al., 2023; Cheng et al., 2026; Jimenez-Fernandez & Ruiz-Martos, 2020) and structural equation modelling (Mouratidis, 2020; Saczewska-Piotrowska, 2023).

To address the research objectives, this study adapts the quantitative methodology from Libório et al. (2026), combining principal component analysis (PCA), structural equation modelling (SEM) and composite indicator construction techniques. PCA was used to reduce the dimensionality of the dataset and identify broader multidimensional structures among QoL indicators. Then, a partial least squares SEM (PLS-SEM) was employed to validate the QoL dimensions identified in the PCA. The latent scores obtained were used to construct a goal-based composite indicator with multiple constraints (GB-CI-MC) (Libório et al., 2026) for each analysed municipality.

4.1. Data and sample

The study combined individual-level survey data (for a subjective assessment) with objective indicators obtained from official statistics and crowdsourced platforms. To capture subjective perceptions of QoL, a questionnaire was developed based on the Flash Eurobarometer 419 (European Commission, 2016), following established studies in the literature (Nicolás-Martinez et al., 2024; Petrovici et al., 2026). Additional items were incorporated to capture residents' sense of place attachment and community (Kourtit et al., 2022), which were not originally present in the European Commission's survey. Additionally, the original four-point Likert scale was expanded to five points to enhance response variability and support more robust quantitative analysis (Huh & Gim, 2025).

Prior to distribution, the questionnaire was pilot tested on four participants, and revisions were made to improve clarity. Three items were eliminated because they were considered ambiguous by the pilot participants. The survey was distributed online, in Portuguese, via Google Forms through personal networks and social media (see Annex 4).

Objective conditions data were collected from Portuguese organizations, such as INE, PorData and *Associação Portuguesa do Ambiente*, which provided socioeconomic and environmental data. In addition, OpenStreetMap was used for spatial data on urban amenities and services. The analysis was conducted for 2024, unless more recent data was unavailable for certain indicators.

The final dataset was structured at the individual level, with each observation corresponding to a survey respondent. Objective indicators were gathered at the municipal level and assigned to individuals based on their place of residence, meaning variance in objective conditions reflects differences between municipalities rather than individual-level variation. This mismatch is acknowledged in the interpretation of results.

4.2. Variables

4.2.1 Overall life satisfaction

Residents' overall satisfaction with their QoL was measured on a 5-point Likert scale ranging from 1 ("very dissatisfied") to 5 ("very satisfied"). In line with the theoretical framework adopted in this study, this variable was not treated as equivalent to multidimensional QoL itself (Diener & Suh, 1997), but as an external criteria used to assess the validity of the multidimensional QoL composite indicators (Libório et al., 2026).

4.2.2 Individual-level variables

Subjective QoL was measured using survey items that captured residents' perceptions of their living conditions and personal well-being. These included satisfaction with municipal infrastructure and services, perceived safety, personal finances, place attachment, and social dynamics. The items were measured on a 5-point Likert scale, ranging from "1 - very dissatisfied" to "5 - very satisfied" or from "1 - totally disagree" to "5 - totally agree".

4.2.3 Municipal-level variables

The objective dimension of QoL was measured using a set of municipal indicators reflecting different aspects of urban living conditions identified in the literature review, including material living standards, labour market conditions, housing, access to services, environmental quality, education, health, and safety. The selection of indicators was based on their conceptual relevance to QoL, data availability at municipal level, and comparability across the AMP (Porto Metropolitan Area).

Purchasing power per capita was included as a proxy for material wealth and access to goods and services that directly influence well-being, such as housing and food (Cardoso et al., 2021; Diener & Suh, 1997). *Income inequality* was incorporated to account for disparities in economic security and social exclusion, which are associated with lower subjective well-being and poorer life outcomes (Diener & Suh, 1997; Dolan et al., 2008). Housing market conditions were represented through *median housing appraisal values,* reflecting affordability pressures related to urban well-being, while *overcrowded dwellings* was used to capture housing adequacy and material deprivation (Perafita & Saez, 2013).

Additional indicators were included to capture broader social and environmental conditions associated with QoL. *Greenhouse gas emissions* served as a proxy for environmental quality and sustainability (Ehigiamusoe et al., 2022). *Secondary education completion rates* were included due to the strong relationship between educational attainment, employment opportunities, income and well-being (Rahmani & Groot, 2023). The *proportion of higher education graduates* was excluded as these rates are measured at the location of higher education facilities, and only a few of the municipalities in the AMP have a university or equivalent institution. *Physicians per 1000 inhabitants* were used as a proxy for healthcare access, while *crime rates* were included as a reverse measure of safety, both of which have been linked to life satisfaction (Saczewska-Piotrowska, 2023; Petrovici et al., 2026). *Net population balance* was

used as an indicator of territorial attractiveness, as migration flows may reflect how residents and non-residents evaluate living conditions within a municipality (Lambiri et al., 2007).

Accessibility to urban amenities was operationalised using an indicator adapted from Dobrowolska and Kopczewska (2024), measuring residents' proximity to essential urban amenities (healthcare, education, transport, dining, sports, shopping and green spaces) using OpenStreetMap data. Access to these services is associated with well-being, with higher QoL typically observed in areas with greater amenity density (Dobrowolska and Kopczewska, 2024; Yarahmadi et al., 2026). While based on the original framework, some adaptations were introduced to better suit the context and data availability of the study. These include measuring proximity to green spaces instead of using vegetation indices and assessing transport accessibility based on proximity to transport infrastructure rather than service frequency. The indicator was calculated at grid level using distance-decay weights, normalised by population, and aggregated to municipal level. In this study, the indicator was named "collective material conditions index".

Because there were no suitable objective indicators available to represent the dimensions of social relationships, leisure and public management, these dimensions were not included in the dataset. A complete list of selected indicators, along with their definitions and data sources, is provided in Annex 5.

4.3. Data preprocessing

The survey data was preprocessed prior to analysis. This involved eliminating responses from non-AMP residents and addressing missing values. In particular, "no response" answers were treated as missing and their values were imputed using the mode for all variables except income, for which a separate "not reported" category was created. Moreover, negatively worded Likert scale items were reverse coded to ensure consistency.

The same approach was taken with objective indicators, where variables that were negatively associated with QoL (e.g. crime rates) were reverse coded by multiplying them by -1 (Cheng et al., 2026). This meant that higher values in all indicators meant a better QoL.

The variables in the final dataset were not standardised before the analysis, since they were already relative indicators, including per capita measures, rates, indices and survey-based scales. In this context, it was considered meaningful to keep the original variance structure of the dataset, as differences in variability across indicators reflect relevant territorial disparities in multidimensional QoL (Cheng et al., 2026).

4.4. Principal component analysis

To reduce the dimensionality of the dataset, a PCA with Promax (Jackson, 2014) rotation was conducted. PCA was chosen because it is widely used in the QoL and composite indicator literature as a method for summarising large groups of correlated indicators into a smaller number of variables, while retaining the maximum information possible (Jimenez-Fernandez & Ruiz-Martos, 2020; OECD, 2008).

Additionally, the choice of an oblique Promax rotation was justified by the fact that the dimensions of QoL are theoretically expected to be correlated (Petrovici et al., 2026). In this case, an orthogonal rotation like Varimax is not suitable because it forces the components to be independent (OECD, 2008). A Promax rotation allows the extracted components to maintain meaningful relationships with one another, which results in a more realistic representation of social phenomena and also improves the interpretability of the results (Jackson, 2014; OECD, 2008).

The dataset's adequacy for PCA was first assessed using the Kaiser-Meyer-Olkin measure and Bartlett's test of sphericity (Kaiser, 1970; OECD, 2008). The final number of components was determined using the Kaiser criterion, retaining components with eigenvalues greater than one (OECD, 2008). Although commonly accepted standards recommend assigning indicators to the component on which they present the highest loading (Nicoletti et al., 2000), the literature on PCA prioritises the conceptual coherence of each component. Therefore, the final component structure was refined to improve the alignment with the theoretical framework and interpretability. Moreover, indicators were retained if they had component loadings greater than 0.30, ensuring sufficient information transfer (Libório et al., 2026; Saczewska-Piotrowska, 2023).

4.5. PLS-SEM model

The component structure identified through PCA was used to define which indicators belong to each construct in the partial least squares structural equation model (PLS-SEM) (Wold, 1982), which was estimated in SmartPLS. Although the present study focuses on multidimensional QoL rather than multidimensional welfare, as in Libório et al. (2026), the methodological approach was considered appropriate due to the conceptual similarities between the two concepts, particularly their inherent multidimensionality and the need to model multiple related constructs (Saczewska-Piotrowska, 2023; Stiglitz et al., 2009).

The reliability and validity of the PLS-SEM model were assessed using standard criteria adopted in the literature (Hair et al., 2022; Libório et al., 2026). Reflective constructs (i.e. when interchangeable indicators are considered manifestations of the latent variable) were evaluated using convergent validity, discriminant validity and composite reliability measures, while formative constructs (i.e. when indicators are not interchangeable and jointly form the latent variable) were assessed through collinearity diagnostics and indicator weights (OECD, 2008).

Although Cronbach's Alpha has been frequently used as a measure of internal consistency in PLS-SEM, the indices of composite reliability (ρ_a and ρ_c) have been recommended as superior alternatives (Hair et al., 2022). This is because, contrary to Cronbach's Alpha, ρ_a and ρ_c incorporate each indicator's outer loadings from the PLS-SEM estimation, resulting in a more robust assessment of internal consistency (Hair et al., 2022). Therefore, Cronbach's Alpha was not interpreted in this study. Table 1 summarises the measures used, their respective purposes, guideline values and literature support.

REFLECTIVE CONSTRUCTS			
Metric	**Assessment type**	**Guideline**	**Reference**
Average variance extracted (AVE)	Convergent validity	≥ 0.5	Fornell & Larcker (1981)
Heterotrait-Monotrait (HTMT)	Discriminant validity	≤ 0.9	Henseler et al. (2015)
Cross-loadings	Discriminant validity	Loads highest on own construct	Henseler et al. (2015)
Composite reliability (ρ_a and ρ_c)	Composite reliability	≥ 0.7	Hair et al. (2022)
FORMATIVE CONSTRUCTS			
Bootstrapping weights	Indicator contributions	$p < 0.05$	Hair et al. (2022)
Variance inflation factor (VIF)	Collinearity	≤ 5	Hair et al. (2022)

Table 1. PLS-SEM statistical assessment measures.

4.6. Goal-based composite indicator with multiple constraints (GB-CI-MC)

Following the estimation of the PLS-SEM model, the standardised latent dimension scores obtained were aggregated into multidimensional composite indicators (CIs) using a weighted linear combination, defined as follows:

$$CI_j = \Sigma_{i=1}^{n} d_{ij} w_i \qquad (1)$$

where CI_j is the composite indicator of respondent j, d_{ij} is the value of respondent j on dimension i, and w_i is the weight assigned to dimension i.

The weighting scheme was inspired by the GB-CI-MC proposed by Libório et al. (2026). It optimises dimension weights to maximise the Pearson correlation between the composite indicator and a conceptually relevant proxy of QoL, while ensuring that constraints on both the weights and the representation of each dimension are met. As a result, the GB-CI-MC method avoids the subjectivity associated with assigning CI weights, a practice often criticised in the literature (OECD, 2008). Moreover, Libório et al. (2026) show that it produces more stable indicators than common data-driven CI construction methods, such as PCA, which attribute dimension weights based only on the statistical structure of the dataset.

Equations (2) to (5) represent Libório et al.'s (2026) constrained optimisation process:

$$\left(\frac{\Sigma_{j=1}^{n}(CI_j - \overline{CI})(I_j - \bar{I})}{\sqrt{\Sigma_{j=1}^{n}(CI_j - \overline{CI})^2 x\, \Sigma_{j=1}^{n}(I_j - \bar{I})^2}} \right) \rightarrow max, 0 < w_i < 1 \quad (2)$$

subject to:

$$0 < w_i < 1 \quad (3)$$

$$\sum_{i=1}^{m} w_i = 1 \quad (4)$$

and:

$$0.30 \leq \frac{\Sigma_{j=1}^{n}(CI_j - \overline{CI})(NA_{ij} - \overline{NA_k})}{\sqrt{\Sigma_{j=1}^{n}(CI_j - \overline{CI})^2 x\, \Sigma_{j=1}^{n}(NA_{ij} - \overline{NA_i})^2}} \leq 0.90 \quad (5)$$

where $\overline{CI}$ is the mean of the CI score, I is the external validation variable, and NA_{ij} is the score of respondent j on dimension i. The lower limit of 0.30 ensures that there is sufficient information transfer from each dimension to the CI, while the upper limit of 0.90 stops any dimension from dominating the construct (Libório et al., 2026).

The external validation variable (or most conceptually relevant indicator) is central to Libório et al.'s (2026) methodology, as it provides an empirical benchmark against which the CI is optimised. This optimisation ensures the resulting indicator is associated with a theoretically relevant outcome, thus increasing its usefulness for policy analysis (Libório et al., 2026). In this study, the external validation variable was self-reported satisfaction with overall QoL, collected directly from AMP residents through the survey. Although it does not entirely capture the multidimensional nature of QoL, self-reported life satisfaction is the most direct measure of how residents integrate their experiences into an overall evaluation of their living conditions (Diener & Suh, 1997). Moreover, it has been previously identified

as a meaningful indicator of societal performance in public policy contexts (Kuentz-Simonet et al., 2023). Consequently, the resulting weights reflect the extent to which each theoretical QoL dimension is associated with residents' overall evaluations of their living conditions. The implications of this are discussed in Chapter 6.

The optimisation problem defined by equations (2) to (5) was solved in Python. As Libório et al. (2026) do not specify the procedure used to solve the optimisation problem, the implementation adopted in this study was based on an interpretation of the authors' methodological specifications. Sequential least squares programming (SLSQP) was selected due to its suitability for nonlinear constrained optimisation problems, such as this one (Virtanen et al., 2020). The optimisation algorithm was repeated over 2000 randomly generated starting points that automatically satisfied the constraint that all weights sum to one. This number was chosen to ensure that the algorithm did not stop at a suboptimal solution, while keeping computation time manageable (Ugray et al., 2009).

Subjective dimensions typically have higher intercorrelations than objective dimensions, as someone satisfied with one aspect of their life tends to report higher satisfaction on other domains (Jimenez-Fernandez & Ruiz-Martos, 2020; Nicolás-Martinez et al., 2024). Consequently, the optimisation algorithm may achieve a high correlation by concentrating weight on a small set of dominant dimensions, while the remaining dimensions continue to satisfy the minimum correlation threshold of 0.30 through their shared variance with those. This leaves them with zero weights despite their conceptual relevance to QoL. This issue was less pronounced in Libório et al. (2026), whose framework included exclusively objective indicators, and is mitigated here by constraining each starting point in the optimisation procedure to a minimum weight of 0.01 to every dimension.

Finally, individual GB-CI-MC scores were aggregated by municipality based on each survey respondent's place of residence, using the mean for each municipal group. Municipalities with less than 10 respondents were excluded because of their small sample sizes. This made it possible to identify spatial differences in multidimensional QoL across municipalities and compare their relative performance on different QoL dimensions.

5. Results

5.1. Descriptive statistics of municipal-level indicators

Annex 6a shows the descriptive statistics for the objective indicators used in the analysis. Overall, the indicators reveal variability between municipalities in the AMP. Notable variation is observed in *crime rates* (SD = 10.18) and *median housing appraisal values* (SD = 419.88), suggesting substantial disparities in safety conditions and housing affordability pressures across the AMP municipalities.

Correlation analysis (see Annex 6b) revealed strong associations between several indicators. *Physicians per 1000 inhabitants* showed very strong positive correlations with *purchasing power per capita* (r = 0.945), *crime rates* (r = 0.933), *inequality* (r = 0.906) and *median housing appraisal values* (r = 0.890). Likewise, *purchasing power per capita* was strongly correlated with *crime rates* (r = 0.910) and *inequality* (r = 0.859), while *median housing appraisal values* showed strong correlations with *inequality* (r = 0.866). These relationships suggest that several indicators were capturing overlapping dimensions of municipal socioeconomic structure in the AMP. To reduce the risk of multicollinearity and "double-counting" information in the model, indicators with correlations over 0.9 were excluded at this stage (Jimenez-Fernandez & Ruiz-Martos, 2020; Libório et al., 2026).

The final set of retained indicators covers different aspects of the municipal environment, including socioeconomic inequality, housing conditions, educational attainment, accessibility, safety, demographic attractiveness, and environmental quality.

5.2. Spatial distribution of accessibility indicators

Figure 1 represents the distribution of median accessibility scores across the AMP, measured by the objective collective material conditions index (Dobrowolska and Kopczewska, 2024). The median was used to reduce the impact of skewed distributions.

The results reveal clear differences in spatial accessibility across municipalities. Those located in the more urbanised and densely populated western and central areas, such as Porto, Matosinhos, Maia and Vila Nova de Gaia, generally have higher accessibility values. In contrast, more peripheral municipalities, such as Arouca and Vale de Cambra, display lower

accessibility levels. São João da Madeira shows particularly high accessibility values, possibly due to its compact urban structure.

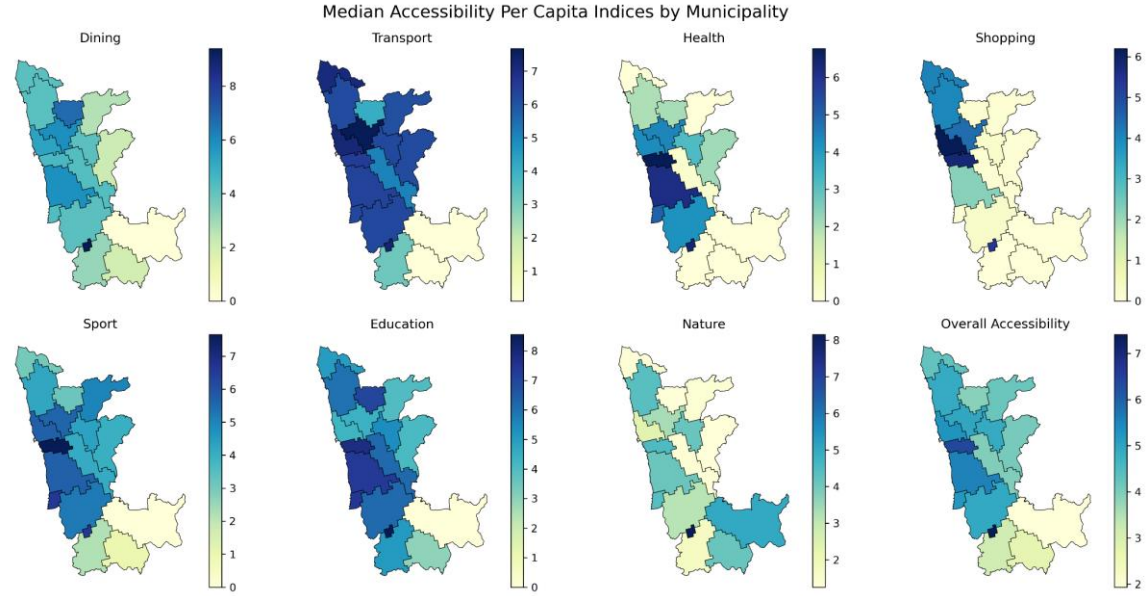


Figure 1. Map of median accessibility indices per capita, by AMP municipality.
Source: Author's elaboration.

A more detailed analysis of the Porto municipality (see Annex 7a) reveals similar spatial patterns, with higher accessibility concentrated in central and western areas, particularly around the historic centre and the riverfront. Accessibility to health, sports and education services appears relatively evenly distributed across the municipality, but accessibility to nature, shopping and dining shows stronger concentration patterns. Correlation analysis with distance from Porto's city centre (see Annex 7b) further supports these findings, indicating that accessibility generally decreases with increasing distance from the centre, particularly when considering non-per-capita measures (r = -0.80).

5.3. Descriptive analysis of survey responses

Responses to the survey were collected between March and April of 2026. A total of 256 responses were obtained, of which 245 were considered valid. Although responses were obtained from all 17 AMP municipalities, their distribution was uneven (see Annex 8a), with approximately 30% of responses coming from Porto, followed by Valongo (18.4%), Matosinhos (9.4%) and Vila Nova de Gaia (9.4%). The sample was characterised by a strong representation of long-term residents, with most respondents reporting having lived in their municipality their entire lives (45.3%) or for more than 10 years (31.4%).

In sociodemographic terms, the sample was mostly female (60%) and largely composed of employed individuals, with 53.5% reporting full-time employment. Respondents were relatively well distributed across age groups, with slightly higher representation of individuals aged 15-24 (23.3%) and 55-64 (22.9%). In terms of household income distribution, respondents in middle-income groups were more strongly represented. Regarding overall QoL satisfaction, responses were mostly positive, with 58% of respondents reporting being "somewhat satisfied" and 20.4% "very satisfied". Only a small proportion expressed dissatisfaction (see Annex 8b). Annex 9 shows the detailed sociodemographic distribution of responses.

Although the survey responses constitute a convenience sample and do not accurately represent the AMP population, this is considered acceptable given the exploratory nature of this study, where the priority is to test the methodology rather than to produce population-level estimates (Hair et al., 2022).

5.4. Principal component analysis results

To reduce dimensionality and identify the dataset's underlying structure, a PCA with Promax rotation was used. The Kaiser-Meyer-Olkin (KMO) statistic (Kaiser, 1970; Kaiser & Rice, 1974) indicated good sampling adequacy (KMO = 0.852) and Bartlett's test of sphericity was statistically significant ($p < 0.001$), confirming the suitability of the dataset for PCA (OECD, 2008). The Kaiser criterion suggested eight components with eigenvalues above one, explaining approximately 66.4% of the total variance, which is acceptable in social science (OECD, 2008) (see Annex 10).

Indicators were generally assigned to the component on which they showed the highest absolute loading (Nicoletti et al., 2000). However, three indicators were assigned to their second highest loading component to improve interpretability and conceptual relevancy (OECD, 2008). One component was eliminated after indicator reassignment, as it no longer had sufficiently strong loadings. Additionally, three indicators were excluded from the analysis because they did not load above 0.30 on any conceptually coherent component. Annex 11 presents the PCA loading matrix, and Annex 12a shows the reassignments done.

The final QoL structure retained seven of the eight components (see Annex 12b). These components were used to specify the PLS-SEM model to validate the consistency of each QoL dimension before CI construction. Six components were operationalised as reflective constructs *(place attachment*, *perceived economic security, social cohesion, satisfaction with urban*

amenities, satisfaction with essential services and *environmental quality satisfaction)* because their indicators represent manifestations of the same latent construct (Saczewska-Piotrowska, 2023). *Municipal objective context* was operationalised as a formative construct, as its indicators capture non-interchangeable dimensions of residents' objective living conditions (Kuentz-Simonet et al., 2023). Given the theoretical framework presented on Chapter 3, the model specified direct paths from all dimensions to *place attachment.*

5.5. PLS-SEM results

The PLS-SEM algorithm was run in SmartPLS using PCA as the weighting scheme. The initial model estimation revealed multicollinearity issues in *municipal objective context*, with four indicators showing variance inflation factor (VIF) values above the recommended threshold of 5 (Hair et al., 2022) (see Annex 13). To address this, indicators with the highest VIF values (*purchasing power per capita* and *median value of housing appraisals*) were removed, and the model was estimated again. The second model revealed that the composite reliability (ρ_a) and the average variance extracted (AVE) did not meet the recommended guidelines for *perceived economic security* (see Annex 14). To improve model quality, indicators with relatively lower dimensional weights (*affordable quality housing* and *satisfaction with job opportunities*) were removed. Table 2 presents the convergent validity and reliability metrics of the final model.

	Composite reliability (ρ_a)	Composite reliability (ρ_c)	Average variance extracted (AVE)
Environmental quality satisfaction	0.80	0.88	0.71
Perceived economic security	**0.66**	0.85	0.75
Place attachment	0.89	0.91	0.64
Satisfaction with essential services	0.72	0.82	0.54
Satisfaction with urban amenities	0.81	0.88	0.64
Social cohesion	0.70	0.81	0.52

Table 2. Convergent validity and composite reliability metrics of reflective constructs of the final model. Source: Author's elaboration.

The results indicate acceptable internal consistency, with most composite reliability values exceeding 0.70 (Hair et al., 2022). *Place attachment* demonstrated the highest reliability (ρ_c = 0.91), followed closely by *environmental quality satisfaction* and *satisfaction with urban amenities* (ρ_c = 0.88). AVE values were above the recommended threshold of 0.5 for all reflective constructs (Hair et al., 2022), suggesting that the indicators share enough variance within

their construct. Although ρ_a for *perceived economic security* remained below 0.70, it exceeded 0.60, which is acceptable for exploratory research (Hair et al., 2022). Given that the construct met all other validation criteria, it was kept in the model.

Discriminant validity was satisfactory. The Fornell-Larcker (1981) criterion was met for all constructs (see Table 3), and the HTMT ratio remained below the threshold of 0.9 on all dimensions (Henseler et al., 2015) (see Table 4), indicating the constructs capture distinct dimensions. Cross-loadings further confirmed discriminant validity, with all indicators loading more strongly on their respective constructs (Henseler et al., 2015) (see Annex 15).

	Environmental satisfaction	Perceived economic security	Place attachment	Satisfaction with essential services	Satisfaction with urban amenities	Social cohesion
Environmental satisfaction	**0.84**					
Perceived economic security	0.19	**0.86**				
Place attachment	0.52	0.26	**0.80**			
Satisfaction with essential services	0.35	0.27	0.55	**0.74**		
Satisfaction with urban amenities	0.52	0.24	0.66	0.62	**0.80**	
Social cohesion	0.44	0.17	0.43	0.25	0.43	**0.72**

Table 3. Discriminant validity of reflective constructs measured using the Fornell-Larcker criterion. Source: Output from SmartPLS software.

	Environmental satisfaction	Perceived economic security	Place attachment	Satisfaction with essential services	Satisfaction with urban amenities	Social cohesion
Environmental satisfaction	-					
Perceived economic security	0.26	-				
Place attachment	0.63	0.36	-			
Satisfaction with essential services	0.46	0.39	0.68	-		
Satisfaction with urban amenities	0.65	0.31	0.78	0.80	-	
Social cohesion	0.61	0.27	0.57	0.49	0.59	-

Table 4. Discriminant validity of reflective constructs measured using the HTMT ratio. Source: Output from SmartPLS software.

Because the *municipal objective context* was specified as a formative construct, it was assessed by collinearity metrics and bootstrapping indicator weights (Hair et al., 2022). Table 5 presents the VIF and outer weights statistics for the formative indicators.

Indicator	Outer weight	t-value	VIF
Collective material conditions index	0.29	67.47*	3.38
Greenhouse gas emissions per 1000 inhabitants	0.09	4.89*	1.20
Net population change per 1000 inhabitants	0.29	40.25*	2.80
Inequality in income distribution (P80/20)	-0.28	40.72*	2.74
Overcrowding per 1000 dwellings	-0.26	34.11*	2.06

*$p < 0.001$

Table 5. Bootstrapping diagnostics of the formative construct.
Source: Output from SmartPLS software.

Although all outer weights appear to be statistically significant at $p < 0.001$, this should be interpreted with caution, as objective indicators vary only across 17 municipalities in the 245-item dataset. This means that their significance cannot be reliably assessed at the individual level. The negative weights of *inequality in income distribution* and *overcrowding* were theoretically expected, as higher values are associated with lower levels of well-being (Diener & Suh, 1997; Perafita & Saez, 2023). All collinearity values remained within recommended thresholds (Hair et al., 2022), supporting the relevance of the formative indicators for capturing complementary dimensions of the municipal environment.

The structural model was assessed through path coefficients and estimated model fit (Hair et al., 2022). Annex 16 presents the final PLS-SEM model with standardised path coefficients. A more complex model was also tested (see Annex 17), but the simplified version analysed below was chosen as it provides a better fit to the data.

Annex 16 shows that *satisfaction with urban amenities* had the strongest statistically significant influence on *place attachment* ($\beta = 0.34$; $t = 5.19$; $p < 0.001$), followed by *environmental quality satisfaction* ($\beta = 0.25$; $t = 4.04$; $p < 0.001$), *municipal objective context* ($\beta = 0.19$; $t = 4.27$; $p < 0.001$) and *social cohesion* ($\beta = 0.17$; $t = 2.80$; $p = 0.005$). In contrast, the paths from *satisfaction with essential services* ($p = 0.085$) and *perceived economic security* ($p = 0.20$) to *place attachment* were non-significant. Overall, the model explained 55.6% of the variance in *place attachment* ($R^2 = 0.556$), indicating a moderate explanatory power (Hair et al., 2022). The model fit was acceptable, with a saturated SRMR of 0.100 (Shi et al., 2022).

5.6. GB-CI-MC results

The QoL dimensions validated in the PLS-SEM were aggregated into composite indicators following the goal-based composite indicator with multiple constraints (GB-CI-MC) approach (Libório et al., 2026). The dimensional weights were obtained through the constrained optimisation procedure described in section 4.6 of this report, using self-reported overall life satisfaction as the external validation criterion.

The optimisation process resulted in weights of 47.7% to *perceived economic security,* 26.9% to *place attachment,* 13.5% to *satisfaction with essential services* and 8.9% to *municipal objective context* (see Table 6). *Satisfaction with urban amenities, social cohesion* and *environmental quality satisfaction* were assigned the minimum weight of 1%. Despite this, all dimensional constraints were satisfied, with correlations between each dimension and the CI being within the required range of 0.30-0.90 and statistically significant. The final CI achieved a correlation of r = 0.645 with self-reported overall life satisfaction.

	Weight (%)	**r**
GB-CI-MC		
Municipal objective context	8.9%	0.30*
Place attachment	26.9%	0.71*
Satisfaction with urban amenities	1.0%	0.56*
Satisfaction with essential services	13.5%	0.64*
Social cohesion	1.0%	0.33*
Perceived economic security	47.7%	0.83*
Environmental quality satisfaction	1.0%	0.39*
CI vs life satisfaction	-	0.645*

*$p<0.001$

Table 6. Results of the GB-CI-MC optimisation algorithm, per dimension.
Source: Author's elaboration.

5.7. Municipal profile analysis

The GB-CI-MC scores were then aggregated at the municipal level to assess spatial variations in QoL across the AMP. Because this is an exploratory study, the analysis was restricted to municipalities with more than ten survey responses to ensure a minimum sample size for aggregation. This excluded most of the AMP and limits the generalisability of the spatial findings to the other municipalities. Table 7 shows the mean standardised GB-CI-MC scores and self-reported life satisfaction of the analysed municipalities, and Figure 2 presents their latent dimension profiles.

	Porto	Vila Nova de Gaia	Matosinhos	Maia	Gondomar	Valongo
Average *municipal objective context*	1.20	-0.25	-0.28	-0.27	-1.21	-0.08
Average *place attachment*	0.46	0.13	0.22	-0.03	-0.15	-0.96
Average *perceived economic security*	0.11	0.07	-0.03	0.02	0.25	-0.15
Average *satisfaction with essential services*	0.43	0.21	0.08	0.19	0.20	-0.48
Average *satisfaction with urban amenities*	0.39	-0.27	-0.12	0.43	0.28	-0.82
Average *social cohesion*	-0.16	0.20	-0.06	0.53	-0.22	-0.45
Average *environmental quality satisfaction*	-0.11	0.23	-0.33	0.35	0.29	-0.56
Average GB-CI-MC	**0.34**	**0.07**	**0.03**	**0.02**	**0.00**	**-0.42**
Average overall life satisfaction	4.04	4.25	4.13	3.62	4.18	3.70

Table 7. Municipal average scores per dimension, GB-CI-MC and self-reported life satisfaction.
Source: Author's elaboration.

Porto was the only municipality with a positive *municipal objective context* score (1.20), meaning that it is the only one whose objective conditions exceed the metropolitan sample average. However, this dimension should be interpreted carefully, as its indicators are measured at municipal level and assigned to all residents of the same municipality, meaning that within-municipality variation in objective conditions is not captured. Of the remaining municipalities, Gondomar presented the lowest *municipal objective context* score (-1.21), followed by Matosinhos (-0.28), Maia (-0.27), and Vila Nova de Gaia (-0.25) with very close dimensional scores. P*lace attachment* varied considerably, with Porto recoding the highest score (0.46), followed by Matosinhos (0.22) and Vila Nova de Gaia (0.13). *Perceived economic security* scores varied less substantially, with Gondomar presenting the highest score (0.25), followed by Porto (0.11), Vila Nova de Gaia (0.07), Maia (0.02) and Matosinhos (-0,03). Regarding *satisfaction with essential services,* Porto took the lead (0.43), while Vila Nova de Gaia (0.21), Gondomar (0.20) and Maia

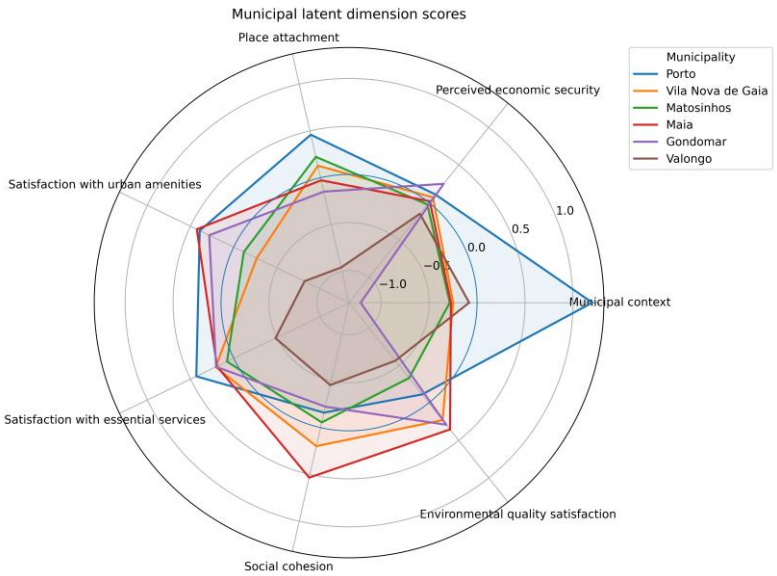


Figure 2. Municipal latent dimensional profile.
Source: Author's elaboration.

(0.19) presented similar scores, but substantially lower than Porto's. Maia presented the highest score on *satisfaction with urban amenities* (0.43), *social cohesion* (0.53) and *environmental quality satisfaction* (0.35). Porto had the second highest *satisfaction with urban amenities* score (0.39) but showed below-average values on *social cohesion* (-0.16) and *environmental quality satisfaction* (-0.11). Valongo presented the lowest scores across all CI dimensions except *municipal objective context,* on which it got a score of -0.08, placing second best.

Figure 3 shows the spatial distribution of the municipal-level GB-CI-MC composite scores. Porto recorded the highest average GB-CI-MC score (0.34), consistent with its dominant position on the dimensions with the highest weights on the composite. On the other hand, Valongo recorded the lowest GB-CI-MC score (-0.42) and the second lowest self-reported life satisfaction (3.70), suggesting a disadvantaged profile across all subjective dimensions. Vila Nova de Gaia, Matosinhos and Maia clustered closely around the metropolitan average, with scores of 0.07, 0.03 and 0.02, respectively. Notably, Gondomar recorded the lowest *municipal objective context* score in the sample yet presented a perfect composite score relative to the metropolitan average (0.00) and a relatively high overall life satisfaction, consistent with its high *perceived economic security*. In contrast, Vila Nova de Gaia achieved the highest average life satisfaction (4.25) and the second highest GB-CI-MC score, despite a difference of 0.27 points to Porto's highest score on the latter. Interestingly, Porto had only the fourth highest self-reported life satisfaction score (4.04), suggesting a disparity between measured QoL and perceived life satisfaction.

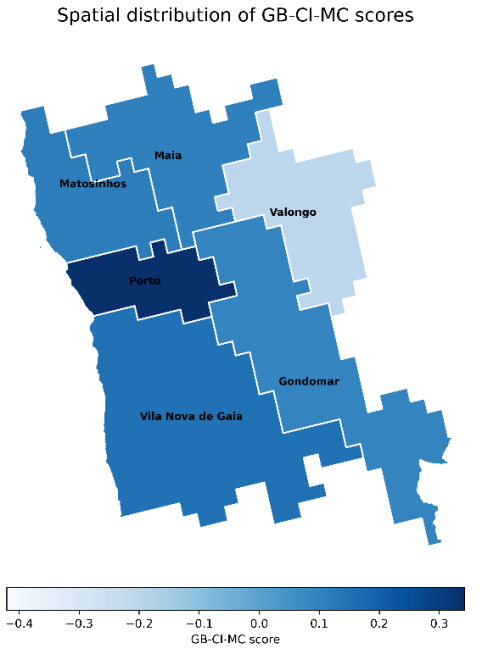


Figure 3. Spatial distribution of GB-CI-MC scores.
Source: Author's elaboration.

6. Discussion

6.1. Insights from the GB-CI-MC analysis

The findings of this study contribute to the literature on QoL and provide insights for urban governance in the AMP. Notably, the GB-CI-MC performed well in terms of both external validity and guarantee of multidimensionality, reaching a correlation of $r = 0.645$ with self-reported life satisfaction. This highlights its usefulness for urban management, where empirically robust indicators are particularly valuable for effective policy design (Libório et al., 2026; OECD, 2008).

The bootstrapping results showed non-significant paths from *perceived economic security* and *satisfaction with essential services* to *place attachment*. Despite that, *perceived economic security* received the highest weight in the GB-CI-MC optimisation (47.7%), while *place attachment* and *satisfaction with essential services* achieved the second and third largest weights (26.8% and 13.5%, respectively). This is consistent with the fact PLS-SEM evaluates the contribution of each construct after accounting for the variance explained by the other constructs in the model (Hair et al., 2022), while the GB-CI-MC determines weights by optimising the composite's correlation with self-reported life satisfaction (Libório et al., 2026). Consequently, dimensions with non-significant structural paths may still receive substantial weights if doing so contributes to maximising the composite's correlation with overall life satisfaction.

In contrast, *satisfaction with urban amenities, social cohesion* and *environmental quality satisfaction* received minimum weights. However, as Libório et al. (2026) argue, low weights do not necessarily mean low influence. Although these dimensions received little weight in the optimisation, they all remained meaningfully represented in the composite, with correlations with the CI between 0.30 and 0.90. This is further supported by the PLS-SEM results, in which *satisfaction with urban amenities* and *environmental quality satisfaction* showed the strongest path coefficients to *place attachment,* indicating that dimensions receiving low CI weights may still play an important role in the QoL framework.

The observed concentration of weights may reflect three connected factors. First, the high intercorrelations between subjective dimensions resulted in concentrated weights despite the minimum weight constraint. Second, because objective indicators vary across municipalities rather than individuals, their contribution to the optimisation is reduced, as reflected in the *municipal objective context* achieving the minimum allowed correlation with the CI ($r = 0.30$). Third, the optimisation was anchored to a measure of life satisfaction.

Together, these factors explain why the optimisation concentrated most of the CI weight on a small number of subjective dimensions, placing greater emphasis on those most closely associated with life satisfaction. This represents an acknowledged trade-off of the choice of validation criteria (Libório et al., 2026). The relatively low weight (8.9%) assigned to the *municipal objective context* should therefore not be interpreted as evidence that objective conditions are unimportant for QoL. Instead, it reflects the structure of the data and the optimisation procedure, which favoured dimensions that varied between individuals and were more strongly associated with self-reported life satisfaction.

Within this context, the results indicate *perceived economic security* and *place attachment* as the primary drivers of variation in the CI, together accounting for 74.5% of the CI weight. This is consistent with Dolan et al. (2008) and Kuentz-Simonet et al. (2023), who identified perceptions of financial security as one of the strongest predictors of life satisfaction, and with Kourtit et al.'s (2021; 2022) work on "city love", which highlights that affective bonds are central to residents' evaluations of their QoL. Accordingly, *perceived economic security* and *place attachment* appeared as the dimensions most strongly associated with differences in residents' overall evaluations of their well-being in the AMP.

Satisfaction with essential services, namely public transport, educational facilities, health centres and commercial variety also plays a relevant role in differentiating residents' QoL perceptions across the AMP, accounting for 13.5% of the CI weight. This is aligned with the literature, which argues that by meeting residents' basic functional needs, these services are strongly associated with overall well-being perceptions (Kourtit et al., 2024; Kuentz-Simonet et al., 2023; Mouratidis, 2021). Public transportation, in particular, has been identified as a "needs facilitator", as it allows individuals to access other essential services (Mouratidis, 2021).

6.2. Spatial inequalities of QoL across the AMP

The municipal-level analysis reveals a centre-periphery pattern in composite QoL across the AMP, as shown in Figure 3. This pattern is consistent with the metropolitan centricity literature, which posits that central municipalities tend to accumulate structural and economic advantages relative to the periphery, and are generally associated with higher levels of QoL (Cardoso et al., 2021; Kourtit et al., 2024). The collective material conditions index further supports this interpretation by revealing a general decline in accessibility with increasing distance from the centre at both the municipal and metropolitan levels. This

suggests that spatial differences in accessibility may partly explain the observed variation in QoL between municipalities, which is consistent with Dobrowolska & Kopczewska's (2024) and Yarahmadi et al.'s (2026) findings.

Three municipalities deserve further discussion, namely Gondomar, Valongo and Porto. Gondomar and Valongo illustrate different forms of divergence between objective and subjective QoL. Although Gondomar had the lowest *objective municipal context* score, its composite score was perfectly average due mostly to its comparatively high *perceived economic security*. This pattern may reflect the adaptation mechanisms discussed by Diener & Suh (1997) and Easterlin (2006), where residents in municipalities with lower objective provision may report relatively positive perceptions of financial security because their financial or job-related expectations are lower. It is also consistent with the literature showing that perceived financial status is strongly associated with how people evaluate their life satisfaction (Dolan et al., 2008; Kuentz-Simonet et al., 2023).

In contrast, Valongo showed the most concerning municipal profile, with the lowest scores across all dimensions except the *objective municipal context*. This finding is consistent with studies on the provision paradox, which argue that favourable objective conditions do not automatically translate into positive experiences or higher levels of well-being (Diener & Suh, 1997; Petrovici et al., 2026). Additionally, Valongo recorded especially low scores in *place attachment* (-0.96) and *satisfaction with urban amenities* (-0.82), potentially reflecting the strong association between these dimensions identified in the PLS-SEM model and discussed by Kourtit et al. (2021).

Porto presents an entirely different QoL profile. It was the only municipality whose objective conditions exceeded the metropolitan sample average. It also achieved the highest scores for *place attachment* (0.46) and *satisfaction with essential services* (0.43), two of the dimensions with the largest CI weights. Porto's strong performance on both objective and place-based dimensions is consistent with the theoretical premise that the material "body" of the city influences the affective "soul" of its residents (Kourtit et al., 2021). In other words, Porto combines favourable objective living conditions with stronger emotional connections to place. A similar pattern at a national scale was observed by Kourtit et al. (2021) in Sweden, where residents of Stockholm, the country's largest and most central city, reported the strongest place attachment among the cities analysed.

Despite this, Porto does not stand out in terms of *perceived economic security*, one of the most important dimensions of QoL (Dolan et al., 2008; Kuentz-Simonet et al., 2023) and

the one with the highest CI weight. Given the city's relatively favourable objective conditions, this pattern may reflect the adaptation mechanisms described by Easterlin (2006). The city also recorded a below-average score for *environmental quality satisfaction,* which suggests that deeply urban areas may have a trade-off in which strong economic perceptions and place attachment coexist with lower perceived environmental quality. This pattern is consistent with Mouratidis (2021), who argues that high urban density can create negative externalities such as noise, pollution and overcrowding, that undermine the advantages associated with central locations.

At the same time, an interesting finding emerges regarding *social cohesion*. Despite reporting relatively weak *social cohesion*, Porto recorded the highest level of *place attachment* among the analysed municipalities. Cardoso et al. (2021) identify this tension as a characteristic of dense urban environments. Building on the sociological concept of *Gesellschaft* (i.e. an urban society characterised by many casual and impersonal connections), they argue that residents may develop a strong attachment to the cultural and symbolic aspects of a city without necessarily forming strong social relationships within it.

Porto's below average *social cohesion* score may also be related to the demographic changes experienced in recent years, particularly those associated with the growth of short-term rentals and immigration (OECD, 2026). From the perspective of Kourtit et al.'s (2022) theory of social capital, increased population turnover may weaken bonding social capital, as existing community networks are likely to be affected by it. At the same time, the development of new forms of bridging social capital require time to develop (Kourtit et al., 2022). Consequently, residents may perceive lower levels of social cohesion despite maintaining a strong emotional attachment to the city, consistent with Cardoso et al.'s (2021) *Gesellschaft* argument.

Moreover, although the methodological procedure was designed to maximise the relationship between the CI and self-reported life satisfaction, some divergence between the two measures is expected. Part of this may be due to methodological limitations, such as convenience sampling. Also, as the optimisation was performed at the individual level, different results might have been obtained through municipal-level optimisation, although this could not be tested due to the limited sample size.

This divergence is illustrated by the municipal results. For instance, Porto achieved the highest composite QoL score but ranked only fourth on self-reported satisfaction, while Maia reported the lowest life satisfaction despite ranking marginally above the metropolitan

average on the CI. This pattern is consistent with Bleys (2012) and Diener and Suh (1997), who argue that overall life satisfaction reflects a holistic cognitive evaluation of one's life, while multidimensional QoL assessments are based on evaluations of specific life domains. As a result, residents may assign different importance to these domains according to their personal expectations, aspirations and recent experiences (Bleys, 2012; Easterlin, 2006), meaning that some divergence between a multidimensional composite and global life satisfaction is to be expected.

6.3. Policy implications for Porto

These findings have important policy implications for Porto. The *environmental quality satisfaction* dimension points to several urban management priorities, such as strengthening waste collection and street cleaning services, expanding low-emission zones to reduce traffic-related pollution and imposing noise regulation more strictly, particularly in areas that are more affected by nightlife and short-term rental activity. Given the municipality's strong performance on most dimensions of QoL, improving these conditions is an opportunity to address an area in which residents' perceptions are still below the metropolitan average.

The *social cohesion* dimension is more challenging to address, as it reflects the levels of mutual trust that may have been influenced by the city's rapid demographic changes (OECD, 2026). CMP already supports immigrant integration through initiatives such as Porto_4_All[10], which facilitates immigrants' access to the Portuguese labour market, and the *Guia de Acolhimento*[11], which provides practical information on legal documentation, housing, education, employment and healthcare. The findings of this study support the continuation of such programmes, as successful integration may be associated with higher levels of perceived social cohesion and place attachment (Kourtit et al., 2022). Additionally, complementary initiatives that promote interactions between new and long-term residents, such as communal gardens (Mouratidis, 2021) and neighbourhood associations (Cardoso et al., 2021), could further strengthen mutual trust and familiarity by creating opportunities for continued contact that existing measures may not fully provide.

[10] https://www.cm-porto.pt/agenda-economia/porto-4-all-programa-de-integracao-profissional-de-migrantes

[11] https://acaosocial.cm-porto.pt/migrantes-e-minorias-etnicas/guia-de-apoio-a-integracao-de-migrantes

7. Conclusion

This report set out to address the lack of a structured framework for assessing QoL in *Leme* Porto, which the benchmarking analysis identified as a differentiator between leading and lagging ODPs. Accordingly, the central research questions focused on how subjective perceptions and objective conditions could be integrated to construct multidimensional QoL indicators for the municipalities of the AMP, and what these indicators can reveal about spatial disparities in well-being.

To address these questions, a theoretically grounded QoL framework was developed and tested. PCA was used to identify the main well-being dimensions in the dataset, which were then validated through PLS-SEM. Finally, CIs were constructed using the GB-CI-MC method inspired by Libório et al. (2026), enabling a municipal-level analysis of QoL in the AMP.

7.1. Main findings

The results provide clear answers to both research questions. First, the GB-CI-MC method successfully produced CIs that combined good external validity and the guarantee of multidimensionality. The study also demonstrated that a methodology originally developed for welfare measurement in Brazilian municipalities (Libório et al., 2026) can be successfully adapted to assess urban QoL in a European metropolitan context. However, because the optimisation was anchored to self-reported life satisfaction, almost three-quarters of the CIs total weight was concentrated on *perceived economic security* and *place attachment*, indicating that these dimensions were most strongly associated with residents' overall evaluations of life satisfaction in the AMP.

Second, the study identified a centre-to-periphery pattern in composite QoL among the analysed municipalities. Porto reported the highest QoL composite score, associated with the city's comparatively favourable objective conditions, high place attachment and satisfaction with essential services. In contrast, Valongo registered the most concerning municipal profile, with very low scores on all subjective dimensions.

The findings further reveal two forms of divergence. First, objective and subjective evaluations did not always align. This is illustrated by Gondomar, which simultaneously registered the lowest *objective municipal context* and the highest *perceived economic security*. Similarly, Valongo recorded a relatively favourable *objective municipal context* but the lowest scores on all

subjective dimensions. Second, measured QoL and perceived life satisfaction also diverged, as illustrated by the cases of Porto and Maia.

7.2. Policy and practical recommendations

Porto's lowest-scored QoL dimensions were *environmental quality satisfaction* and *social cohesion*. Although these dimensions contributed relatively little to the optimisation, the PLS-SEM results showed that both significantly influence *place attachment*. Therefore, CMP could strengthen investments in community-building initiatives and interventions aimed at reducing urban noise and other stressors.

At the same time, policy should also seek to preserve the dimensions in which Porto performs well. Porto recorded the highest levels of *place attachment* in the metropolitan area. As previous research has linked place attachment to higher QoL evaluations and lower intentions to leave (Barreira et al., 2019), maintaining the cultural, historical and symbolic characteristics that foster this attachment should also be considered a policy priority.

Finally, given the importance of *perceived economic security* in the CI, improving residents' sense of financial stability should remain a policy priority. Measures aimed at increasing housing affordability and expanding employment opportunities may help strengthen this dimension, which was most strongly associated with residents' overall evaluations of well-being.

In addition to informing policy priorities, the proposed framework can also strengthen the municipality's long-term monitoring capacity. It can be integrated into the *Leme* platform and updated every four years to monitor changes in residents' well-being as the AMP evolves economically, socially and politically. A four-year interval is appropriate, as meaningful changes in QoL indicators are unlikely to happen from one year to the next. This also aligns with the assessment frequency of Porto's previous QoL monitoring framework[12].

To maximise the effectiveness of this monitoring framework, future assessments should ensure a representative survey sample of individuals within municipalities and include all 17 AMP municipalities in the analysis. Additionally, using a 7-point Likert scale instead of a 5-point scale may help capture greater variation in responses across municipalities (Huh & Gim, 2025).

[12] Between 2003 and 2011, the *Sistema de monitorização da qualidade de vida urbana* developed by CMP published three reports, corresponding to an average interval of approximately four years between reports.

Lastly, publicly communicating the results of this framework may also be strategically valuable. As Lambiri et al. (2007) point out, well-being measurement frameworks can support place branding and promotion, which may strengthen Porto's ability to attract skilled labour and investments, and contribute to its long-term competitiveness.

7.3. Brief reflection on internship activities

Overall, the internship activities provided valuable insights into the practical challenges of using data within local public administrations, particularly in the Portuguese context where official statistics are still highly centralised. Despite these unfavourable circumstances, CMP has demonstrated its commitment to evidence-based policymaking by making the most out of the limited information available at the municipal level. The *Boletim Económico do Porto,* the *Pulsar* factsheets and the QoL CIs developed in this study are examples of this, as they illustrate how available data can be used to support municipal monitoring and policy prioritisation processes. In this sense, these initiatives align with Janssen et al.'s (2012) argument that data only generates public value when it is effectively integrated into decision-making processes.

Additionally, one of the lessons learnt during the internship was how difficult it was to build a multidimensional QoL assessment framework within the constraints of public data systems. Although QoL is conceptualised as a multidimensional latent construct (Diener & Suh, 1997; Stiglitz et al., 2009), many dimensions were difficult to capture through available municipal statistics. Consequently, constructing the CI required the use of proxy variables for most objective dimensions. Therefore, dimensions that are more difficult to quantify risk being underrepresented in public policies, which reinforces the idea that indicators are not neutral (Anderson & Whitford, 2018; Kitchin et al., 2015; Prince, 2020).

Working on the *Leme* platform and attending meetings with data and software providers also revealed that data limitations are often institutional. As the platform relies entirely on external suppliers, many socioeconomic indicators are published several months after the reference period, which reduces their usefulness for monitoring rapidly changing urban dynamics. At the same time, CMP does not have the financial or institutional capacity to produce most of these data internally, as primary data collection is costly. These constraints illustrate how the effectiveness of OGD initiatives depends not only on technological infrastructure but also on institutional arrangements governing data production and sharing (Abraham et al., 2019; Janssen et al., 2012).

In conclusion, the internship highlighted the challenges of implementing evidence-based policymaking in Portugal, where the highly centralised statistical system limits the availability of timely and spatially disaggregated data at the municipal level. Even a municipality with comparatively good resources such as Porto faces these constraints and often has to use data aggregated at the AMP or Northern Region level, limiting its capacity to monitor local dynamics and respond to challenges.

7.4. Limitations and future research

As an exploratory study, this report prioritised the development and validation of a methodological framework. Consequently, three main methodological limitations should be acknowledged: the use of convenience sampling, the common method bias from using self-reported life satisfaction as the external validation variable, and the level mismatch between survey responses and objective indicators.

The convenience sampling resulted in an uneven distribution of responses across municipalities, leading to the exclusion of most AMP municipalities from the spatial analysis. This reduces the generalisability of the findings to the six municipalities with sufficient responses.

Regarding the common method bias, using self-reported life satisfaction as the external validation variable means that the optimisation process is anchored to life satisfaction rather than an independent measure of QoL. Future research could explore external validation variables that are less dependent on subjective judgements.

The mismatch between individual-level survey responses and municipal-level objective indicators could be addressed through multilevel SEM, which explicitly models relationships on both levels of analysis. However, this would require extending the analysis beyond the AMP to a larger set of municipalities, such as those in the Northern Region of Portugal.

Other avenues for future research include incorporating sociodemographic moderators into the framework to assess how different population groups evaluate urban conditions. Future studies could also apply the framework in other Portuguese or European metropolitan areas to assess its generalisability.

7.5. Concluding remarks

This report supports the "beyond GDP" perspective by demonstrating that QoL cannot be reduced to a single dimension. The analytical framework developed in this study translates this multidimensional understanding of QoL into evidence that can support urban monitoring and policymaking. As such, it is intended as a foundation that can be adapted and applied in different urban contexts and at different spatial scales. If it contributes to more resident-centred approaches to urban monitoring and policy design in Porto and beyond, it will have served its purpose.

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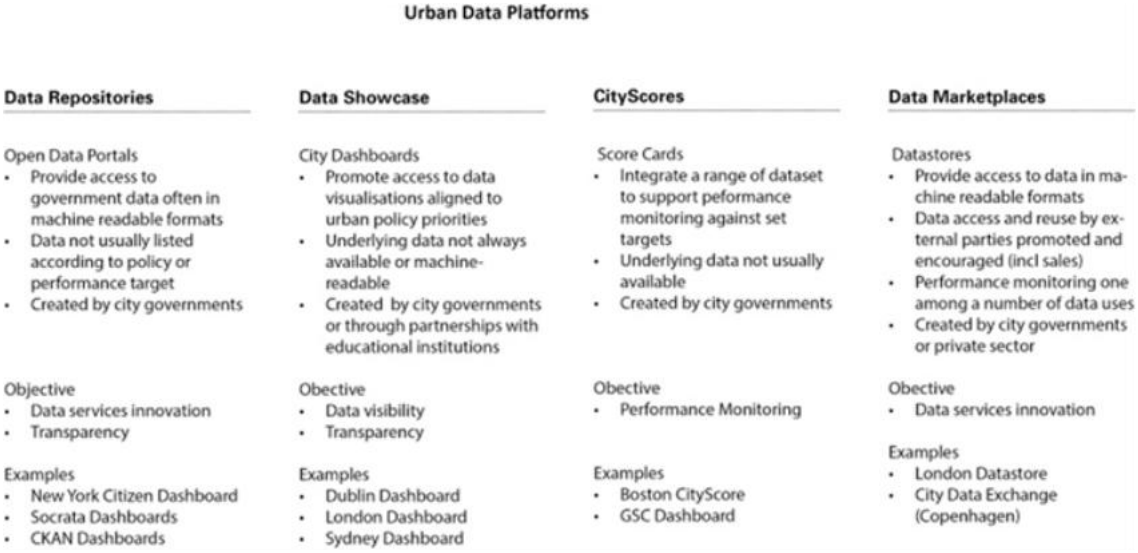
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Annexes

Annex 1 – Urban data platform classification.
Source: Barns (2018).



Annex 2 - Examples of datasets considered for each information type.
Source: Author's elaboration.

Type of information	Examples
Socio-economic	Household disposable income per capita, Unemployment rate, Consumer price index, Housing prices
Industry	Hotel occupation rate, Tourism demand forecasts, Commercial licensing, Workplaces in a given area
Environment	Precipitation, Relative humidity, Location of green spaces, Air quality monitoring
Health	Vaccinations, Health clinic locations, Well-being reports, Disease case counts
Governance	Municipal service surveys, Public administration budgets, Electoral results, Public complaints
Infrastructure	Map of public bathrooms, Street sweeping schedules, Recycling facilities
Mobility	Traffic congestion index, Average travel time, Public transport journeys by type of transport
Culture	Map of landmarks, Location of public art, Location of museums, Location of libraries
Crime and safety	Police department incidents, Fire incidents, Use of force, Recorded crimes

Annex 3 – Benchmarking of international open data portals (abridged).
Source: Author's elaboration.

Data portal	Type of dashboard/data portal (Barns, 2018)	Geographic granularity (parish or equivalent*: 1; municipality/city: 2; region: 3; country: 4)	Type of information (socioeconomic: 1; industry: 2; environment: 3; health: 4; governance: 5; infrastructure: 6; mobility: 7; culture: 8; crime and safety: 9)	Update frequency (daily/weekly: 1; monthly: 2; quarterly: 3; bi-anually: 4; anually: 5)	Does it have an indicator framework that measures and monitors QoL?	Nº of indicators/datasets
Leme Porto	**Data showcase**	**1 /2 / 3 (AMP and Northern region)**	**1 / 2 / 3 / 4**	**2 / 4 / 5**	**No**	**300-350**
Barcelona Datastore	Data marketplace	1 / 2	1 / 2 / 3 / 4 / 5 / 6 / 7	1 / 2 / 3 / 5	Yes, but last published for 2017	>1500
London Datastore	Data marketplace	1 / 2 / 3	1 / 3 / 5 / 7 / 8 / 9	2 / 3 / 5	Yes	700-1000
Dados Recife	Data showcase and marketplace	1 / 2	1 / 5 / 6 / 7 / 8 / 9	1 / 2 / 4 / 5	No	200-250
Data South Australia	Data repository	1 / 2 / 3	1 / 2 / 3 / 4 / 5 / 6 / 7 / 8 / 9	1 / 2 / 5	Yes, but not on the platform	>1500
Amsterdam Open Data	Data repository	1 / 2	1 / 3 / 6 / 7 / 8 / 9	1 / 3	No	50-100
City of Chicago	Data marketplace	1 / 2	1 / 3 / 5 / 7 / 9	1 / 2 / 5	No	>1500
City of Vancouver open data	Data marketplace	1 / 2	1 / 5 / 7 / 9	N/A	No, but has a dashboard that tracks progress in each indicator (Healthy City dashboard)	150-200
VanDashboard	Data showcase	1 / 2	1 / 3 / 4 / 6	2 / 3 / 5	No	70
Vancouver Healthy City Dashboard	Data showcase	2	1/ 3 / 4 / 7	N/A	No	23
Urban data platform Hamburg	Data repository	1 / 2	1 / 3 / 5 / 6 / 7 / 8	N/A	No	>8000
Dublinked	Data marketplace	1 /2 / 4	1/ 3 / 5 / 7 / 8 / 9	N/A	No	800-850
Helsinki region infoshare	Data marketplace	2 / 4	1 / 3 / 5 / 6 / 7 / 8	5	No, but monitors SDG indicators	500-550
Lisboa Aberta	Data repository	1 / 2	1 / 2 / 3 / 5 / 7 / 8 / 9	3 / 5	No	350-400
Buenos Aires Data	Data marketplace	1 / 2	1 / 3 / 5 / 6 / 7 / 8	1 /2 / 5	No	450-500
The City Observatory Birmingham	Data marketplace	1 / 2 / 3 / 4	1 / 3 / 5 / 6 / 7 / 9	2 / 3 / 5	Yes	650-700
City of Milan open data	Data marketplace	2	1 / 3 / 5 / 7 / 8	1 / 2 / 4 / 5	No	>2500
Open Baltimore	Data repository	1 / 2	1 / 2 / 5 / 7 / 9	N/A	No	600-650
Brisbane open data	Data repository and showcase	1 / 2	3 / 5 / 6 / 7 / 8 / 9	3 / 4 / 5	No	400-450
Open data Morocco	Data repository	3 / 4	1 / 2 / 5 / 7 / 8	1 / 5	No	650-700

Annex 4 – Survey employed to collect subjective QoL perceptions in the AMP.
Source: Adapted from European Commission's Flash Eurobarometer nº 149.

1. **Qual o município onde reside atualmente?**
   - Arouca
   - Espinho
   - Gondomar
   - Maia
   - Matosinhos
   - Oliveira de Azeméis
   - Paredes
   - Porto
   - Póvoa de Varzim
   - Santa Maria da Feira
   - Santo Tirso
   - São João da Madeira
   - Trofa
   - Vale de Cambra
   - Valongo
   - Vila do Conde
   - Vila Nova de Gaia
   - Outro
2. **De um modo geral, indique o seu nível de satisfação com a acessibilidade e o funcionamento de cada um dos seguintes aspetos no município onde reside, utilizando a seguinte escala: nada satisfeito (1), pouco satisfeito (2), nem satisfeito nem insatisfeito (3), bastante satisfeito (4) ou muito satisfeito (5).**
   - Transportes públicos (autocarro, metro, comboio)
   - Serviços de saúde (médicos, hospitais)
   - Instalações desportivas (campos, pavilhões, ginásios)
   - Equipamentos culturais (teatros, museus, bibliotecas, salas de concerto)
   - Estado das ruas e edifícios
   - Espaços verdes (parques e jardins)
   - Disponibilidade de lojas e comércio (comida, roupa, tecnologias)
   - Escolas e outros estabelecimentos de ensino
   - Qualidade do ar
   - Nível de ruído
   - Limpeza
3. **De seguida, serão apresentadas algumas afirmações. Para cada uma delas, indique o seu grau de concordância usando a seguinte escala: discordo totalmente (1), discordo em parte (2), nem concordo nem discordo (3), concordo em parte (4) ou concordo totalmente (5).**
   - Estou satisfeito por viver no meu município
   - É fácil encontrar emprego no meu município
   - A presença de estrangeiros (turistas e emigrantes) é posistiva no meu município
   - Tenho sorte em viver no meu município
   - Os imigrantes que vivem no meu município estão bem integrados
   - É fácil encontrar habitação de boa qualidade a um preço razoável no meu município
   - Tenho orgulho em viver no meu município
   - Sinto-me seguro no meu município
   - Tenho vontade de mudar de município num futuro próximo
   - Sinto-me conectado ao meu município
   - De um modo geral, a maioria das pessoas no meu município é de confiança
   - De um modo geral, a maioria das pessoas que vivem no meu município conhecem-se entre si
   - De um modo geral, a maioria das pessoas que vivem no meu município ajudam-se mutuamente
   - De um modo geral, a administração pública do meu município é de confiança
4. **No geral, está nada satisfeito (1), pouco satisfeito (2), nem satisfeito nem insatisfeito (3),**

bastante satisfeito (4) ou muito satisfeito (5) com...
- A sua situação profissional
- A situação financeira do seu agregado familiar
- O lugar onde vive
- A sua qualidade de vida, no geral

5. **Qual a composição do seu agregado familiar?**
   - Pessoa a viver sozinha
   - Casal (casado ou em coabitação), sem filhos ou sem filhos a viver em casa
   - Casal (casado ou em coabitação), com um ou mais filhos a viver em casa
   - Pai ou mãe solteira(o), com um ou mais filhos a viver em casa
   - Outro
   - Não respondo
6. **Há quanto tempo vive no seu município atual?**
   - Nasci aqui/vivi aqui toda a minha vida
   - Vivo aqui há mais de 10 anos
   - Vivo aqui há entre 5 e 10 anos
   - Vivo aqui há entre 1 e 4 anos
   - Vivo aqui há menos de 1 ano
   - Não respondo
7. **Como classifica a sua situação professional**
   - Empregado a tempo inteiro
   - Empregado a tempo parcial
   - Trabalhador por conta própria
   - Desempregado à procura de trabalho
   - Desempregado sem procurar trabalho
   - Estudante
   - Reformado
   - Outro
   - Não respondo
8. **Qual a sua idade?**
   - 15-24 anos
   - 25-34 anos
   - 35-44 anos
   - 45-54 anos
   - 55-64 anos
   - 65+ anos
   - Não respondo
9. **Qual é o seu sexo?**
   - Masculino
   - Feminino
   - Outro
   - Não respondo
10. **Qual é, aproximadamente, o rendimento mensal líquido (após impostos) do seu agregado familiar? (*A informação será utilizada apenas para análise estatística e tratada de forma totalmente anónima.*)**
    - Menos de 750€
    - 750€ - 1.249€
    - 1.250€ - 1.999€
    - 2.000€ - 2.999€
    - 3.000€ - 4.499€
    - 4.500€ ou mais
    - Não respondo

Annex 5 - Objective indicators collected to assess the context of AMP municipalities.
Source: Author's elaboration.

Indicator	Description	Unit	Source	Year
Purchasing power per capita	Index of municipal purchasing power per capita	Index (Portugal = 100)	INE	2023
Income inequality (P80/P20)	Ratio between top 20% and bottom 20% income	Ratio	INE	2024
Median housing appraisal value	Median value of housing appraisals for bank purposes	€	INE	2024
Greenhouse gas emissions	Emissions of greenhouse gases (CO2, CH4, N2O) at municipal level	per 1000 inhabitants	Associação Portuguesa do Ambiente	2023
Crime rate	Recorded criminal offences	per 1000 inhabitants	INE	2024
Physicians	Practicing physicians	per 1000 inhabitants	INE	2024
Secondary education completion	Completion rate of secondary education	%	INE	2023/2024
Net population balance	Difference between population inflows and outflows	per 1000 inhabitants	PorData	2024
Collective material conditions index	Proximity to key services	Index	own elaboration	n.a.
Overcrowded dwellings	Dwellings with insufficient rooms for household size	per 1000 dwellings	INE	2021

Annex 6 – Descriptive statistics of objective municipal-level indicators (a) and correlation matrix of considered objective indicators (b).
Source: Author's elaboration.

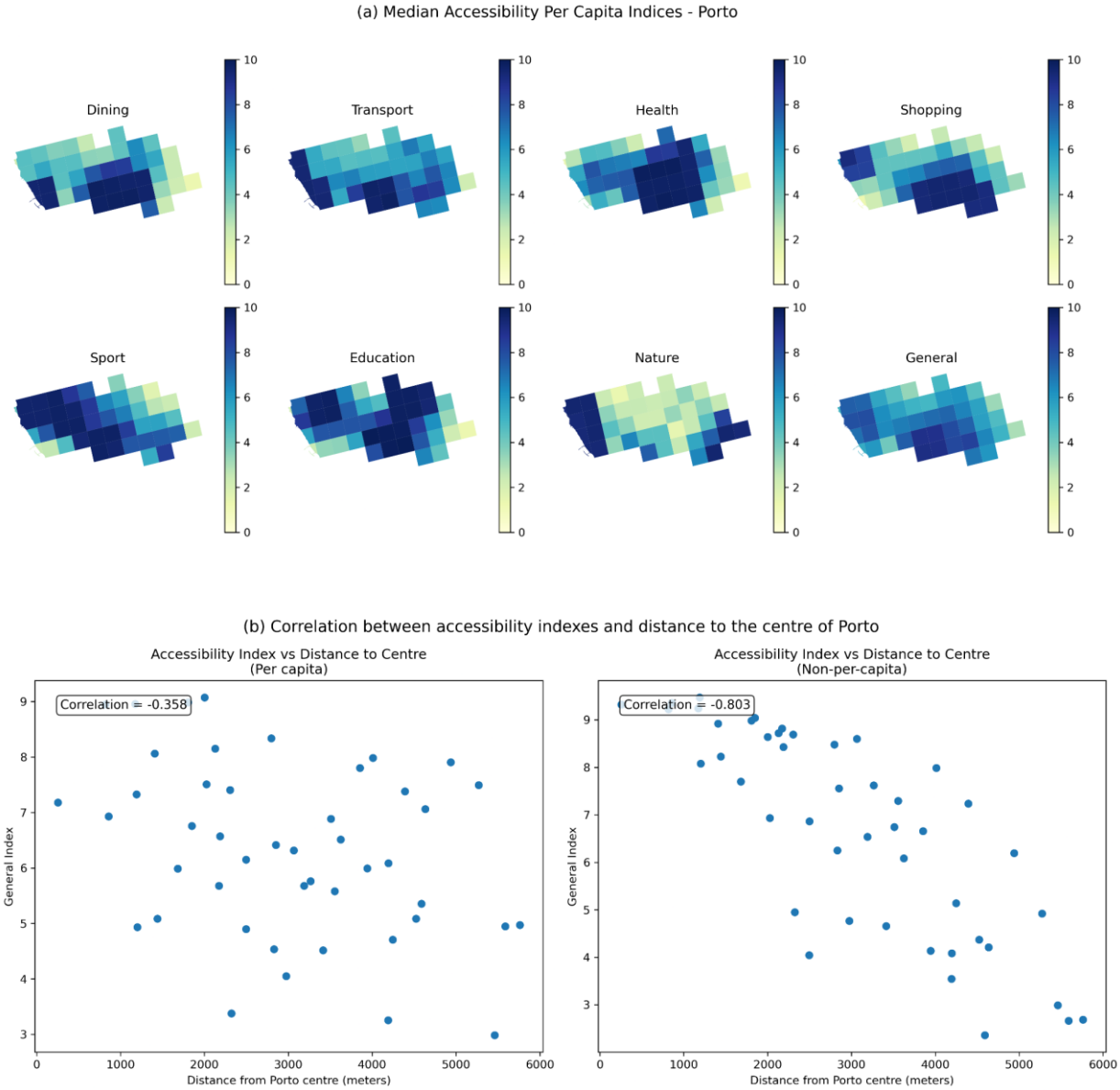
(a)

Indicator	Mean	Standard deviation	Min	P25	Median	P75	Max
Physicians per 1000 inhabitants	6.10	4.61	2.00	3.90	4.80	7.00	22.00
Net population change per 1000 inhabitants	7.53	6.13	-4.32	4.76	7.37	12.79	15.84
Secondary education completion rate	93.51	1.85	89.40	92.70	93.30	94.60	96.80
Crimes per 1000 inhabitants	25.67	10.18	14.60	21.10	22.60	28.00	60.60
Inequality in income distribution (P80/20)	3.05	0.3	2.70	2.90	3.00	3.10	4.00
Purchasing power per capita	98.03	20.02	75.46	86.76	92.55	101.25	162.18
Median value of housing bank appraisal	1524.94	419.88	1013.00	1214.00	1495.00	1744.00	2580.00
Greenhouse gas emissions per 1000 inhabitants	3.06	1.88	1.61	2.17	2.49	2.97	9.63
Collective material conditions index	4.57	1.31	1.93	3.96	4.88	5.14	7.41
Overcrowding per 1000 dwellings	130.30	20.65	84.13	119.64	132.41	149.03	158.27

(b)

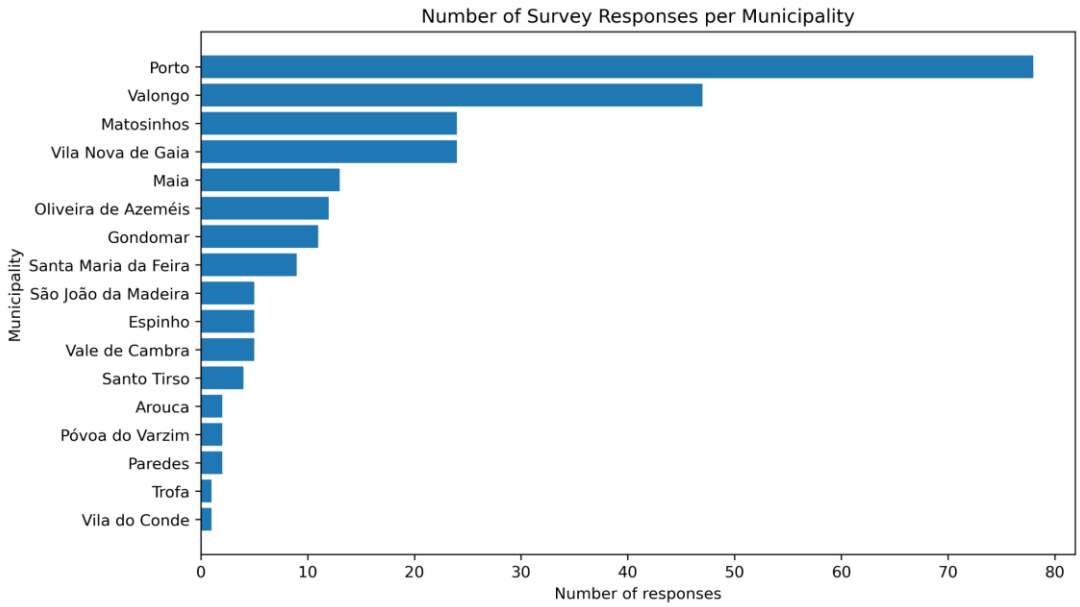
	Physicians per 1000 inhabitants	Net population change per 1000 inhabitants	Secondary education completion rate	Crimes per 1000 inhabitants	Inequality in income distribution (P80/20)	Purchasing power per capita	Overcrowding per 1000 dwellings	Median value of housing bank appraisal	Greenhouse gas emissions per 1000 inhabitants	Collective material conditions index
Physicians per 1000 inhabitants	1									
Net population change per 1000 inhabitants	0,478013	1								
Secondary education completion rate	-0,36396	-0,50613	1							
Crimes per 1000 inhabitants	0,932837	0,498819	-0,14732	1						
Inequality in income distribution (P80/20)	0,905926	0,628981	-0,43216	0,854553	1					
Purchasing power per capita	0,944706	0,630346	-0,37858	0,909696	0,858531	1				
Overcrowding per 1000 dwellings	0,422543	0,416777	-0,58032	0,280796	0,522074	0,351574	1			
Median value of housing bank appraisal	0,890339	0,61946	-0,6114	0,76533	0,865693	0,832239	0,637504	1		
Greenhouse gas emissions per 1000 inhabitants	0,007806	-0,06069	-0,11791	-0,12183	0,042462	-0,05325	0,257197	0,111505	1	
Collective material conditions index	0,52266	0,776886	-0,34797	0,563244	0,479831	0,704184	0,347963	0,561375	-0,09935	1

Annex 7 - Map of median accessibility per capita indices for the municipality of Porto (a) and scatterplots of the correlation between accessibility indexes and distance to the centre of Porto (b).
Source: Author's elaboration.



Annex 8 - Number of survey responses per municipality (a) and distribution of answers to the question "Overall, how satisfied are you with your quality of life?"(b).
Source: Author's elaboration.

(a)



(b)

Value	Overall QoL satisfaction level	n	%
1	Very dissatisfied	2	0.8
2	Somewhat dissatisfied	7	2.9
3	Neither satisfied nor dissatisfied	44	18
4	Somewhat satisfied	142	58
5	Very satisfied	50	20.4

Annex 9 - Sociodemographic distribution of survey responses.
Source: Author's elaboration.

Variable	Response	Percentage (%)
Household Composition	Couple with children living at home	45,71
	Couple without children living at home	16,33
	Other	15,92
	Living alone	11,43
	Single parent	10,61
Years In Municipality	Born in / lived all life	45,31
	More than 10 years	31,43
	1–5 years	14,69
	5–10 years	5,31
	Less than 1 year	3,27
Employment Status	Full-time employed	54,69
	Student	17,96
	Self-employed	10,61
	Retired	8,16
	Other	4,08
	Part-time employed	2,04
	Unemployed, looking for work	1,22
	Unemployed, not looking for work	1,22
Age Group	15–24	23,67
	55–64	22,86
	45–54	17,14
	35–44	15,51
	25–34	15,1
	65+	5,71
Gender	Female	60
	Male	39,59
	Other	0,41
Household Income	€3,000–€4,499	22,04
	€1,250–€1,999	19,59
	€2,000–€2,999	19,59
	€750–€1,249	13,47
	Not reported	11,43
	€4,500 or more	11,02
	Less than €750	2,86

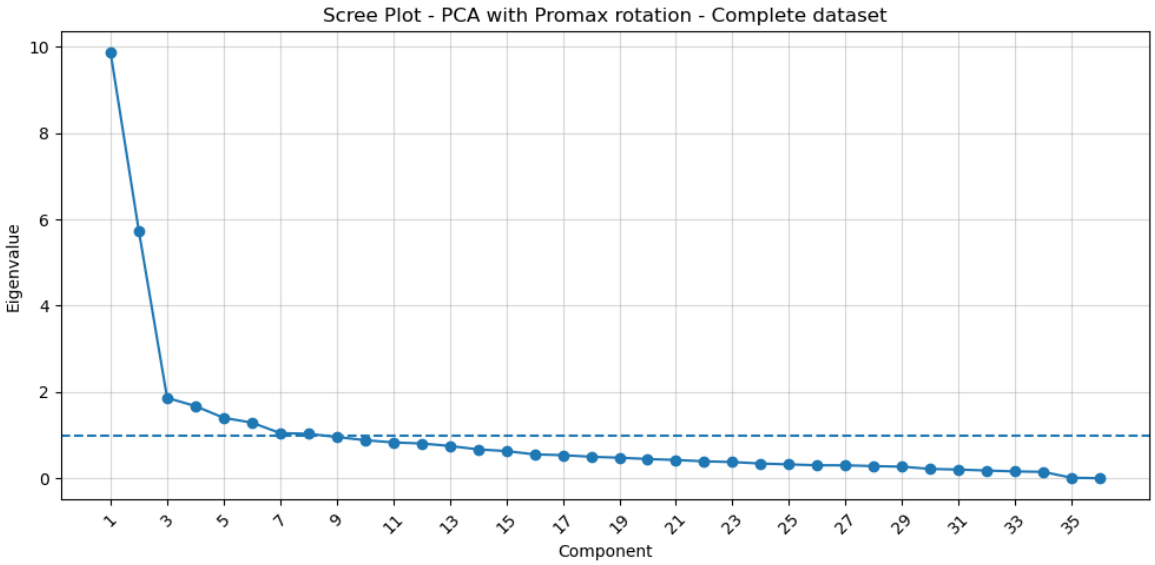
Annex 10 - Principal component analysis eigenvalues table (a) and scree plot (b).

Source: Author's elaboration.

(a)

Component	Eigenvalue	Variance Explained (%)	Cumulative Variance (%)
1	**9,856**	**27,378**	**27,378**
2	**5,732**	**15,922**	**43,299**
3	**1,867**	**5,187**	**48,487**
4	**1,676**	**4,655**	**53,141**
5	**1,405**	**3,904**	**57,045**
6	**1,293**	**3,591**	**60,636**
7	**1,051**	**2,919**	**63,555**
8	**1,035**	**2,875**	**66,43**
9	0,961	2,669	69,099
10	0,887	2,465	71,564
11	0,835	2,318	73,882
12	0,811	2,252	76,134
13	0,753	2,091	78,225
14	0,674	1,871	80,096
15	0,634	1,762	81,858
16	0,558	1,55	83,408
17	0,54	1,5	84,909
18	0,503	1,397	86,306
19	0,481	1,337	87,643
20	0,451	1,252	88,895
21	0,429	1,191	90,086
22	0,397	1,103	91,189
23	0,38	1,056	92,245
24	0,346	0,961	93,205
25	0,326	0,906	94,111
26	0,306	0,85	94,961
27	0,304	0,845	95,807
28	0,286	0,796	96,602
29	0,273	0,759	97,361
30	0,222	0,615	97,977
31	0,207	0,574	98,551
32	0,184	0,51	99,061
33	0,163	0,453	99,515
34	0,153	0,424	99,939
35	0,017	0,047	99,986
36	0,005	0,014	100

(b)


Scree Plot - PCA with Promax rotation - Complete dataset
Eigenvalue
Component
0
2
4
6
8
10
1
3
5
7
9
11
13
15
17
19
21
23
25
27
29
31
33
35

Annex 11 – Principal component analysis rotated loading matrix.

Source: Author's elaboration.

	Component 1	Component 2	Component 3	Component 4	Component 5	Component 6	Component 7	Component 8
Satisfaction with Public Transport	-0,245	0,186	-0,097	-0,321	-0,088	0,124	0,773	0
Satisfaction with Healthcare Services	-0,009	-0,026	0,12	-0,145	0,231	-0,012	0,546	-0,021
Satisfaction with Sports Facilities	0,057	-0,246	-0,149	-0,268	0,546	-0,095	0,383	0,11
Satisfaction with Cultural Facilities	0,094	0,186	0,012	0,013	0,666	-0,031	0,035	0,005
Satisfaction with Streets and Buildings	0,044	0,216	-0,041	-0,135	0,532	0,103	0,18	0,067
Satisfaction with Green Spaces	0,241	-0,002	-0,113	-0,169	0,632	0,074	0,05	-0,052
Satisfaction with Retail Availability	0,027	0,281	-0,033	0,044	0,347	-0,005	0,473	-0,141
Satisfaction with Educational Facilities	0,072	-0,069	0,023	0,119	0,173	0,168	0,622	-0,213
Satisfaction with Air Quality	-0,025	-0,022	0,012	0,103	-0,003	0,857	0,129	-0,07
Satisfaction with Noise Levels	0,206	-0,115	-0,148	0,126	-0,091	0,796	0,079	0,042
Satisfaction with Cleanliness	0,203	-0,039	-0,014	0,053	0,202	0,521	0,168	-0,038
Satisfied Living in Municipality	0,577	-0,019	0	0,001	0,159	0,226	0,155	-0,022
Ease of Finding a Job	-0,018	-0,082	0,424	0,197	0,483	-0,181	0,137	-0,138
Foreigners Positively Contribute	0,058	-0,013	0,465	0,109	-0,087	-0,275	0,26	0,296
Lucky to Live in Municipality	0,72	0,049	-0,016	-0,057	0,221	-0,038	-0,085	0,081
Immigrants are Well Integrated	0,01	-0,129	-0,006	0,183	-0,124	0,075	0,589	0,425
Housing is Affordable	-0,4	0,092	0,425	-0,065	0,11	0,406	-0,142	0,261
Proud of Municipality	0,886	0,002	-0,009	-0,05	0,085	-0,006	-0,082	0,001
Feel Safe in Municipality	0,252	-0,032	0,097	0,076	0,028	0,404	0,12	0,249
No Desire to Move	0,894	0,011	-0,051	0,22	-0,223	0,08	-0,009	-0,018
Feel Connected to Municipality	0,761	0,043	-0,084	-0,051	0,136	-0,128	-0,078	0,195
Trust in Other Residents	0,116	0,146	-0,01	-0,149	0,246	0,082	-0,124	0,531
Residents Know Each Other	0,031	-0,156	-0,146	0,138	-0,092	0,071	-0,115	0,758
Residents Help Each Other	0,071	-0,012	-0,016	-0,042	0,008	-0,085	0,02	0,803
Trust in Public Administration*	0,27	0,06	0,155	0,025	0,285	0,012	0,016	0,219
Satisfaction with Job Situation	0,011	-0,009	0,748	0,127	-0,066	0,065	0,046	-0,066
Satisfaction with Household Finances	-0,016	-0,046	0,906	-0,23	-0,024	-0,025	-0,101	-0,108
Satisfaction with Place of Residence	0,546	-0,059	0,397	-0,132	-0,086	0,285	-0,129	-0,199
Net population change per 1000 inhabitants	-0,247	0,928	-0,099	0,228	0,018	0,039	0,074	0,042
Secondary education completion rate	-0,287	-0,268	-0,101	0,301	0,553	0,151	-0,189	-0,035
Inequality in income distribution (P80/20)	-0,105	-0,914	0	-0,132	-0,204	0,063	0,146	0,034
Collective material conditions index	0,018	0,863	-0,054	0,233	0,015	-0,031	0,1	-0,002
Greenhouse gas emissions per 1000 inhabitants	0,028	0,339	-0,023	0,846	-0,125	0,157	-0,105	0,031
Overcrowding per 1000 dwellings	0,096	-0,78	-0,075	0,128	0,296	-0,084	-0,172	0,083
Median value of housing bank appraisal	-0,18	-0,885	-0,005	-0,03	-0,031	0,084	0,037	0,033
Purchasing power per capita	0,17	0,885	-0,009	0,173	0,191	-0,109	-0,14	-0,031

Annex 12 - Indicators reassignments and exclusions from the principal component analysis (a) and final multidimensional quality of life structure informed by the principal component analysis (a).
Source: Author's elaboration.

(a)

Indicator	Highest loading	Assigned component	Reason	Notes
Ease of finding a job	5	3	Conceptual coherence	
Immigrants are well-integrated	7	8	Conceptual coherence	
Greenhouse gas emissions	4	2	Objective municipal context indicator; although it had a relatively high loading on component 4 (0.846), it had greater conceptual coherence on component 2 (0.339)	Because this indicator was the only one with a high loading on component 4, the component was excluded
Secondary education completion rate	5	Excluded	No coherent loading	Component 5 captured satisfaction with urban amenities
Foreigners positively contribute	3	Excluded	No coherent loading	Component 3 captured personal finances
Feel safe in municipality	6	Excluded	No coherent loading	Component 6 captured environmental quality

(b)

Component 1	**Place attachment**	Satisfied Living in Municipality
		Lucky to Live in Municipality
		Proud of Municipality
		Satisfaction with Place of Residence
		No Desire to Move
		Feel Connected to Municipality
Component 2	**Municipal objective context**	Net population change per 1000 inhabitants
		Overcrowding per 1000 dwellings
		Median value of housing bank appraisal
		Purchasing power per capita

		Inequality in income distribution (P80/20)
		Collective material conditions index
		Greenhouse gas emissions per 1000 inhabitants
Component 3	**Perceived economic security**	Housing is Affordable
		Ease of Finding a Job
		Satisfaction with Job Situation
		Satisfaction with Household Finances
Component 4	**Satisfaction with urban amenities**	Satisfaction with Cultural Facilities
		Satisfaction with Streets and Buildings
		Satisfaction with Sports Facilities
		Satisfaction with Green Spaces
Component 5	**Environmental quality satisfaction**	Satisfaction with Air Quality
		Satisfaction with Noise Levels
		Satisfaction with Cleanliness
Component 6	**Satisfaction with essential services**	Satisfaction with Public Transport
		Satisfaction with Healthcare Services
		Satisfaction with Retail Availability
		Satisfaction with Educational Facilities
Component 7	**Social cohesion**	Immigrants are Well Integrated
		Trust in Other Residents
		Residents Know Each Other
		Residents Help Each Other

Annex 13 - Variance inflation factor values of the first PLS-SEM model.
Source: Output from SmartPLS software.

	VIF
Collective material conditions index	**6.62**
Ease of finding a job	1.14
Feel connected to municipality	2.43
Feel lucky to live in municipality	2.44
Feel proud living in municipality	3.73
Greenhouse gas emissions per 1000 inhabitants	1.34
Immigrants are well integrated	1.20
Inequality in income distribution (P80/20)	**51.82**
Median value of housing bank appraisal	**27.99**
Net population change per 1000 inhabitants	3.36
No desire to move	1.64
Overcrowding per 1000 dwellings	4.91
Perceived affordable quality housing	1.13
Purchasing power per capita	**87.90**
Residents help each other	1.56
Residents know each other	1.36
Satisfaction with air quality	1.69
Satisfaction with cleanliness	1.57
Satisfaction with cultural facilities	1.68
Satisfaction with educational facilities	1.44
Satisfaction with green spaces	1.78
Satisfaction with health services	1.33
Satisfaction with noise level	1.91
Satisfaction with place of residence	1.39
Satisfaction with public transport	1.26
Satisfaction with retail availability	1.48
Satisfaction with sports facilities	1.61
Satisfaction with streets and buildings	1.75
Satisfied living in municipality	2.53
Satisfied with household finances	1.43
Satisfied with professional situation	1.36
Trust in other residents	1.22

Annex 14 - Composite reliability and average variance extracted values of the second PLS-SEM model.
Source: Output from SmartPLS software.

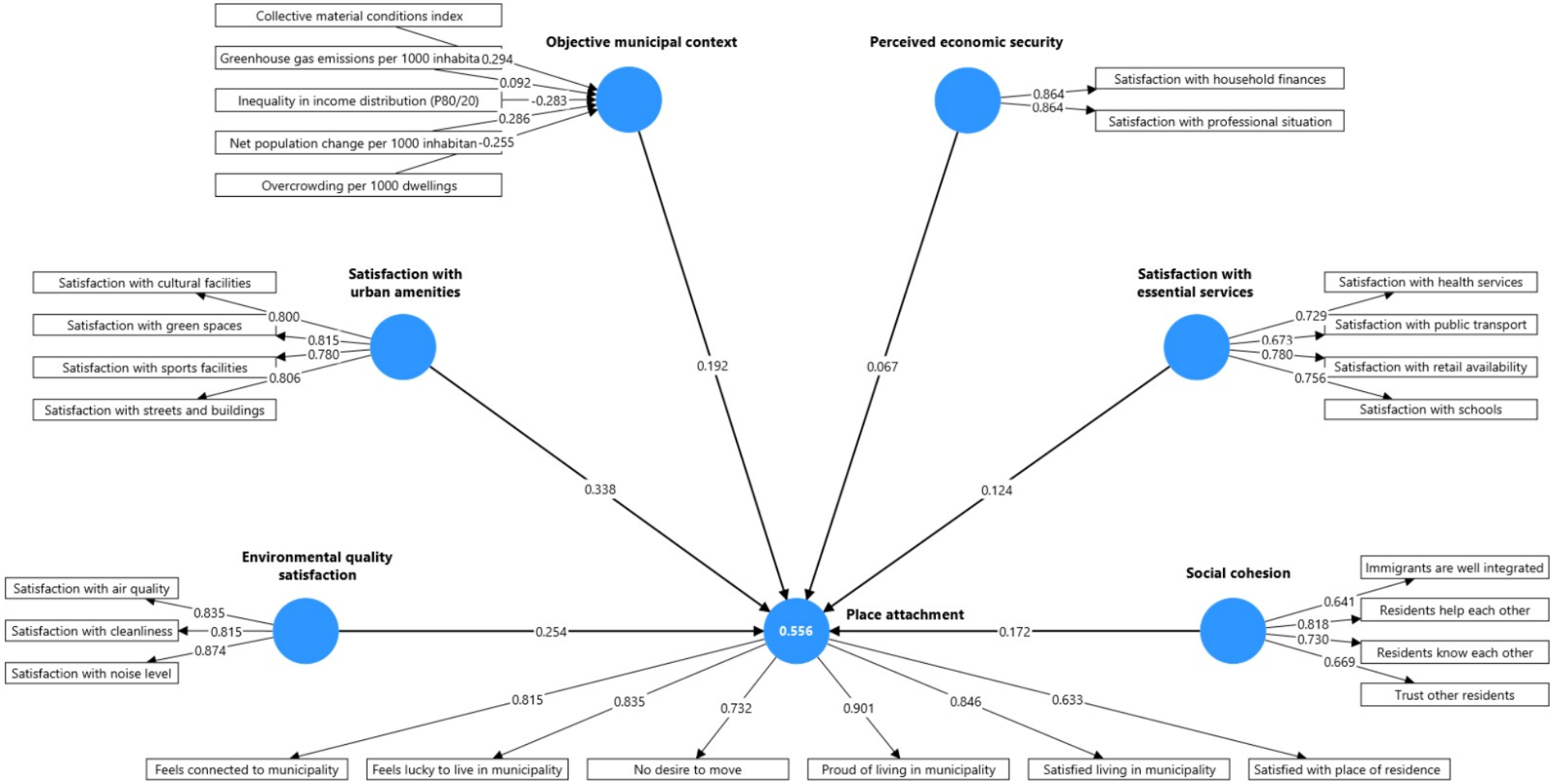
	Composite reliability (ρ_a)	Composite reliability (ρ_c)	Average variance extracted (AVE)
Environmental satisfaction	0.80	0.88	0.71
Perceived economic security	**0.65**	0.78	**0.48**
Place attachment	0.90	0.91	0.64
Satisfaction with essential services	0.71	0.82	0.54
Satisfaction with urban amenities	0.81	0.88	0.64
Social cohesion	0.70	0.81	0.52

Annex 15 - Discriminant validity measured using cross-loadings of reflective constructs.

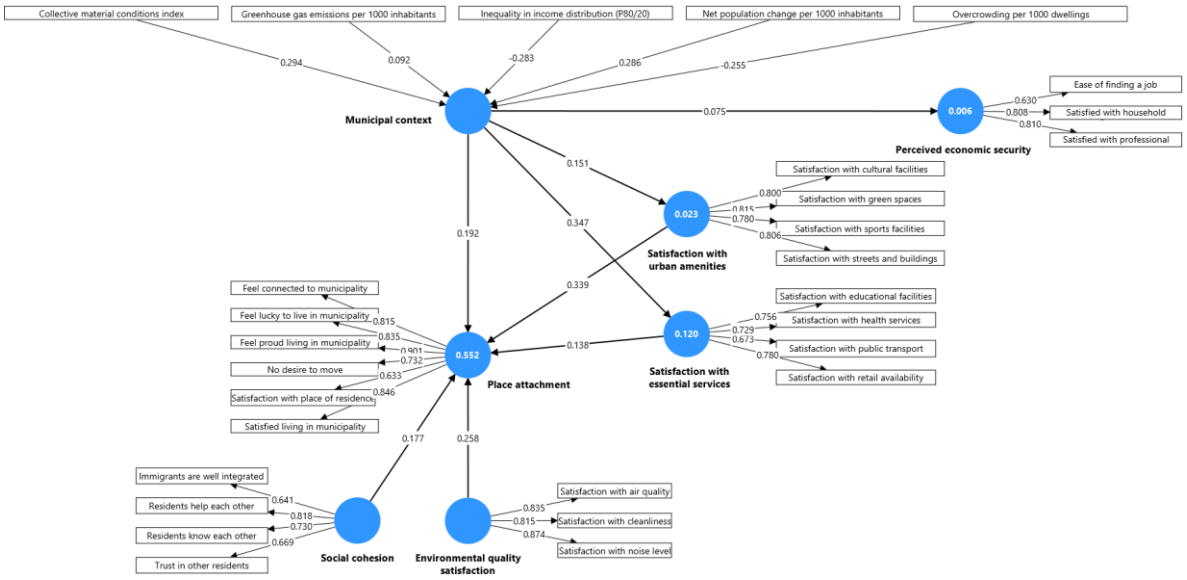
Source: Output from SmartPLS software.

	Environmental satisfaction	Municipal objective context	Perceived economic security	Place attachment	Satisfaction with essential services	Satisfaction with urban amenities	Social cohesion
Collective material conditions index	-0,147	**0,914**	0,046	0,252	0,366	0,198	-0,101
Feel connected to municipality	0,336	0,208	0,140	**0,815**	0,429	0,550	0,400
Feel lucky to live in municipality	0,434	0,185	0,155	**0,835**	0,452	0,602	0,380
Feel proud living in municipality	0,422	0,200	0,189	**0,901**	0,476	0,560	0,340
Greenhouse gas emissions per 1000 inhabitants	-0,089	0,287	-0,067	-0,017	-0,096	-0,106	-0,010
Immigrants are well integrated	0,358	-0,062	0,155	0,356	0,361	0,387	**0,641**
Inequality in income distribution (P80/20)	0,098	**-0,881**	-0,079	-0,336	-0,350	-0,278	0,111
Net population change per 1000 inhabitants	-0,240	**0,889**	-0,010	0,051	0,241	0,085	-0,191
No desire to move	0,326	0,211	0,132	**0,732**	0,328	0,365	0,283
Overcrowding per 1000 dwellings	0,201	**-0,793**	-0,093	-0,099	-0,314	0,003	0,267
Residents help each other	0,283	-0,124	0,160	0,337	0,186	0,304	**0,818**
Residents know each other	0,253	-0,338	0,023	0,111	-0,100	0,114	**0,730**
Satisfaction with air quality	**0,835**	-0,178	0,185	0,356	0,255	0,410	0,313
Satisfaction with cleanliness	**0,815**	-0,071	0,211	0,552	0,428	0,547	0,394
Satisfaction with cultural facilities	0,333	0,260	0,239	0,527	0,474	**0,800**	0,302
Satisfaction with educational facilities	0,358	0,146	0,230	0,439	**0,756**	0,465	0,227
Satisfaction with green spaces	0,487	0,076	0,155	0,587	0,474	**0,815**	0,346
Satisfaction with health services	0,306	0,155	0,274	0,445	**0,729**	0,487	0,267
Satisfaction with noise level	**0,874**	-0,247	0,083	0,416	0,198	0,367	0,396
Satisfaction with place of residence	0,416	0,044	0,406	0,633	0,317	0,407	0,213
Satisfaction with public transport	0,110	0,277	0,111	0,251	**0,673**	0,306	0,056
Satisfaction with retail availability	0,230	0,436	0,165	0,458	**0,780**	0,542	0,164
Satisfaction with sports facilities	0,395	-0,075	0,142	0,464	0,497	**0,780**	0,408
Satisfaction with streets and buildings	0,453	0,218	0,183	0,545	0,531	**0,806**	0,314
Satisfied living in municipality	0,566	0,125	0,281	**0,846**	0,584	0,660	0,433
Satisfied with household finances	0,133	0,008	**0,864**	0,205	0,200	0,201	0,095
Satisfied with professional situation	0,191	0,079	**0,864**	0,249	0,261	0,187	0,201
Trust in other residents	0,381	0,011	0,158	0,462	0,293	0,449	**0,669**

Annex 16 - Final PLS-SEM model with standardised path coefficients.
Source: Output from SmartPLS software



Annex 17 – Alternative PLS-SEM model, its path coefficients and estimated model fit.
Source: Output from SmartPLS software.



	Original sample	T statistics	P-values
Environmental quality satisfaction -> Place attachment	0.258	4.166	0.000
Municipal context -> Perceived economic security	0.051	0.757	0.449
Municipal context -> Place attachment	0.192	4.217	0.000
Municipal context -> Satisfaction with essential services	0.347	5.737	0.000
Municipal context -> Satisfaction with urban amenities	0.151	2.593	0.010
Satisfaction with essential services -> Place attachment	0.138	1.945	0.052
Satisfaction with urban amenities -> Place attachment	0.339	5.195	0.000
Social cohesion -> Place attachment	0.177	2.875	0.004
Estimated model fit (SRMR)	0.183		

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