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SPATIAL ANALYSIS OF E-SCOOTER TRIPS IN PORTO

MADHU BELBASE

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Knowledge is Power

Francis Bacon

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ABSTRACT

This dissertation examines the spatial and temporal distribution of shared e-scooter activity in Porto, Matosinhos, Vila Nova de Gaia and Espinho, and its relationship with public transport, designated parking, cycle infrastructure and the surrounding urban environment.

Operational trip records from a single operator were analysed for the period from January 2024 to February 2025. After data cleaning, 125,874 valid trips were retained from 142,476 records. The work followed three main phases: analysis of trip origins and destinations to identify spatial and temporal patterns; proximity and interaction analysis around public transport stops and designated parking; and grid-based modelling of trip-start demand using a 300 m × 300 m spatial grid and Zero-Inflated Negative Binomial models. A post-model GIS classification was then used to identify infrastructure-support and planning-priority areas.

The average trip distance was 2.82 km and the average duration was 15.34 minutes. Activity was concentrated from midday onward and was strongest in Porto, which accounted for 76.71% of trips. Approximately 80.21% of trip points were within 100 m of public transport, while 24.30% of both trip origins and destinations were within 100 m of designated parking. The models identified significant associations with parking and public transport accessibility, population density, tourism, cycle-lane length and commercial activity.

The GIS analysis identified 106 high-demand cells, about 3% of the analytical grid, accounting for approximately 83% of trip starts. Of these, 74 showed infrastructure gaps and 32 were classified as supported high-demand locations near public transport.

The study provides a multi-scale framework for identifying where e-scooter demand and supporting infrastructure are aligned or mismatched.

KEYWORDS: shared e-scooters, micromobility, spatial analysis, public transport, parking infrastructure, Zero-Inflated Negative Binomial model.

RESUMO

Esta dissertação analisa a distribuição espacial e temporal da utilização de trotinetes elétricas partilhadas no Porto, Matosinhos, Vila Nova de Gaia e Espinho, e a sua relação com os transportes públicos, o estacionamento designado, a infraestrutura ciclável e o contexto urbano envolvente.

Foram analisados registos operacionais de viagens de um único operador, relativos ao período entre janeiro de 2024 e fevereiro de 2025. Após a limpeza dos dados, foram retidas 125 874 viagens válidas de um total inicial de 142 476 registos. O trabalho desenvolveu-se em três fases principais: análise das origens e destinos das viagens para identificar padrões espaciais e temporais; análise de proximidade e interação em torno das paragens de transporte público e dos locais de estacionamento designado; e modelação da procura, medida pelas origens das viagens, numa grelha espacial de 300 m × 300 m, através de modelos Binomiais Negativos Inflacionados de Zeros. Posteriormente, foi aplicada uma classificação SIG para identificar áreas de suporte infraestrutural e prioridades de planeamento.

A distância média das viagens foi de 2,82 km e a duração média de 15,34 minutos. A atividade concentrou-se a partir do meio-dia e foi mais intensa no Porto, que representou 76,71% das viagens. Cerca de 80,21% dos pontos das viagens localizaram-se a menos de 100 m de transportes públicos, enquanto 24,30% das origens e dos destinos se situaram a menos de 100 m de estacionamento designado. Os modelos identificaram associações significativas com a acessibilidade ao estacionamento e aos transportes públicos, densidade populacional, turismo, extensão de vias cicláveis e atividade comercial.

A análise SIG identificou 106 células de elevada procura, cerca de 3% da grelha analítica, responsáveis por aproximadamente 83% das origens das viagens. Destas, 74 apresentavam lacunas de infraestrutura e 32 foram classificadas como áreas de elevada procura com suporte próximo de transporte público.

O estudo apresenta uma abordagem multiescala para identificar onde a procura por trotinetes elétricas e as infraestruturas de apoio estão alinhadas ou desajustadas.

PALAVRAS-CHAVE: trotinetes elétricas partilhadas, micromobilidade, análise espacial, transporte público, estacionamento, modelo Binomial Negativo Inflacionado de Zeros

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SYMBOLS, ACRONYMS AND ABBREVIATIONS

GIS *Geographic Information System*

GPS *Global Positioning System*

KDE *Kernel Density Estimation*

MAUP *Modifiable Areal Unit Problem*

NLOGIT *Econometric and statistical modelling software*

OD *Origin-Destination*

OSM *OpenStreetMap*

PT *Public Transport*

QGIS *Quantum Geographic Information System*

RQ *Research Question*

ZINB *Zero-Inflated Negative Binomial*

IRR *Incidence Rate Ratio*

EPSG *European Petroleum Survey Group (the coordinate-system registry code, e.g. "EPSG:3763")*

INE *Instituto Nacional de Estatística*

1
INTRODUCTION

1.1 Overview and Research Context

Shared e-scooters have become a common sight in many cities, particularly in areas with busy streets, mixed land uses and many short-distance journeys. Their main difference from conventional public transport is that they do not follow a fixed route or timetable. Users locate a vehicle through an application, unlock it and usually leave it at or near their destination. This makes the service flexible, but it also means that trips are closely connected to the location of vehicles, local demand and the rules that govern where scooters can operate and park.

The use of shared e-scooters varies considerably between cities and serve different transport functions. Studies in several American cities found that e-scooter activity was higher in urban centres and university areas, although the timing of peak demand differed between locations (Huo et al., 2021). They can provide a first- or last-mile connection to public transport, replace part of a walking journey, substitute for a bicycle or public transport trip, or replace a short private-car journey. The balance between these functions depends on the local transport network, the built environment, the availability of other modes and the way the service is managed. A review of recent research found that the modes replaced by shared e-scooters vary considerably between cities, with walking, public transport, cycling and car travel all reported in different settings (Wang et al., 2023).

The connection with public transport is particularly important because e-scooters can help users reach or leave a station when walking is inconvenient or when the distance between the station and the final destination is too long. Fearnley et al. (2020) found that e-scooters were used by many public transport passengers for first- and last-mile journeys in Oslo. A comparison of 124

European cities also found that the extent to which shared e-scooters acted as feeders to public transport differed widely between cities (Li et al., 2024).

However, a trip that starts or ends near a public transport stop does not prove that a transfer took place. A stop may also be located close to offices, shops, universities, tourist attractions or residential buildings. Operational trip data usually provide the location and time of a trip, but not the rider's purpose or the mode used immediately before or after the journey. Studies that seek to identify actual public transport connections therefore use additional information, such as surveys, journey-planner data or travel records (Aarhaug et al., 2023). Yin et al. (2024) used post-ride survey information to identify e-scooter trips that were connected to public transport, demonstrating the value of data that records the traveller's purpose.

The urban environment is another important part of the analysis. E-scooter activity tends to be higher in areas with greater population and employment density, mixed land uses, better access to transport and a larger number of nearby destinations. Huo et al. (2021) found positive relationships between e-scooter ridership, population density, employment density and proximity to central areas. Research in Chicago also linked e-scooter demand with population density, mixed land use, parks, parking conditions and public transport-related variables (Tuli et al., 2021).

These variables often occur together in central areas. A location with high e-scooter activity and many public transport stops may also have more jobs, shops, visitors and housing. It can therefore be difficult to determine whether the activity is related specifically to public transport or to the wider concentration of urban functions. This is one reason why the present study examines public transport proximity together with land use, population, parking, cycling infrastructure and other local characteristics.

Parking is another important issue in shared e-scooter systems. The dockless model gives users more freedom over where a trip ends, but vehicles may be left on pavements or in other locations that interfere with pedestrians and other street users. Research in Oslo and Trondheim found that dedicated parking measures reduced the number of scooters obstructing pedestrian movement, although the results varied between locations. The study also showed that the exact placement of parking facilities was important (Karlsen et al., 2025).

The presence of parking facilities does not automatically mean that users will use them. Parking locations need to be close enough to users' destinations and convenient enough to avoid

unnecessary walking. Hemphill et al. (2022) found that dedicated parking improved compliance, while built-environment conditions associated with busy pedestrian areas increased the likelihood of parking problems. More recent research across twelve cities found that a denser network of designated parking areas was associated with higher compliance, although the appropriate level of provision varied according to land use and local activity (Meng et al., 2025).

These findings suggest that parking should be studied in terms of both availability and location. A designated parking space may exist in a municipality, but it may not be located where users actually finish their trips. For this reason, the present study examines the spatial alignment between trip locations and designated parking rather than assuming that proximity is the same as confirmed compliance.

These issues are particularly relevant to the Porto Metropolitan Area. The study covers Porto, Matosinhos, Vila Nova de Gaia and Espinho. The four municipalities form a connected urban area, but they differ in population density, land use, transport provision, tourism, commercial activity, housing and cycling infrastructure. Metropolitan-wide averages could hide important differences between the central city, the coastal areas and the more peripheral parts of the study area.

1.2 Conceptual Framework

The conceptual framework for this study starts from the idea that e-scooter activity is shaped by the interaction between users, vehicle availability, land use, transport infrastructure and local urban conditions. Trips are not distributed randomly. They are more likely to occur near where vehicles are available, where people want to travel and where the street and transport network make short trips practical.

The framework operates at three levels as shown in Fig. 1.1. The first level is the individual trip. Origins and destinations are analysed separately because they represent different parts of the journey. An origin shows where a user accessed a scooter and may be related to vehicle availability, local activity and operator redistribution. A destination shows where the trip ended and where the scooter may have been left. It may therefore be related to the attraction of the location and to parking pressure.

The second level is the facility, meaning the infrastructure location itself: an individual public transport stop or station, or a designated e-scooter parking location defined by the municipalities. At this level, the e-scooter activity surrounding each individual facility is examined by counting the trip starts and trip ends that occur nearby. This makes it possible to identify differences between individual infrastructure locations that would be hidden by a single metropolitan-wide proximity percentage.

The third level is the urban context. Trip starts and urban characteristics are brought together within 300 m × 300 m cells so that demand can be compared with population, land use, public transport, parking, cycling infrastructure, tourism, education and other local conditions. The grid is the analytical tool; the object of analysis at this level is the urban context in which e-scooter activity occurs.

As mentioned before, public transport is central to the framework because shared e-scooters may provide access to or from transit stops. However, proximity to a stop or a station is not considered proof of a transfer. The study therefore uses proximity to identify locations where a public transport connection may be possible, while recognising that the available trip records do not reveal the rider's purpose.

The distinction between proximity and confirmed behaviour is important. A trip near a stop or station may be part of a first- or last-mile journey, but it may also be an independent trip to a nearby workplace, shop, university, tourist attraction or home. The analysis, therefore, avoids describing all trips near public transport as integrated trips.

Parking is treated in a similar way. A trip near designated parking may indicate that a parking location is conveniently placed, but it does not confirm that the scooter was left inside the marked area. GPS error, the use of point locations to represent parking areas and overlapping catchments can all affect the interpretation of the results.

Throughout the framework, proximity is therefore treated as a spatial relationship rather than proof of user intention.

These three levels are connected through a GIS-based workflow followed by statistical modelling, described in Chapter 3. The area-level analysis focuses on observed trip-start demand and the characteristics of the urban context in which it occurs, including infrastructure, land use and activity locations. It does not estimate the total potential demand for e-scooters across the metropolitan area. The statistical models examine associations between observed trip

starts and selected urban, demographic, land-use and infrastructure variables. These associations are not interpreted as direct causal effects.

The logic of the framework is summarised in Fig. 1.1 , which shows the three analytical levels and the relationships between them.

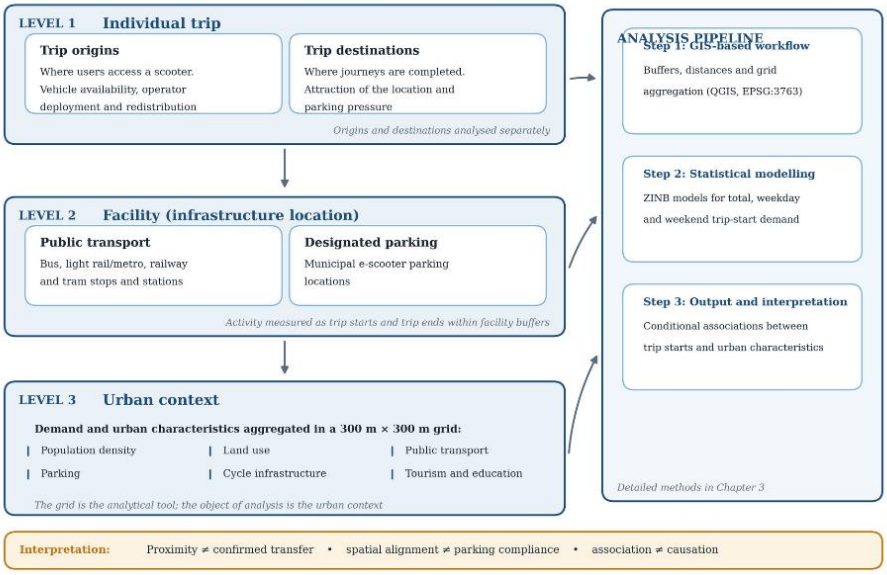


Fig. 1.1.Conceptual framework of the study.

The framework is deliberately cautious. It does not assume that public transport proximity represents a confirmed transfer, that parking proximity represents confirmed compliance, or that statistical association represents causation. Instead, it identifies where e-scooter activity and urban infrastructure appear to align and where gaps may require further planning attention.

The research developed in this dissertation has also contributed to two scientific papers. The paper *"Mobility Patterns of Shared E-Scooter Users in Porto"* has been accepted for publication in the CSUM conference proceedings, while the paper *"Shared E-Scooter Demand in the Porto Metropolitan Area: Spatial Concentration, Built Environment, and Infrastructure Gaps"* is currently under revision for an IEEE publication. The two papers address complementary parts of the dissertation, with the first focusing mainly on spatial and temporal trip patterns and infrastructure proximity, and the second on grid-level demand modelling and infrastructure gaps.

1.3 Research Aim and Objectives

1.3.1 Research Aim

The main aim of this dissertation is to examine how shared e-scooter activity is distributed across Porto, Matosinhos, Vila Nova de Gaia and Espinho, both spatially and temporally, and to assess how this activity relates to public transport, designated parking, cycling infrastructure and the surrounding urban environment.

The study also aims to identify locations where e-scooter activity and supporting infrastructure appear to be well aligned, as well as locations where demand is high but parking or cycling infrastructure appears limited.

1.3.2 Research Objectives

The specific objectives are:

- To describe the spatial and temporal distribution of shared e-scooter activity across Porto, Matosinhos, Vila Nova de Gaia and Espinho.
- To assess the proximity of e-scooter trips to public transport stops using immediate and broader walking-distance thresholds.
- To examine the distribution of activity around individual public transport stops and identify stops with relatively high, low or no nearby e-scooter activity.
- To assess the spatial alignment between e-scooter trip starts and designated parking locations.
- To compare parking alignment across the four municipalities and around individual parking locations.
- To identify the urban, demographic, land-use and transport-infrastructure characteristics associated with trip-start demand.
- To use the observed spatial patterns to identify location-specific planning priorities, particularly parking and cycling infrastructure.

1.4 Research Questions

This study is guided by the following research questions:

RQ1: How is shared e-scooter activity distributed spatially and temporally across the Porto Metropolitan Area?

RQ2: How does e-scooter activity relate spatially to public transport stops and designated parking across the study area?

RQ3: Which urban, demographic, land-use and transport-infrastructure characteristics are associated with e-scooter trip-start demand, and where does high demand coincide with limited supporting infrastructure?

The research questions will guide the work activities and the applied methodology to contribute to the knowledge about e-scooter trips and to support the planning priorities to improve the current situation.

1.5 STRUCTURE OF THE THESIS

This thesis is organised into seven chapters.

Chapter 1: introduces the research topic and the conceptual basis of the study. It presents the overview and research context, the conceptual framework, the research aim and objectives, and the research questions that guide the analysis.

Chapter 2: reviews the existing literature on shared e-scooter mobility. It discusses spatial and temporal activity patterns, the influence of the built environment, relationships with public transport, parking infrastructure, mode substitution, and the spatial and statistical methods used in previous studies.

Chapter 3: presents the data and methodology. It describes the study area, and explains the preparation and cleaning of the trip records, the creation of origin and destination layers, the temporal and trip-level variables, the public transport and parking proximity methods, the facility-level comparisons, the construction of the 300 m × 300 m grid, and the preparation of the statistical dataset.

Chapter 4: presents the study results. It covers the spatial and temporal distribution of trips, differences between municipalities and parishes, proximity to public transport, activity around individual stops, parking alignment, activity around individual parking locations, grid-level characteristics, and the statistical model results.

Chapter 5: discusses the findings in relation to the research questions and the wider literature. It interprets the results concerning shared e-scooter activity, the urban context, public transport and parking, and considers what these findings mean for the study.

Chapter 6: develops an infrastructure intervention planning perspective. It brings together the GIS-based infrastructure support results and the planning implications, identifying locations where observed demand and infrastructure provision appear misaligned and examining potential planning priorities and interventions from a Civil Engineering perspective.

Chapter 7: presents the conclusions and recommendations. It summarises the main findings and contribution of the study, discusses the limitations that affect the interpretation of the results, and suggests directions for future research.

2
LITERATURE REVIEW

2.1 INTRODUCTION

Research on shared e-scooters has grown quickly, but studies have focused on different questions about how these services are used and how they affect cities. Review studies identify multiple lines of enquiry, including mobility patterns, user perceptions, environmental effects, public transport integration, and policy and operational questions (Badia & Jenelius, 2023; Orozco-Fontalvo et al., 2023).

Some studies examine when and where trips occur, including differences between neighborhoods, times of day, weekdays, weekends, and seasons (Abouelela et al., 2023; Foissaud et al., 2022; Garus et al., 2025; McKenzie, 2019; Shah et al., 2023). Other studies examine how demand relates to the built environment, including population and employment density, land-use diversity, street connectivity, proximity to the city centre, public transport accessibility, and local destinations (Huo et al., 2021; Heumann et al., 2025). Research has also considered the modes that e-scooter trips may replace, with walking, cycling, public transport, and car travel all reported in different settings (Badia & Jenelius, 2023; Wang et al., 2023).

Individually, each strand offers valuable evidence. Read together, however, they leave one question largely unresolved: spatial proximity between an e-scooter trip and a public transport stop or designated parking space is often interpreted as evidence of a potential functional relationship, although proximity alone cannot confirm that a transfer occurred or that a scooter was parked compliantly. Distance-based approaches are widely used because they provide a practical way to analyse large datasets, but the choice of a threshold does not by itself establish the purpose or outcome of a trip (Li et al., 2024).

A smaller group of studies uses surveys, linked data, or more detailed classification methods to examine public transport connections and distinguish access, egress, complementary, substitutive, and independent trips (Aarhaug et al., 2023; Vinagre Díaz et al., 2024; Yin et al., 2024). This distinction matters throughout the review because proximity does not necessarily reveal why a trip occurred or how the scooter was used.

Research on spatial and temporal patterns identifies demand concentrations across particular locations and periods, but location and timing alone do not always reveal whether trips are associated with commuting, tourism, leisure, short errands, or public transport access. Detailed trip analyses show that different purposes can produce distinct temporal and spatial patterns, while cross-city studies demonstrate that weekday, weekend, and seasonal profiles vary according to local conditions (Abouelela et al., 2023; Foissaud et al., 2022; Garus et al., 2025; Shah et al., 2023). Built-environment research commonly relates demand to population density, employment density, land-use mix, centrality, intersection density, public transport access, and destination concentration (Huo et al., 2021; Heumann et al., 2025). However, the strength and direction of these relationships vary between cities and user groups, which limits the direct transfer of findings from one context to another.

The proximity-versus-integration problem is particularly important in the public transport literature. Studies use distance thresholds, catchment areas, trip-end locations, service-level measures, surveys, and network-based approaches to examine whether e-scooters extend access to public transport or operate independently of it (Fearnley et al., 2020; Li et al., 2024; Oeschger et al., 2020; Reynolds et al., 2025). A trip located near a stop may represent a first or last-mile connection, but it may also be a separate journey occurring near the same workplace, university, commercial area, or other destination. Evidence from user-validated data shows that buffer-based approaches can overestimate the number of transit-connecting trips and identify imprecise spatial and temporal patterns (Yin et al., 2024). Confirming actual integration therefore requires information about travel purpose, the mode used before or after the e-scooter trip, or the sequence of movements across the transport network.

Parking research addresses a related but distinct problem. Studies show that designated parking, legally parkable space, the density of parking facilities, and the location of parking measures influence parking behaviour and compliance (Hemphill et al., 2022; Karlsen et al., 2025; Meng et al., 2025). However, the presence of a designated space near a trip does not demonstrate that

the scooter was parked inside that space. Parking compliance is affected by the physical characteristics of the street, the availability and convenience of designated facilities, the location of natural trip-end points, and the accuracy of the available spatial data (Hemphill et al., 2022; Karlsen et al., 2025).

The methods used to measure demand and proximity also shape the findings. Trip-level analysis provides information about the timing, location, and characteristics of individual journeys (McKenzie, 2019; Shah et al., 2023). Facility and stop-level approaches allow researchers to examine activity around specific infrastructure locations, while grid-based approaches permit comparisons between demand and area-level characteristics such as population, land use, accessibility, and infrastructure (Huo et al., 2021; Currie et al., 2025). Distance buffers offer a consistent and practical basis for comparison, but they simplify walking access and may produce misleading estimates when used as a direct substitute for observed multimodal behaviour (Li et al., 2024; Yin et al., 2024).

To conduct the literature review covering the three levels of the framework and related methods, five themes were chosen also to reflect the main questions addressed in this study. The first four cover the main areas examined in this study: where and when shared e-scooter trips occur, how demand relates to the urban environment, how trips relate spatially to public transport, and how they relate to designated parking. The fifth addresses how these relationships should be measured and interpreted in the first place. The review covers 45 unique papers, with some studies contributing to more than one theme. Section 2.2 explains the literature-search procedure and thematic classification. Sections 2.3 to 2.6 examine the four substantive areas, Section 2.7 considers spatial units and analytical approaches, and Section 2.8 brings the resulting empirical and methodological gaps together to position the contribution of this study.

This chapter, therefore, treats the existing literature not only as a source of established findings but also as evidence of how shared e-scooter activity has been defined, measured, and interpreted. The aim of this chapter is to identify what is currently known, where findings remain context-dependent or methodologically limited, and how the reviewed evidence establishes the rationale for the research questions and analytical approach developed in the following chapters.

2.2 Literature Search and Thematic Classification

A structured literature search was carried out to identify studies relevant to shared e-scooter use in urban areas. The procedure was designed to make clear how the studies were found, selected, and organized. This follows the recommendation that a literature review should explain its search and selection process rather than present the choice of sources as informal or unexplained (Van Wee & Banister, 2016).

The main searches were conducted using Scopus and ScienceDirect database sources. The search terms combined expressions related to shared e-scooters with terms describing the main topics of this thesis. The core terms were "shared e-scooter," "e-scooter sharing," and "shared micromobility." These were combined with terms such as "spatial analysis," "spatiotemporal patterns," GIS, "public transport," "first mile," "last mile," parking, "built environment," "land use," and "demand modelling." The following combinations illustrate the search approach:

- ("shared e-scooter" OR "e-scooter sharing") AND ("spatial analysis" OR spatiotemporal OR GIS)
- ("shared e-scooter" OR "shared micromobility") AND ("public transport" OR "first mile" OR "last mile")
- ("shared e-scooter" OR "e-scooter sharing") AND (parking OR "built environment" OR "land use")
- ("shared e-scooter" OR "shared micromobility") AND ("demand modelling" OR "trip data" OR "spatial demand")

The search results were first screened by title and abstract. A study was considered relevant when it examined shared e-scooters, or a closely related shared micromobility service, in an urban setting and provided evidence related to one or more of the research questions.

Among the relevant studies, inclusion was restricted to research based on operational trip records, GIS analysis, user surveys, spatial demand models or statistical analysis, because these approaches correspond directly to the analytical needs of the present study. This approach allowed the review to include both studies describing observed use and studies examining the factors associated with that use.

Studies were excluded when their main focus was vehicle engineering, battery performance, medical injuries, or legal issues without a clear empirical analysis of urban mobility. Studies

dealing only with privately owned e-scooters were also excluded unless they provided useful background for understanding shared services. This distinction was necessary because the behaviour, operating model, and planning implications of shared and privately owned devices are not the same.

The full texts of the remaining studies were then examined. For each paper, information was recorded on the study location, data source, observation period, spatial unit, analytical method, variables, main findings, and stated limitations. This information was used to compare the studies within and across themes rather than to describe each paper separately. Relevant studies cited in the selected papers were identified through backward snowballing, while more recent studies related to important papers were identified through selective forward searching.

The selected studies were organised into five themes:

1. Spatial and temporal patterns of shared e-scooter use;
2. Built environment and urban context;
3. Relationships between shared e-scooters and public transport;
4. Parking infrastructure and trip-end behaviour; and
5. Spatial units and analytical approaches.

The search, screening and classification procedure summarised in Fig. 2.1 yielded 45 unique papers, organised into the five themes introduced in Section 2.1. The full summary of the reviewed papers, including their locations, data sources, methods, findings and limitations, is provided in Appendix A.3.

The purpose of this process was not to claim that every publication on shared e-scooters was identified. Instead, the review focused on urban studies that were directly relevant to the research questions and that provided evidence useful for analysing spatial and temporal activity, the built environment, public transport, parking, and analytical methods.

The resulting thematic organisation provides the basis for comparing previous findings, identifying limitations in the existing research, and positioning the present study.

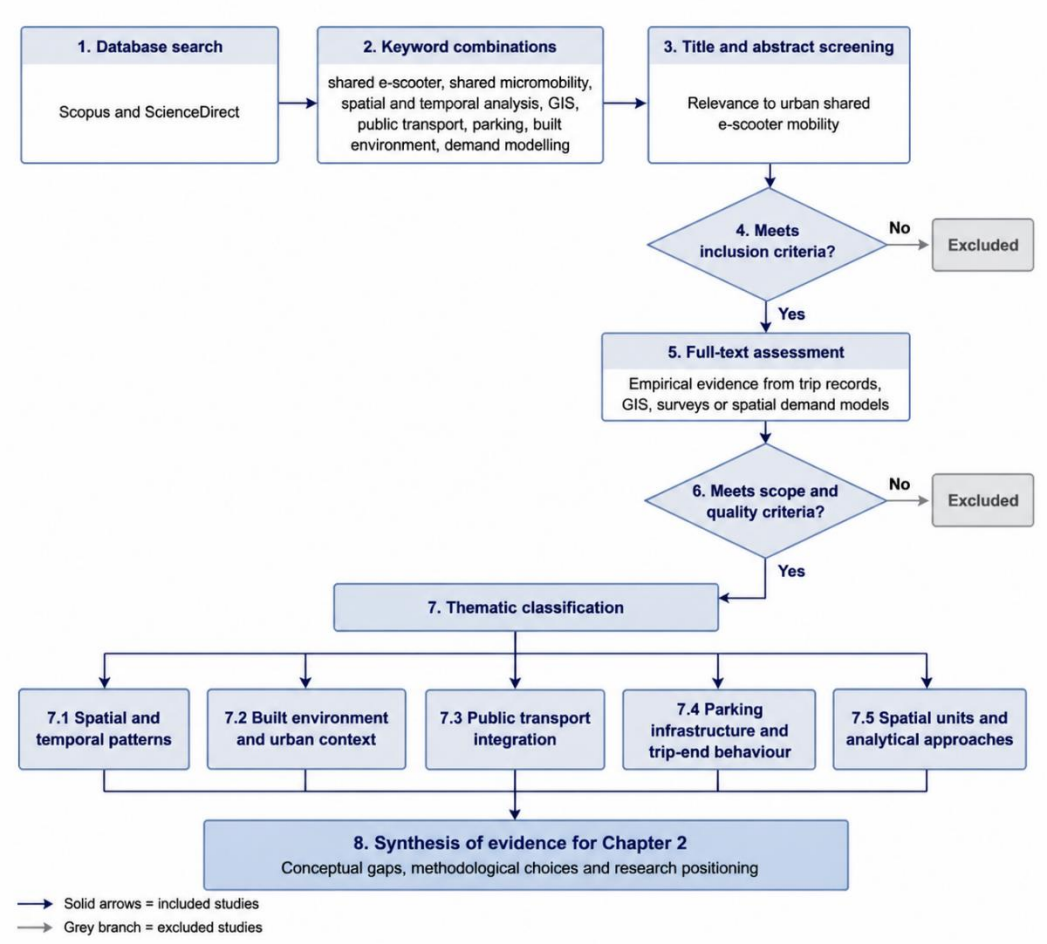


Fig. 2.1.Literature search, screening and thematic classification process.

2.3 Literature Spatial and Temporal Patterns of Shared E-Scooter Use

The studies reviewed under this theme mainly use operational trip records containing the location and time of individual journeys. Thirteen of the 45 reviewed papers examined the spatial and temporal distribution of shared e-scooter use. Most focused on one city or compared a small number of cities, using descriptive statistics, GIS mapping, spatial clustering, temporal profiles, regression models, or trip-classification methods. Some studies also combined trip records with land-use, weather, public transport, or point-of-interest data (Abouelela et al., 2023; Huo et al., 2021; McKenzie, 2019; Shah et al., 2023).

The spatial evidence is fairly consistent. Shared e-scooter activity is usually concentrated in central districts, commercial areas, university campuses, tourist locations, and other places where many destinations are close together. McKenzie (2019) found a clear concentration of scooter-share trips around the centre of Washington, D.C. Huo et al. (2021), using data from

five U.S. cities, also found higher ridership in urban centres and university areas. A multi-city study in North America reported similar patterns, with weekday activity concentrated around downtown areas and educational institutions, while weekend activity was more closely associated with leisure destinations such as restaurants, bars, parks, and recreational areas (Abouelela et al., 2023).

These patterns suggest that shared e-scooter demand is closely related to the concentration of activities and destinations in urban space. Central and mixed-use areas offer more possible origins and destinations within a relatively short distance, which may make flexible, station-free travel more useful. However, the presence of high activity in a particular location does not explain the purpose of every trip. The same area may attract commuters, students, tourists, shoppers, and leisure users.

Time is also an important part of the pattern. Several studies report higher demand from the middle of the day through the afternoon, although the shape of the daily profile varies between cities. Huo et al. (2021) found that ridership in five U.S. cities generally reached its highest level between late morning and late afternoon. Abouelela et al. (2023) reported two main weekday peaks in the cities they examined, while weekend demand generally had a single late-afternoon peak. Full-year studies also show that demand changes across seasons, holidays, weather conditions, and local weekly routines (Foissaud et al., 2022; Garus et al., 2025).

The difference between weekdays and weekends is not simply a difference in the amount of use. It can also reflect different types of activity. Shah et al. (2023) identified several temporal and spatial usage patterns in Nashville, including work and school trips, daytime errands, social trips, nighttime entertainment, and other utilitarian journeys. Weekend social and entertainment trips were concentrated in commercial areas, downtown locations, and areas around leisure destinations. Foissaud et al. (2022) similarly distinguished between local and tourist use and found differences in trip timing, duration, and location.

These findings show why location and time should be analysed together. A concentration of trips in a central area during the afternoon may be associated with work, education, tourism, shopping, or leisure. Operational trip records can identify when and where a journey took place, but they usually do not record the traveller's purpose. It is therefore difficult to label a particular time period as commuting or leisure without additional information such as a survey, trip-purpose classification, or linked travel record.

The literature also differs in the way it measures spatial and temporal demand. Some studies count trips by administrative area or census zone, while others use regular grids, traffic analysis zones, origin-destination points, or smaller spatial units. Temporal analysis may be based on hours, weekdays, weekends, months, seasons, or special events. These choices affect the patterns that become visible. A large spatial unit may conceal differences between nearby neighbourhoods, while a small unit may produce many areas with few or no observations.

Two limitations stand out from the reviewed studies. First, much of the literature describes where and when shared e-scooter activity is concentrated without fully explaining the combination of factors that produces those patterns. Second, the results are not always directly comparable because the studies use different cities, observation periods, spatial units, data sources, and definitions of demand. A weekday peak in one city may not have the same meaning as a weekday peak in another city, particularly where tourism, public transport, weather, or local travel routines differ.

Overall, previous research provides strong evidence that shared e-scooter use varies across both space and time. Activity commonly concentrates in central, destination-rich areas, while the timing of demand changes according to the day of the week, season, weather, local events, and the functions of different places. The literature also shows that descriptive patterns alone are not enough to explain why demand occurs where it does. This provides the basis for the next section, which examines how the built environment and wider urban context are related to shared e-scooter activity. A study-by-study summary of research on spatial and temporal patterns is provided in Appendix A.3, under ‘Spatial and Temporal Patterns of Shared E-Scooter Use’.

2.4 Built Environment and Urban Context

The built environment and wider urban context were examined in 10 of the 45 reviewed papers. The reviewed studies on the built environment and urban context are summarised in Appendix A.3, under ‘Built Environment and Urban Context’. These studies investigate how the physical, functional, and social characteristics of urban areas are associated with shared e-scooter activity. Most combine trip records with information on population, employment, land use, street networks, public transport, cycling infrastructure, parking, and local destinations (Huo et al., 2021; Tuli et al., 2021; Jin & Sui, 2024).

A consistent finding is that e-scooter activity tends to be higher in dense and accessible parts of cities. Huo et al. (2021), using data from five U.S. cities, found positive relationships between ridership and population density, employment density, intersection density, land-use mix, and bus stop density. Ridership was also higher in areas closer to the city centre. Research in Chicago identified similar relationships, with higher demand associated with population density, mixed land use, parks, parking conditions, and several transport-related variables (Tuli et al., 2021).

These relationships are not explained by density alone. Areas with a large population may generate more trips, but the type and arrangement of activities in those areas also matter. Commercial areas, university districts, offices, parks, restaurants, and other destinations can attract trips because they bring different activities within a relatively short distance. Studies comparing Austin and Minneapolis found that land-use diversity and proximity to the city centre were associated with higher ridership, although some relationships differed between the two cities (Bai & Jiao, 2020). This suggests that shared e-scooter demand depends not only on how many people live in an area, but also on what people can reach from it.

Land use can also help distinguish between different types of users and trips. Research in Bordeaux separated tourist and local activity and found that both groups responded to different combinations of destinations, public transport, employment, and cycling infrastructure (Christoforou et al., 2023). In Louisville, commercial and recreational land uses were linked to higher trip density, while the effect of employment and other land-use variables differed between all-day and peak-period trips (Hosseinzadeh et al., 2021). These findings reinforce the point that a location may attract e-scooter trips for several reasons at the same time.

Transport and cycling infrastructure are also part of the urban context in which e-scooter use takes place. Several studies include public transport access, bus stop density, bicycle infrastructure, street connectivity, or the density of multimodal networks among the factors associated with demand (Huo et al., 2021; Tuli et al., 2021; Javadiansr et al., 2024). These variables may make short trips easier or safer, but their effects should not be interpreted in isolation. Transport stops, cycle lanes, commercial destinations, and dense land uses often occur in the same parts of a city, making it difficult to identify the separate contribution of each factor.

Socio-demographic characteristics and temporary conditions can also affect demand. Population age, income, education, weather, fleet availability, and local events have all been

considered in the reviewed studies. For example, Huo et al. (2021) found lower ridership in areas with older populations, while multi-city research showed that weather, day of the week, land use, infrastructure, and public transport accessibility were associated with changes in demand (Abouelela et al., 2023). Survey research in Braga also found differences in e-scooter use according to gender, trip origin, and the main mode of transport (Dias et al., 2024).

The reviewed evidence, therefore, supports a broad view of the built environment. Population and employment density, land-use diversity, accessibility, street connectivity, nearby destinations, transport infrastructure, and socio-demographic characteristics can all be related to e-scooter activity. However, these factors are often closely connected to one another, and their effects vary between cities and user groups. Comparative research has reported both consistent and inconsistent findings for variables such as land-use mix, centrality, cycling infrastructure, and transit access (Bai & Jiao, 2020; Jin & Sui, 2024; Tuli et al., 2021).

A further limitation is that most studies identify statistical associations rather than direct causal effects. A positive relationship between demand and a particular variable may partly reflect other characteristics of the same area. For example, central locations often have higher population and employment density, more mixed land use, more transport stops, more commercial destinations, and better cycling infrastructure at the same time. This makes it difficult to determine which factor is most important without a model that considers several variables together.

Overall, the built-environment literature shows that shared e-scooter use is closely related to the places where people live, work, study, shop, and spend their free time. It also shows that these relationships depend on local conditions and cannot be transferred directly from one city to another. The next section examines public transport in more detail, focusing on whether spatial proximity between e-scooter activity and transport stops indicates actual first or last-mile integration.

2.5 Transport and the First- and Last-Mile Question

Public transport relationships were examined in 11 of the 45 reviewed papers. The reviewed studies on the built environment and urban context are summarised in Appendix A.3, under ‘Public Transport Interaction’.These studies ask whether shared e-scooters help people reach public transport, leave a station or stop more easily, replace part of a public transport journey,

or operate independently of the public transport network. The literature uses several types of evidence, including trip records, surveys, distance measures, service-level comparisons, and network-based analysis.

The first and last-mile idea is based on the gap between a person's origin or destination and the nearest suitable public transport stop. An e-scooter may provide access from the origin to a station, known as an access trip, or help a passenger travel from a station to the final destination, known as an egress trip. Li et al. (2024) found that the potential for shared e-scooters to act as public transport feeders varied considerably across 124 European cities. Their findings suggest that the usefulness of e-scooters depends on the arrangement of the transport network, the location of destinations, and the distance that passengers would otherwise need to walk.

Several studies provide evidence that e-scooters can complement public transport in particular situations. Javadiansr et al. (2024) found that population density, intersection density, multimodal network density, and transit service characteristics were associated with e-scooter access and egress trips in Chicago. Gödde and Scheiner (2025) also identified access and egress trips to rail transit in Hanover, although their results showed that not all trips near rail stations had the same relationship with public transport. These findings suggest that e-scooters may improve access to public transport where walking distances are inconvenient or where the transport network does not adequately connect origins and destinations.

The relationship is not always complementary. Aarhaug et al. (2023) found that shared e-scooters both complemented and competed with public transport in Oslo. Some trips were used to reach or leave public transport, while others replaced public transport because the e-scooter provided a faster or more convenient alternative. Research from Melbourne similarly found that e-scooter trip ends were often concentrated in areas and at times when public transport service was already relatively strong, rather than mainly filling gaps in areas with poor service (Currie et al., 2025). The mode that an e-scooter replaces also varies between cities. Walking, cycling, public transport, and car travel have all been identified as possible alternatives (Wang et al., 2023).

The different findings partly reflect differences in how public transport relationships are identified. Some studies use surveys to ask users whether an e-scooter trip was connected to public transport. Others classify trips using origin and destination locations, time of travel, transport service levels, or the relationship between trip points and transit stops. Vinagre Díaz

et al. (2024), for example, used a data-driven classification method to distinguish between different types of relationships with public transport rather than relying on one predefined distance threshold.

Distance-based methods are useful when large operational datasets need to be analysed consistently, but they have clear limits. Li et al. (2024) note that there is no perfect way to infer public transport integration from trip locations alone. Yin et al. (2024) compared buffer-based estimates with user-validated trip information and found that buffer zones could substantially overestimate the number of e-scooter trips actually connected to rail transport. Network-based approaches provide a more detailed alternative because they can consider route directness, walking paths, slope, cycling infrastructure, and the quality of access around stops (Oeschger et al., 2025).

The distinction between proximity and integration is therefore central to this literature. A trip that starts or ends near a public transport stop may involve a transfer, but it may also be a separate journey to a workplace, shop, university, home, or tourist destination located in the same area. Public transport stops and e-scooter activity are often concentrated in central and busy parts of cities, so spatial overlap can result from shared urban conditions rather than from a direct connection between the two modes.

Overall, the literature shows that shared e-scooters can support first and last-mile travel, but they do not serve this function on every trip. Their relationship with public transport depends on the quality and location of the public transport network, walking distances, trip purpose, time of day, service levels, and the availability of suitable parking and routes around stops. Proximity analysis can identify places where interaction is possible, but it cannot by itself confirm that a transfer took place. The next section examines the related issue of parking infrastructure and trip-end behaviour, where the location of designated spaces also affects how e-scooter activity is interpreted.

2.6 Parking Infrastructure and Trip-end Behavior

Parking infrastructure and trip-end behaviour were examined in six of the 45 reviewed studies as summarized in Appendix A.3 under ‘Parking Infrastructure and Trip-End Behaviour’. Parking is an important issue in shared e-scooter research because it affects both user convenience and the use of public space. Free-floating services allow users to finish a trip close

to their destination, but the same flexibility can leave scooters in locations that obstruct pedestrians or reduce the accessibility of sidewalks. Designated parking is intended to preserve the convenience of the service while giving users and operators clearer places to leave the vehicles.

Parking problems are not distributed evenly across a city. They are more likely to occur around commercial areas, transport interchanges, tourist locations, and other places with a high concentration of trip ends. This makes trip-end analysis particularly useful. A large number of trip destinations near a parking facility may indicate that the facility is located close to places where users want to finish their journeys. However, the trip starts and the trip ends do not have the same meaning. Trip starts may be influenced by operator deployment or vehicle redistribution, while trip ends are more closely related to user decisions about where to leave the scooter.

The surrounding built environment has an important influence on parking compliance. Hemphill et al. (2022) found that compliance in Portland varied according to sidewalk width, legally parkable space, and other features of the street environment. Their results also showed higher compliance on blocks with designated e-scooter parking. This suggests that parking behaviour is not only a matter of individual choice. It is also affected by whether the street provides a practical and acceptable place to leave the vehicle.

The amount and distribution of parking infrastructure also matter. Meng et al. (2025), using data from 12 cities, found that denser networks of designated parking areas were associated with higher parking compliance. Their results also showed that the appropriate level of provision varied according to land use and local activity. Areas with offices, public transport, mixed land use, tourism, or leisure destinations may require more parking capacity because they attract a larger number of trips and have greater pressure on public space.

Dedicated parking spaces can reduce the number of scooters that obstruct pedestrians, but their effect depends on their location and convenience. Karlsen et al. (2025) found that many riders ending trips near a parking measure left their scooters in or near the designated parking area. The effect was strongest close to the facility and became weaker with distance. Their findings also showed that dedicated parking did not eliminate problematic parking completely. A parking facility may therefore be available but still fail to attract users if it is difficult to reach, too far from the destination, poorly located, or unable to accommodate the level of demand.

Several studies have examined how trip data can be used to improve parking provision. Sandoval et al. (2021) developed a data-based method for identifying parking locations and allocating capacity according to observed demand. Their approach also considered sidewalk width so that parking facilities could be placed where they would reduce problems on narrow sidewalks. Hurlet et al. (2024) used an agent-based approach to examine different parking regulations and found that stricter regulations can improve public-space management while also increasing walking distances and reducing the convenience of e-scooter use.

The reviewed studies also show the difficulty of measuring parking compliance with operational trip data. A trip ending within a chosen distance of a designated parking location can reasonably be described as spatially aligned with that facility, but it does not confirm that the scooter was actually left inside the marked space. GPS error, the physical size of the facility, incomplete parking data, and the use of a single point to represent a larger parking area can all affect the result. Hemphill et al. (2022) also note that GPS accuracy and the definition of a parking violation influence how compliance is assessed.

The distance threshold used in the analysis also changes the interpretation. A wider buffer identifies more nearby trips but weakens the connection between the recorded destination and the actual parking space. A smaller buffer gives a more precise measure of proximity but may exclude trips affected by GPS error or by the physical size of the facility. For this reason, distance thresholds should be treated as analytical choices rather than direct observations of user behaviour.

Overall, the literature suggests that parking should be considered in terms of both availability and location. A city may have a large number of designated spaces, but those spaces may not be where users usually finish their trips. The most useful analysis, therefore, considers the relationship between observed trip activity, individual parking facilities, land use, pedestrian space, and the wider street environment. The evidence describes spatial alignment and the conditions associated with compliance, but proximity alone cannot confirm that a scooter was parked correctly.

The next section examines the spatial units and analytical methods used in this literature. This is important because the choice between trip-level, facility-level, buffer-based, and grid-based analysis affects what can be observed about parking, demand, and the relationship between infrastructure and user activity.

2.7 Spatial Units and Analytical Approaches

The choice of spatial unit and analytical method influences what can be observed and how the results are interpreted. Previous studies have used point mapping, heat maps, Kernel Density Estimation (KDE), hotspot analysis, spatial aggregation, accessibility measures and statistical modelling to examine different aspects of shared e-scooter demand. Each method provides useful information, but each also simplifies the mobility system in a different way. The reviewed studies on spatial units and analytical approaches are summarised in Appendix A.3, under 'Spatial Units and Analytical Approaches'.

Early studies commonly used descriptive spatial methods to identify concentrations of activity. Point maps preserve the recorded locations of trip origins and destinations, while KDE converts these points into a continuous surface that makes areas of higher activity easier to see. These methods are useful for identifying possible hotspots, but they mainly describe where activity occurs. They do not, by themselves, explain why demand is higher in one location than another.

For example, Jiao and Bai (2020) used hexagonal spatial units and GIS analysis to identify major e-scooter activity clusters in Austin. Their results showed that Downtown Austin and the University of Texas campus had different spatial roles, with one area functioning mainly as an origin zone and the other as a destination zone. This demonstrates the value of distinguishing between trip starts and trip ends rather than combining them into a single measure of activity.

Later studies have combined trip data with demographic, land-use, transport and accessibility variables to examine possible explanations for spatial differences in demand. Hosseinzadeh et al. (2021) aggregated e-scooter trips to Traffic Analysis Zones and used a Generalized Additive Model to examine relationships between trip density, land use, employment and urban characteristics. Christoforou et al. (2023), in contrast, used 200 m × 200 m grid cells and geographically weighted regression to examine how the factors associated with e-scooter use varied across space.

The spatial unit used for analysis affects the type of comparison that can be made. Administrative areas, such as neighborhoods, census zones and Traffic Analysis Zones, are useful because demographic and planning data are often available at these levels. They also correspond to familiar areas used by local authorities. However, these units can differ considerably in size, shape and internal composition, which may make direct comparisons difficult.

Regular grids provide an alternative by dividing the study area into units with a consistent shape and nominal size. This makes it possible to combine trip counts with public transport, parking, land-use, population and other indicators within the same spatial framework. Grid-based studies have used different cell sizes depending on the research purpose, including 200 m × 200 m cells, 300 m × 300 m cells and hexagonal units. Meng et al. (2025), for example, used H3 hexagons to compare parking conditions across cities.

A regular grid provides a consistent basis for spatial comparison, but the results may change when the cell size, grid alignment or boundary definition changes. This limitation is commonly referred to as the Modifiable Areal Unit Problem (Openshaw, 1984). Conditions within a single cell may also vary considerably, so a public transport stop located in one part of a cell does not mean that every location within that cell has the same level of access.

Trip origins and destinations require separate consideration. Origins may reflect scooter availability, vehicle deployment and the location where users access the system. Destinations may indicate the places that attract users or where trips are completed. Combining both into one measure gives a general indication of activity, but it removes part of the directional meaning of the journey. Separating origins and destinations, therefore, makes it possible to identify areas that mainly function as access points, destination areas or locations where vehicles accumulate.

Infrastructure interaction is often examined through buffer analysis. Fixed-distance buffers around public transport stops or parking locations provide a consistent measure of geometric proximity. However, Euclidean buffers do not represent actual route-based accessibility and may ignore barriers, crossings, gradients, station entrances and route directness. Buffer-based methods can also overestimate the number of trips that are genuinely connected to public transport (Oeschger et al., 2025; Yin et al., 2024). Network-based approaches provide a more realistic representation of accessibility, but they require more detailed network data and additional assumptions

The choice of statistical model must also reflect the structure of the dependent variable. E-scooter trip data are usually expressed as non-negative counts and may contain many zero values or substantial variation between areas. Previous studies have therefore used count-based and flexible modelling approaches, including negative binomial models, Generalized Additive Models, geographically weighted regression and machine-learning methods. Jin and Sui (2024), for example, used a gradient boosting decision tree model to examine spatial determinants of

shared e-bike and e-scooter link flows. These models can identify complex relationships, although their results may be more difficult to interpret than those from conventional regression.

Taken together, the literature shows that no single spatial method captures every aspect of shared e-scooter activity. Point-level analysis preserves the location of individual trips, buffer analysis measures proximity to infrastructure, and spatial aggregation supports comparison with urban characteristics and statistical modelling. These methods are therefore most useful when their different purposes and limitations are kept clear.

The present study combines these approaches across three connected analytical levels. The first level examines individual trip origins and destinations. The second compares activity around individual public transport stops and designated parking locations. The third aggregates trip activity and urban characteristics into a regular 300 m × 300 m grid. This framework retains the detail of individual journeys while also allowing demand to be compared with the wider urban environment.

2.8 Research Gap and Study Positioning

The existing literature shows that shared e-scooter activity varies across space and time. Studies have identified concentrations around city centres and university areas (McKenzie, 2019; Huo et al., 2021). Multi-city evidence also shows stronger weekday activity around downtown areas and educational institutions, while weekend activity is more closely associated with restaurants, bars, parks and other leisure destinations (Abouelela et al., 2023). The relationship with public transport also varies considerably between cities, with the potential feeder role of e-scooters depending on the spatial and temporal structure of the transport network (Li et al., 2024).

However, several gaps remain when these findings are considered together. The first concerns the separation between describing e-scooter patterns and explaining local demand. Many studies show where and when trips are concentrated, while other studies examine population density, land use, employment, accessibility or street characteristics. Fewer studies bring these factors together within one spatial and temporal framework. Research on built-environment determinants also often focuses on a limited number of variables or on a single city.

This separation makes it difficult to determine whether higher activity in a particular area is mainly associated with population concentration, commercial and tourism activity, public transport access, parking provision or the combination of several factors. Central urban areas

often contain many of these characteristics at the same time. An integrated analysis is therefore useful, although observational data cannot fully establish causal relationships.

A second gap concerns the interpretation of proximity to public transport. Many studies identify e-scooter trips located near stops or stations and interpret this as evidence of possible first- or last-mile use. Proximity analysis provides important spatial information, but it does not confirm that the user transferred between e-scooters and public transport. Reynolds et al. (2025), for example, compared e-scooter trip patterns with public transport service levels, but the authors also recognised that identifying transport-related trips from spatial thresholds remains an approximation.

A trip near a public transport stop may be connected to a transfer, but it may also be related to a nearby workplace, shop, university, home or tourist destination. In dense urban areas, public transport and e-scooter activity may overlap simply because both are concentrated around the same busy locations. There is, therefore, a need to use proximity measures while avoiding the stronger claim that spatial closeness proves functional integration.

A third gap relates to parking. Recent research has examined parking compliance, the density of designated parking areas and the relationship between parking facilities and land-use intensity. Meng et al. (2025) showed that the distribution and density of designated parking areas are related to parking compliance across different cities. However, further questions remain about how parking locations correspond to actual trip starts and ends, and whether a system with many facilities is necessarily well matched to the spatial distribution of demand.

This suggests the value of combining two perspectives. Overall parking proximity indicates how much trip activity occurs near the designated parking network. Location-specific analysis shows which individual facilities have high, low or unbalanced levels of nearby activity. These measures answer different questions and should be interpreted together rather than treated as equivalent indicators.

A fourth gap concerns the distinction between trip origins and destinations. Some studies combine trip starts and ends into a single measure of activity. This simplifies mapping and modelling, but it removes part of the directional information contained in the trip data. Origins may be influenced by scooter availability, operator deployment, and redistribution, whereas destinations provide information about where users chose to end their journeys. Jiao and Bai

(2020) demonstrated that origin and destination patterns can differ substantially between areas, with some locations functioning mainly as trip origins and others mainly as destinations.

A fifth gap concerns the spatial scale of analysis. Point-based studies preserve the location of individual trips but are difficult to combine directly with demographic and land-use information. Aggregated studies support statistical modelling but may hide differences between individual trips, infrastructure locations and smaller neighborhoods. Recent work has also noted that grid-based spatial demand modelling remains limited in Portuguese cities, and that statistical findings are not always translated into practical spatial planning guidance.

These limitations are particularly relevant to the Porto Metropolitan Area. Porto, Matosinhos, Vila Nova de Gaia and Espinho differ in urban density, land use, tourism activity, transport provision and local accessibility. Analyzing the area only through overall totals would hide these differences, while focusing only on Porto would provide an incomplete picture of the operator's service area.

This study responds to these gaps through a connected spatial and temporal framework. Trip origins and destinations are first examined separately to identify differences across months, seasons, weekdays and weekends, time periods, distance classes, municipalities and parishes. This preserves the directional and temporal information contained in the operational records.

The relationship with public transport is then examined through proximity measures representing both immediate and broader potential access. These results are interpreted as indicators of spatial interaction rather than confirmation that a transfer occurred. Designated parking is analysed in a similar but distinct way. Overall proximity measures describe the alignment between trip activity and the parking network, while location-level counts show how trip starts and ends vary around individual facilities. Parking proximity is therefore treated as spatial alignment, not as confirmed parking compliance.

Finally, a regular 300 m × 300 m grid is used to combine trip demand with public transport, parking, cycle infrastructure, tourism, education, land use, population, housing and accessibility variables. This common spatial framework supports comparisons across the study area and allows the relationship between local demand and the surrounding urban context to be examined statistically.

The contribution of the study does not depend on applying one entirely new method. Its contribution lies in bringing several forms of evidence together within the same case study.

Spatial and temporal patterns, public transport proximity, parking interaction and built-environment characteristics are examined as connected parts of one mobility system rather than as separate topics. The study also maintains a cautious interpretation: proximity is not treated as proof of integration, parking alignment is not treated as confirmed compliance, and statistical associations are not presented as causal effects.

3

DATA AND METHODOLOGY

3.1 RESEARCH DESIGN

This study adopted a quantitative, spatial and temporal research design to examine shared e-scooter activity across Porto, Matosinhos, Vila Nova de Gaia and Espinho. The methodology was organised around three connected analytical levels: individual trips, transport and parking infrastructure, and urban characteristics, which are connected through a spatial grid.

At the trip level, the analysis examined where and when e-scooter journeys started and ended. Trip origins and destinations were analysed separately because they may represent different mobility functions. Origins indicate where users accessed the service, whereas destinations may indicate arrival locations, activity areas or locations where scooters were left. Separating these two points is consistent with micromobility studies that use origin and destination locations to distinguish access and egress relationships with public transport (Javadiansr et al., 2024).

At the infrastructure level, trip locations were compared with public transport stops and designated parking locations. This level of analysis was used to identify spatial proximity, activity around individual facilities and differences between infrastructure locations. The results were interpreted as spatial association and potential interaction rather than direct evidence of user intention or confirmed modal transfer.

At the area level, trip starts were aggregated within a regular 300 m × 300 m grid. The grid combined trip demand with public transport, parking, cycling, land-use, tourism, education, population and housing variables. Grid-based aggregation is commonly used to connect individual mobility observations with urban characteristics that cannot be analysed directly at the point level. Previous micromobility research has aggregated origin points into regular

spatial units and time intervals to examine the distribution of departures across space and time (Arias-Molinares et al., 2023).

The methodology followed six main stages:

1. preparation and cleaning of the operator trip records;
2. creation of separate origin and destination point layers;
3. construction of temporal and trip-characteristic variables;
4. trip-level and infrastructure-level proximity analysis;
5. construction of the analytical grid and aggregation of spatial variables;
6. estimation of the effect of the variables for total, weekday and weekend demand using statistical models.

The overall methodological workflow adopted in this study is summarised in Fig. 3.1. Three derived datasets were used at different stages, and each is constructed in the corresponding section of this chapter. The trip-level analyses (Sections 3.5 and 3.6) used the complete cleaned dataset of 125,874 trips, analysed as separate origin and destination layers. The proximity analyses (Sections 3.7 and 3.8) used the same trip points together with dissolved and undissolved buffer layers around public transport stops and designated parking locations; no grid was involved at this stage. The grid-based analyses (Sections 3.9 to 3.13) used two further datasets derived from the trip origins: the area-ratio-filtered descriptive grid of 3,432 cells containing 125,865 trip starts, used for spatial description and GIS classification, and the pre-filtered model grid of 3,531 cells used for the ZINB estimations.

The use of separate spatial, temporal and built-environment components follows the wider methodological direction of micromobility research, where operational trip records are combined with land use, points of interest, transport infrastructure and other contextual variables to explain demand patterns (Shah et al., 2023).

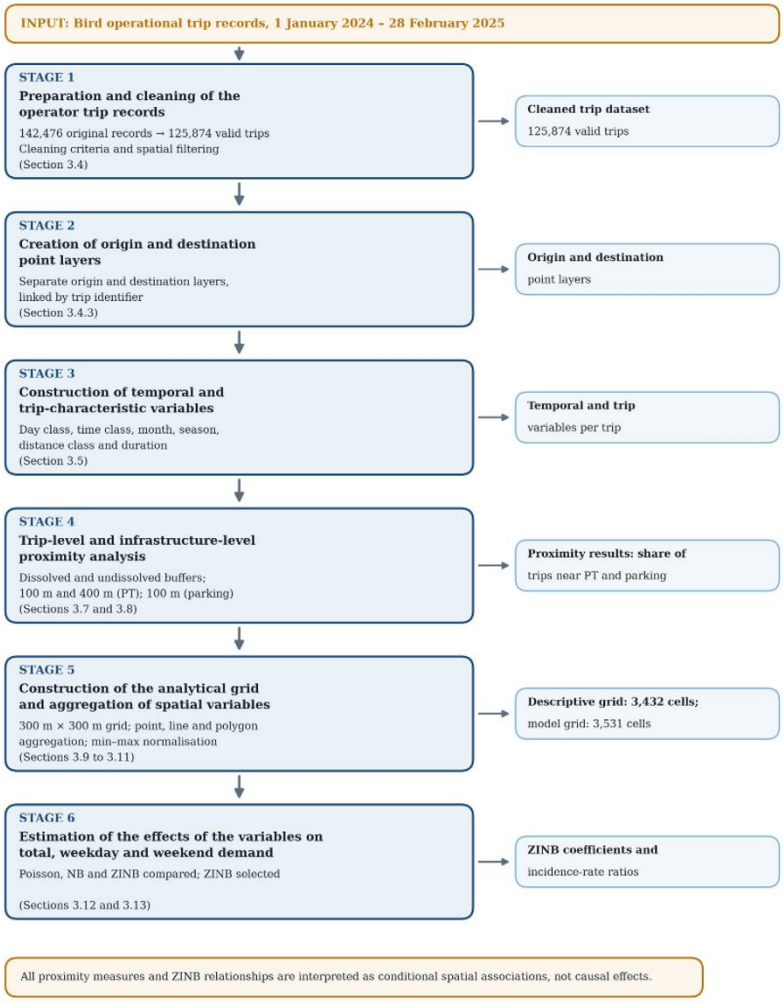


Fig. 3.1.Methodological workflow adopted in the study.

3.2 Study Area

The study area covers Porto, Matosinhos, Vila Nova de Gaia and Espinho, within the Porto Metropolitan Area in north-western Portugal, as shown in Fig. 3.2. Together the four municipalities form a connected coastal urban area, but they differ considerably in size, population distribution, urban structure, transport provision and intensity of activity.



Fig. 3.2.Study area comprising Porto, Matosinhos, Vila Nova de Gaia and Espinho.

Porto forms the main metropolitan core, with a dense concentration of commercial activity, tourism, employment and public transport services. Matosinhos stretches north along the Atlantic coast and includes established urban areas, commercial centres, coastal destinations and more peripheral neighbourhoods. Vila Nova de Gaia sits south of the Douro River and combines a dense riverfront and central area with much more suburban, lower-density territory. Espinho is a smaller coastal municipality at the southern edge of the study area.

These four municipalities were chosen because the operator dataset contained journeys beginning or ending within their boundaries. Most of the observed activity was concentrated in Porto, but restricting the analysis to the central municipality alone would have cut out part of the operating area and made it impossible to compare the metropolitan core with the surrounding municipalities.

Municipal boundaries were used for metropolitan-level comparison, while parish boundaries supported a more detailed look at local variation. The combined municipal boundary was also used to clip the contextual datasets and build the analytical grid.

3.3 Data Sources

The analysis combined operator-provided e-scooter records with public transport, parking, cycle infrastructure, tourism, education, land-use and socio-demographic datasets. The operator records captured observed e-scooter activity, while the contextual datasets described the transport and urban conditions surrounding it.

Spatial processing and mapping were carried out in QGIS 3.44 Solothurn, statistical modelling was conducted in NLOGIT 5, and spreadsheet-based checks and descriptive summaries were completed in Microsoft Excel where appropriate. All distance- and area-based spatial operations were carried out in ETRS89 / Portugal TM06 (EPSG:3763). Since this projected coordinate reference system expresses distance in metres, it was used throughout for buffer creation, nearest-distance calculations, line-length measurement, polygon-area calculation and grid construction. The main datasets used in the analysis, their sources and their role in the study are summarised in Table 3.1.

Table 3.1 - Main datasets used in the study

Dataset	Main content	Source	Use in the study
E-scooter trip records	Start and end coordinates, timestamps, distance and duration	Bird	Cleaning, temporal analysis, origin and destination layers, and grid-level demand counts
Public transport	Bus, light rail/metro, railway and tram stops or stations	OpenStreetMap-derived spatial layer	100 m and 400 m proximity analysis, stop-level interaction, mode-specific grid counts and nearest distance
Designated parking	Mapped bicycle/e-scooter parking locations		100 m parking proximity, location-level interaction, grid counts and nearest distance
Cycle infrastructure	Cycle-lane and cycleway line features		Length and presence within grid cells
Tourism locations	Tourism-related points of interest		Tourism presence within grid cells
Education facilities	Schools, universities and other education-related locations		Education presence within grid cells
Land use	Commercial, industrial and residential features		Land-use presence and descriptive land-use classification
Socio-demographic data	Population, housing and age-group indicators	Instituto Nacional de Estatística	Population density, young-population share and working-age share
Administrative boundaries	Municipal and parish polygons	Official administrative data	Study-area definition, clipping and local comparison

The public transport, designated parking, cycle infrastructure, tourism, education and land-use layers were built from the spatial datasets available in the QGIS project, including OpenStreetMap-derived information. Socio-demographic indicators came from the Portuguese National Statistics Institute, Instituto Nacional de Estatística (INE).

3.4 E-Scooter Trip Data Cleansing and Preparation

3.4.1 Original Trip Dataset

The main dataset came from Bird, one of the shared e-scooter operators active in the study area during the observation period. It originally contained 142,476 records, covering 1 January 2024 to 28 February 2025. The available attributes included geographic, temporal and trip-related information, as summarised in Table 3.2.

Table 3.2 - Principal attributes of the operator trip dataset

Attribute group	Fields used
Identification	Trip or record identifier and anonymised user identifier, where available
Geographic information	Start longitude and latitude; end longitude and latitude
Temporal information	Start timestamp; completion timestamp; date; month; weekday; start hour; end hour
Trip characteristics	Cleaned trip distance and trip duration
Derived spatial information	Origin and destination municipality and parish

Because each record included coordinates for both ends of the journey, every valid trip could be represented as an origin point and a destination point.

3.4.2 Cleaning Criteria

The original records were checked before any spatial analysis began. Records were dropped where they had missing or unusable start or end coordinates, missing or invalid timestamps, unusable duration values, or other inconsistencies that made the journey impossible to interpret reliably.

Trips shorter than 50 m were also removed. Very short records can represent failed unlocking attempts, cancelled journeys, GPS drift, or movements too small to count as a genuine, completed trip. This threshold was applied as a practical data-quality rule, not a claim that every trip under 50 m was necessarily invalid.

The records were then spatially filtered to the combined boundary of the four municipalities. After cleaning and spatial filtering, 125,874 valid trips remained for the main trip-level analysis.

3.4.3 Creation of Origin and Destination Layers

The cleaned table was converted into two-point layers:

- the trip-origin layer, built from the start longitude and latitude;
- the trip-destination layer, built from the end longitude and latitude.

Both layers kept a shared trip identifier along with the relevant temporal and distance attributes, so the two ends of the same journey stayed linked back to the original record.

Origins and destinations were analysed separately because they represent different stages of the trip. An origin shows where a user accessed an available scooter, and can be shaped by vehicle availability, operator deployment and redistribution. A destination shows where the user chose to end the journey, and where the scooter was subsequently left.

Combining starts and ends into a single point measure would hide these differences, so the two layers were kept separate throughout the temporal analysis, the municipal and parish summaries, and the public transport and parking proximity analyses.

3.5 Temporal and Trip Classification Variables

Several variables were derived from the trip timestamps and cleaned distance to support consistent comparisons across time and trip characteristics. Where relevant, these classifications were applied separately to origins and destinations. Start-time categories were based on the departure hour, and end-time categories on the recorded completion hour. The temporal and trip-classification variables used in the analysis are summarised in Table 3.3.

Table 3.3 - Temporal and trip classification variables

Variable	Categories or definition	Purpose
Day class	Weekday; weekend	Comparison of working-day and weekend activity
Time class	Morning peak: 06:00–09:59; midday/afternoon: 10:00–16:59; evening peak: 17:00–20:59; night: 21:00–05:59	Comparison of daily activity periods
Season	Winter, spring, summer and autumn, derived from month	Seasonal comparison
Trip-distance class	Short: <1,000 m; medium: 1,000–2,999 m; long: ≥3,000 m	Comparison of parking and public transport relationships by trip length
Trip duration	Difference between completion and start time, in minutes	Descriptive trip characteristic
Month	Calendar month and month identifier	Monthly aggregation and long-format analysis

Weekdays ran from Monday to Friday, while Saturday and Sunday were classified as weekends. The cleaned dataset contained 87,714 weekday trips and 38,160 weekend trips. These counts refer to the complete trip-level dataset used for the temporal and trip-level analyses; the corresponding counts within the analytical grid are reported in Section 3.9, after the grid has been constructed.

Seasonal comparison was mainly based on the full 2024 calendar year. Since the complete dataset also includes January and February 2025, folding those extra months in without adjustment would have given winter a longer observation window than the other seasons.

These variables were used for descriptive summaries, charts and maps. They were built to organise the observed trips consistently, not to serve as universal behavioural thresholds (Shah et al., 2023). A trip during the morning peak was not automatically classed as commuting, and a night trip was not automatically read as leisure travel.

3.6 Trip-Level Spatial and Temporal Analysis

The first analytical stage described the spatial and temporal distribution of the cleaned journeys, before looking at their relationship with infrastructure or the surrounding urban environment.

Trip origins and destinations were assigned to municipalities and parishes through spatial joins, and separate counts and percentages were then prepared for the four municipalities and their parishes.

Temporal patterns were examined using month, season, weekday/weekend, hour of day and time class. Trip distance and duration were summarised both as continuous values and using the categories in Table 3.3. The main trip-level descriptive analyses, their units of analysis and corresponding outputs are summarised in Table 3.4.

Table 3.4 - Trip-level descriptive analyses

Dimension	Unit of analysis	Principal output
Spatial distribution	Municipality and parish	Separate origin and destination counts and shares
Weekly pattern	Weekday and weekend	Trip counts, percentages and average daily activity where appropriate
Daily pattern	Hour and time class	Origin and destination temporal profiles
Seasonal pattern	Month and season	Monthly and seasonal trip distributions
Trip characteristics	Distance and duration	Mean, median, distribution and category totals
Origin–destination comparison	Separate start and end points	Identification of areas with relatively stronger origin or destination activity

Absolute totals were paired with percentages because the four municipalities differ a lot in area and observed activity. Raw counts alone would make it hard to compare the relative role of infrastructure and activity within each municipality.

Differences between starts and ends were read as observed spatial patterns rather than a direct measure of fleet imbalance, since operator redistribution and the number of scooters available at any given place and time weren't part of the dataset.

3.7 Public Transport Proximity and Stop Interaction

Throughout this section and Section 3.8, the analysis operates on the individual trip points; the analytical grid is not introduced until Section 3.9.

The relationship between shared e-scooter trips and public transport was examined through two complementary approaches:

- a trip-level proximity analysis;
- an individual stop-level interaction analysis.

The trip-level method estimated the share of unique origins and destinations that sat near any public transport facility. The stop-level method compared how much e-scooter activity surrounded individual stops or stations.

Two distance thresholds were used:

- 100 m, representing immediate spatial proximity;
- 400 m, representing a broader potential walking catchment.

Previous studies have used catchment areas of approximately 300 to 400 m when examining e-scooter relationships with public transport, while other studies apply different fixed thresholds. The 400 m value was therefore used as a consistent analytical threshold rather than as a universal behavioural limit (Gödde & Scheiner, 2025; Vinagre Díaz et al., 2024).

3.7.1 Public Transport Data Preparation

The public transport dataset covered four modal groups:

- bus stops;
- light rail/metro stops or stations;
- railway stations;
- tram stops.

This modal breakdown was maintained because the services differ in spatial coverage, stop density and function. Bus stops are spread widely across the study area, while railway, tram and metro facilities sit along more specific corridors and activity areas.

The public transport layer contained 5,369 stops and stations. After aggregation within the retained AR-filtered grid, 5,365 public transport points were represented.

3.7.2 Trip-level Proximity Using Dissolved Buffers

Buffers of 100 m and 400 m were created around the public transport stops, and for each distance, the overlapping polygons were dissolved into a single combined catchment.

Trip origins and destinations were then classified by whether they intersected these dissolved catchments. Binary proximity indicators were created for the 100 m and 400 m thresholds, as defined in Equations (3.1) and (3.2), respectively-

$$PT100_i = 1 \text{ if trip point } i \text{ was within 100 m of public transport, 0 otherwise} \quad (3.1)$$

$$PT400_i = 1 \text{ if trip point } i \text{ was within 400 m of public transport, 0 otherwise} \quad (3.2)$$

Dissolving the buffers removed the internal overlap between individual stop catchments, so each trip point was counted once, even where it sat near several stops at once.

The binary fields were used to work out the number and share of origins and destinations:

- within 100 m;
- between 100 m and 400 m;
- beyond 400 m.

The same indicators were summarised by municipality and, where relevant, by day class, time class, season and trip-distance class.

This method identifies spatial proximity and a potential opportunity for interaction with public transport. It does not show whether a traveler actually transferred between an e-scooter and another mode.

3.7.3 Stop-level Interaction Using Undissolved Buffers

A second set of buffers was kept separate around each public transport stop. QGIS's Join attributes by location (summary) tool was used to count trip origins and destinations within each individual buffer.

This produced stop-level measures such as:

- nearby trip-start count;
- nearby trip-end count;
- total surrounding activity;
- interaction class, where needed for mapping.

This made it possible to identify stops with no observed e-scooter activity at all, alongside locations surrounded by comparatively high trip starts or ends.

Unlike the dissolved method, individual stop buffers can overlap, so a single trip may be linked to more than one stop. The resulting counts describe how intense the interaction is around each stop and shouldn't be added together as a network-wide count of unique trips. The distinction between the dissolved trip-level approach and the individual stop-level approach is summarised in Table 3.5.

Table 3.5 - Complementary public transport analysis methods

Analytical level	Buffer treatment	Main measure	Interpretation
Trip level	Dissolved 100 m and 400 m buffers	Share of unique origins and destinations near any public transport facility	Overall spatial proximity to the public transport network
Stop level	Individual 100 m and 400 m buffers	Starts and ends surrounding each stop	Local interaction intensity around individual stops

These two methods answer different questions, which is why both were used together.

A trip ending near a public transport station could represent access to a transit service, but it could just as easily serve a nearby office, shop, home, university or tourist destination. In the same way, a trip beginning near a station might represent egress from public transport, but the operational record simply doesn't say what mode the traveler used beforehand. For that reason, public transport proximity was read as potential spatial interaction, not as confirmed first- or last-mile integration.

3.8 Parking Proximity and Parking-Location Interaction

Designated parking was analyzed using the same general two-level logic as public transport:

- Trip-level proximity to the parking network;
- Interaction around individual parking locations.

A 100 m threshold was used for both methods, representing a short spatial alignment with a mapped parking facility while allowing some tolerance for positional uncertainty in the trip and infrastructure coordinates.

3.8.1 Trip-level Parking Proximity

A 100 m buffer was created around all designated parking locations, and the overlapping polygons were dissolved into a single combined parking catchment.

Trip origins and destinations were classified separately by whether they intersected this dissolved catchment, with binary fields created for both starts and ends.

This method was used to compute:

- the number and percentage of trip origins within 100 m of parking;
- the number and percentage of trip destinations within 100 m of parking;
- differences between municipalities;
- variation by temporal and trip-distance categories where relevant.

The dissolved approach made sure every trip point was counted only once in the network-wide parking-proximity percentage, even where several parking buffers overlapped.

3.8.2 Parking-location Interaction

Separate 100 m buffers were kept around individual parking locations, and nearby trip origins and destinations were counted through a spatial summary join.

For each parking location, this produced:

- nearby start count;
- nearby end count;
- total surrounding activity;
- difference between end and start activity where relevant.

These measures made it possible to tell apart locations that mainly worked as points of scooter access, locations associated with more trip endings, relatively balanced facilities, and locations with little or no observed interaction.

Parking locations were grouped into descriptive interaction classes for mapping. These classes reflected the observed distribution within this particular dataset and weren't meant as universal capacity or performance standards.

Individual parking catchments can overlap, so one trip may contribute to the local count of more than one facility. Parking-location counts were used to compare local interaction, not added

together as unique totals. The two complementary approaches used for the designated-parking analysis are summarised in Table 3.6.

Table 3.6 - Complementary designated parking methods

Analytical level	Buffer treatment	Main measure	Interpretation
Trip level	Dissolved 100 m buffer	Share of unique origins and destinations near any parking facility	Overall spatial alignment with the parking network
Parking-location level	Individual 100 m buffers	Starts and ends surrounding each parking location	Local interaction intensity and start–end balance

Parking proximity was not treated as proof of compliance. A trip ending within 100 m of a parking location may still have ended outside the marked facility, and the trip coordinates do not show whether the scooter was positioned correctly or ended up creating an obstruction. In the same way, a trip outside the threshold does not necessarily mean deliberate non-compliance. It could just as easily reflect GPS uncertainty, incomplete parking data, the physical size of the facility, or a mismatch between the mapped infrastructure and the operator's actual parking rules. For this reason, the terms parking proximity, spatial association and alignment with designated parking were used throughout, rather than confirmed compliance.

3.9 Construction of the 300 m Analytical Grid

3.9.1 Grid Creation

A regular 300 m × 300 m polygon grid was created in QGIS using EPSG:3763. The area of a complete 300 m × 300 m grid cell was calculated using Equation (3.3):

$$300\ m \times 300\ m = 90{,}000\ m^2 = 0.09\ km^2 \tag{3.3}$$

This grid gave a common spatial unit for bringing together trip demand, infrastructure, land use, activity locations and socio-demographic variables.

A regular grid was preferred over municipalities or parishes for statistical modelling because administrative units differ substantially in size, shape and internal composition. The 300 m

resolution kept local variation around public transport, parking and cycle infrastructure visible, while still giving cells large enough to hold meaningful combinations of variables.

3.9.2 Clipping to the Study Boundary

The regular grid was clipped to the combined boundary of Porto, Matosinhos, Vila Nova de Gaia and Espinho, producing 3,531 initial cells.

Clipping created small, irregular fragments along the coast and outer boundary as shown in Fig. 3.3. These fragments could distort density measures, since one trip or infrastructure feature divided by a very small area would produce an unusually high value.

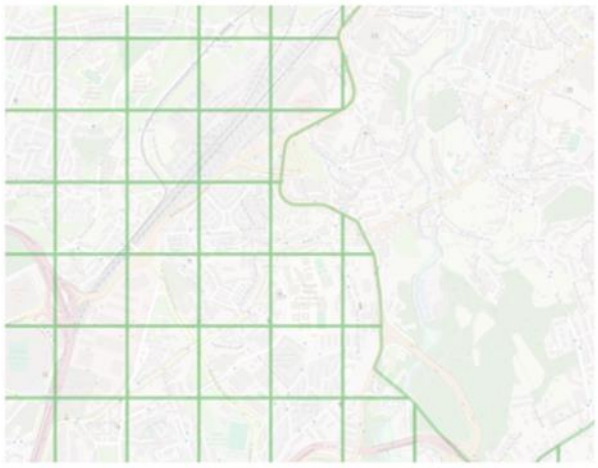


Fig. 3.3. Example of complete and clipped 300 m grid cells along the study area boundary.

3.9.3 Area-ratio Filtering

The actual area of each clipped cell was compared with the area of a complete grid cell using the area ratio defined in Equation (3.4):

$$AreaRatio_i = ActualArea_i \,/\, 0.09\ km^2 \tag{3.4}$$

Cells were excluded according to the threshold defined in Equation (3.5):

$$AreaRatio_i \leq 0.10 \tag{3.5}$$

This threshold removed fragments containing no more than 10% of a full grid cell.

The filter removed 99 boundary fragments, leaving 3,432 cells and 125,865 start trips in the AR-filtered grid. The completely cleaned trip-level dataset contained 125,874 trips, so the

filtering removed nine start points. The statistical models' output is aligned with the pre-filtered 3,531-cell grid because its total-start zero count is 2,779, the same as the no-activity count in that grid. The model-selection diagnostics are therefore reported in relation to the 3,531-cell model dataset, whereas the AR-filtered grid is used for the final grid-level spatial analysis. Removing these fragments improved the comparability of the grid units while excluding only a negligible share of observed demand.

3.9.4 Grid Attributes

Each retained cell was assigned:

- a unique grid identifier;
- actual area;
- area ratio;
- centroid coordinates;
- municipality;
- parish, where required.

Municipality was kept as a categorical model variable, with Vila Nova de Gaia chosen as the reference category and separate indicators representing Porto, Matosinhos and Espinho.

3.10 Grid-Level Variable Construction

The grid-level dataset combined start-trip demand with transport, parking, cycle infrastructure, activity, land-use and socio-demographic indicators.

Trip origins were aggregated using QGIS's Count points in polygon tool, producing three variables, which are the dependent variables used in the statistical models:

- total start-trip count;
- weekday start-trip count;
- weekend start-trip count.

The three grid-level dependent variables and their corresponding trip totals are summarised in Table 3.7.

Table 3.7 - Grid-level dependent variables

Dependent variable	Definition	Total trips
Total starts	All trip origins in each retained grid cell	125,865
Weekday starts	Origins recorded from Monday to Friday	87,706
Weekend starts	Origins recorded on Saturday and Sunday	38,159

Trip starts were chosen because they represent locations where users accessed the service and are directly relevant to local demand and vehicle availability. Trip-end counts were kept for descriptive analysis but weren't used as dependent variables in the final models.

The explanatory variables represented the municipality, the demographic composition, infrastructure provision and the land-use context of each cell. Municipality was included through indicator variables for Espinho, Matosinhos and Porto, with Vila Nova de Gaia used as the reference category, so that the municipality coefficients represent differences relative to Vila Nova de Gaia after controlling for the remaining explanatory variables. Three socio-demographic variables were also included: population density, represented as residents per square kilometre; the young-population share, representing residents aged 15 to 24; and the working-age share, representing residents aged 25 to 64. These fields describe the resident population within each spatial unit; they do not describe the actual e-scooter users, who may include tourists, visitors, students and people who live elsewhere.

Parking was represented by two complementary variables: the number of designated parking locations within the cell, capturing provision inside the cell, and the distance from the cell centroid to the nearest parking location, capturing access to the wider network, including facilities in neighbouring cells. Public transport was represented by separate counts of bus stops, light rail/metro stops or stations, railway stations and tram stops, together with the distance from the cell centroid to the nearest public transport stop or station, calculated using the combined public transport layer. This modal separation followed the revised model supplied by the supervisory team and allowed different public transport types to have different relationships with e-scooter demand rather than treating every stop as identical. Stop counts describe provision within the cell, while nearest distance represents proximity to the broader network.

Cycle infrastructure was represented by the total length of mapped cycle lanes or cycleways within each cell, calculated by intersecting the line layer with the grid and summing the length

of each resulting segment. A binary presence field was also created for descriptive mapping and planning-priority analysis. Cycle-lane length shows how much mapped infrastructure is located within a cell; it does not measure continuity, physical separation, surface quality, direction, safety or whether e-scooters are legally permitted to use it.

Tourism, education and land use were represented by binary presence indicators, defined for each grid cell using Equation (3.6):

$$Presence_i = 1 \text{ if at least one relevant feature occurred in cell } i, 0 \text{ otherwise} \quad (3.6)$$

This coding was used for tourism presence, education presence and the three land-use categories (commercial, industrial and residential presence, each coded 1 where the mapped land-use category occurred within the cell). Binary coding was chosen because these features were concentrated in a limited number of cells, and their presence gave a clearer interpretation than small differences in facility counts.

A broader land-use-mix field was also prepared for descriptive mapping, distinguishing cells with no mapped use, a single use and different levels of mixed use. This composite field was not included in the final model alongside the individual land-use indicators, since that would have duplicated related information. The complete set of variables and their coding is summarised in Table 3.8.

Table 3.8 - Grid-level variables used in the statistical models

Group	Variable	Definition and coding	Model role
Demand	Total starts	Number of trip origins per grid cell	Dependent
	Weekday starts	Number of weekday trip origins per cell	
	Weekend starts	Number of weekend trip origins per cell	
Municipality	Espinho	1 for Espinho; otherwise 0	Explanatory
	Matosinhos	1 for Matosinhos; otherwise 0	
	Porto	1 for Porto; otherwise 0	
	Vila Nova de Gaia	Omitted reference category	
Demographics	Population density	Residents/km², min–max normalised	
	Young share	Proportion of residents aged 15–24	
	Working-age share	Proportion of residents aged 25–64	
Parking	Parking count	Number of designated parking locations in the cell	
	Distance to parking	Centroid-to-nearest-parking Euclidean distance, normalised	
Public transport	Bus count	Number of bus stops in the cell	
	Light rail/metro count	Number of light rail or metro facilities in the cell	
	Railway count	Number of railway stations in the cell	
	Tram count	Number of tram stops in the cell	
	Distance to PT	Centroid-to-nearest-PT Euclidean distance, normalised	
Cycle infrastructure	Cycle-lane length	Length of mapped cycle infrastructure, normalised	
Activity	Tourism presence	1 if present; otherwise 0	
	Education presence	1 if present; otherwise 0	
Land use	Commercial presence	1 if present; otherwise 0	
	Industrial presence	1 if present; otherwise 0	
	Residential presence	1 if present; otherwise 0	

Variables were transferred into the grid through the aggregation procedures described above. Trip origins, public transport stops, designated parking locations, tourism locations and education facilities were aggregated using QGIS's Count points in polygon tool, which produced one record per grid cell and avoided the duplicated features that a standard spatial join can create. The Euclidean distance from each grid centroid to the nearest designated parking location and nearest public transport facility was calculated using the QGIS nearest-hub procedure; centroid-based Euclidean distance does not represent the exact distance from

every point within a cell and does not follow the street network, so it was used as a consistent relative accessibility measure rather than a precise one. Continuous variables measured in substantially different units were normalised to values between 0 and 1 using the min–max transformation shown in Equation (3.7):

$$X^*_i = (X_i - X_{min}) / (X_{max} - X_{min}) \quad (3.7)$$

This was applied to population density, distance to parking, distance to public transport and cycle-lane length. For a normalised variable, a one-unit difference represents movement from the observed minimum to the observed maximum; therefore, a distance coefficient should not be interpreted as the effect of one additional metre. Normalisation put continuous predictors on a similar numerical scale and helped keep estimation stable; it does not make the coefficients of count, binary, categorical and continuous variables fully comparable with one another. The complete variable dictionary, including variable definitions, units, sources or derivations, and analytical uses, is provided in Appendix A.1. Detailed definitions, coding, processing procedures and model roles for the grid-level variables are provided in Appendix A.2.

3.11 Statistical Model Selection

Candidate predictors were drawn from the themes identified in the literature review: socio-demographic context, parking, public transport, cycle infrastructure, tourism, education and land use. Variables representing the same underlying concept in different forms were not automatically entered together; count, density, presence and distance variables were reviewed to avoid unnecessary duplication. Derived fields such as demand classes, accessibility classes, gap categories and planning-priority classifications were excluded from the predictor set, since these were built from observed demand or other model variables, and including them would have introduced circular interpretation. The final dataset was checked for missing values, impossible and extreme values, sparse predictors, redundant variables and consistency between the three dependent-variable models.

The dependent variables are non-negative integer counts whose distributions contain a large number of cells with zero trips alongside a small number of cells with very high demand. The distributions were also strongly overdispersed, with the variance substantially exceeding the

mean. These characteristics made ordinary linear regression unsuitable and violated the Poisson assumption that the conditional variance equals the conditional mean.

Three regression model families usually applied to count data were compared: Poisson, Negative Binomial and Zero-Inflated Negative Binomial. The Poisson model offers a basic framework for count data but assumes that the conditional mean and variance are equal. The Negative Binomial model relaxes that assumption through a dispersion parameter. The Zero-Inflated Negative Binomial model combines an overdispersed count process with a separate process for excess zeros, making it appropriate for count data with both strong overdispersion and many zero observations (Abouelela et al., 2023). The zero-count structure of the three dependent variables in the 3,531-cell model dataset is summarised in Table 3.9.

Table 3.9 - Zero-count structure of the trip starts

Model	Zero cells	Share of the 3,531 cells
Total starts	2,779	78.7%
Weekday starts	2,842	80.5%
Weekend starts	2,942	83.3%

The higher share of zeros in the weekend model shows that weekend activity was concentrated in fewer cells. The comparison of the three specifications drew on the dispersion parameter, the zero-inflation parameter, the log-likelihood values and the Vuong statistic, and is summarised in Table 3.10.

Table 3.10 - Model-selection diagnostics for total, weekday and weekend trip-start models.

Diagnostic	Total starts	Weekday starts	Weekend starts
Poisson log-likelihood	−138,481.54	−95,961.20	−44,560.04
Negative Binomial log-likelihood	−4,623.52	−4,174.60	−3,385.38
ZINB log-likelihood	−4,529.41	−4,090.46	−3,294.12
Vuong statistic	9.717	9.076	8.588
Dispersion parameter, α	6.682***	6.566***	6.314***
Zero-inflation parameter, τ	−1.070***	−1.067***	−1.403***

As Table 3.10 shows, all Vuong statistics exceeded 1.96(the value of the Z distribution for 97.5%), supporting the ZINB specification in all three cases. The positive and significant dispersion parameters confirmed strong overdispersion, and the significant negative zero-inflation parameters supported an additional zero-generating process. These diagnostics justify the methodological choice; the substantive effects of the explanatory variables are presented in Chapter 4.

3.12 Zero-Inflated Negative Binomial Model

Let Y_i represent the observed number of trip starts in grid cell i. The expected trip count was estimated using a logarithmic link shown in equation (3.8):

$$ln(\lambda_i) = x_i'\beta \tag{3.8}$$

where λ_i is the expected trip-start count in cell i, x_i is the vector of explanatory variables, and β is the vector of estimated coefficients. The Negative Binomial component allows the variance to exceed the mean,as expressed in equation(3.9):

$$Var(Y_i \mid x_i) = \lambda_i + \alpha\lambda_i^2 \tag{3.9}$$

where α is the dispersion parameter. A statistically significant α shows the data are overdispersed relative to a Poisson specification.

The zero-inflation component represents the probability that an observation belongs to the structural-zero state. This probability was specified using equation(3.10):

$$\pi_i = F[\tau \ln(\lambda_i)] \tag{3.10}$$

where $F(\cdot)$is the logistic cumulative distribution function, $\tau\tau$ is the zero-inflation parameter, and λ_i is the expected mean from the count component. The estimated model did not include a separate set of explanatory variables for an independent zero-inflation equation; instead, the excess-zero probability was linked directly to the expected count through $\tau\ln(\lambda_i)$, matching the formulation of the final estimated model.

The coefficients from the count component represent changes in the logarithm of the expected trip count, holding the remaining variables constant. The incidence-rate ratio for predictor *j* was calculated from the estimated coefficient using equation(3.11):

$$IRR_j = e^{(\beta_j)} \tag{3.11}$$

For a continuous variable, the incidence-rate ratio represents the multiplicative change in expected demand tied to a one-unit increase in that predictor. For binary variables, it compares cells where the characteristic is present against cells where it's absent. That is the case of municipality variables in which the coefficients compare Porto, Matosinhos and Espinho against Vila Nova de Gaia.For min–max-normalised variables, a one-unit increase represents movement from the observed minimum to the maximum. Therefore, large coefficients for trip distance or cycle-lane length describe variation across the full observed range, not the effect of a one-metre change.

These coefficients are interpreted as conditional associations. A positive coefficient for a public transport variable does not prove that the transport service caused e-scooter demand; public transport and e-scooter activity may simply both be concentrated in central, accessible and commercially active areas.

3.13 GIS-Based Planning Analysis

The statistical models identify variables associated with e-scooter trip-start demand, but they do not directly indicate where infrastructure gaps or planning priorities are located. Post-model

GIS classifications were therefore developed to translate the statistical findings into spatial planning information. These classifications were created after model estimation and were not included as explanatory variables in the ZINB models.

3.13.1 Demand–Accessibility Classification

A demand–accessibility classification was developed to examine how observed e-scooter activity corresponded spatially with accessibility to public transport and designated e-scooter parking.

Grid cells were first classified according to trip-start activity as No Activity (0 starts), Low (1–30 starts), Moderate (31–300), High (301–1,000) and Very High (more than 1,000 starts). Accessibility was classified using the Euclidean distance from the grid-cell centroid to the nearest facility: High Accessibility for distances up to 200 m, Moderate Accessibility for distances greater than 200 m and up to 500 m, and Low Accessibility for distances greater than 500 m. The same accessibility thresholds were applied to public transport and designated parking.

The combination of demand and accessibility produced four relationship categories:

- Good Match: High or Very High demand combined with High or Moderate accessibility;
- Gap: High or Very High demand combined with Low accessibility;
- Underused: Low or No Activity combined with High or Moderate accessibility;
- Mixed: all remaining combinations.

For public transport, this classification was based on trip-start activity and distance to the nearest public transport stop. For the general designated-parking relationship analysis, the same demand–accessibility logic was applied using distance to the nearest designated parking location. The classification was intended to identify spatial correspondence between activity and infrastructure accessibility rather than to establish that infrastructure caused the observed demand.

3.13.2 Cycle-Infrastructure Readiness Classification

A separate cycle-infrastructure readiness classification was developed to compare e-scooter trip-start activity with the presence of mapped cycle-lane infrastructure. Cycle support was

identified where a grid cell contained mapped cycle-lane infrastructure, represented by the cycle-lane presence indicator or a positive cycle-lane density.

Four categories were defined:

- High demand with cycle support: High or Very High trip-start activity with mapped cycle-lane infrastructure;
- High demand without cycle support: High or Very High trip-start activity without mapped cycle-lane infrastructure;
- Cycle infrastructure with low demand: No Activity or Low trip-start activity with mapped cycle-lane infrastructure;
- Mixed: all remaining combinations.

This classification was used as a planning-screening tool to distinguish high-demand locations where mapped cycling infrastructure was already present from high-demand locations where such infrastructure was absent. It does not evaluate the quality, continuity, width, physical separation or safety performance of the mapped cycle infrastructure.

3.13.3 Integrated Planning-Priority Classification

A more targeted integrated planning-priority classification was developed after model estimation by combining e-scooter demand with designated-parking gaps, cycle-lane support and public transport accessibility.

For this integrated classification, the parking component was based on the relationship between trip-end activity and parking accessibility, because trip ends more directly represent locations where journeys are completed and therefore provide a more relevant spatial indicator for parking pressure. High-demand trip-start activity was used for the cycle-infrastructure and public transport components.

The final planning-priority categories were:

- Priority 1 – Parking and cycle-lane gap: locations classified as a parking Gap and without mapped cycle-lane support;
- Priority 2 – Parking gap: locations classified as a parking Gap but with cycle-lane support;

- Priority 3 – Cycle-lane gap: High or Very High trip-start activity without mapped cycle-lane support;
- Supported high demand near public transport: High or Very High trip-start activity combined with a Good Match public transport relationship;
- Lower priority: all remaining grid cells.

The categories were applied sequentially in this order so that cells meeting the Priority 1 conditions were identified before Priority 2 and Priority 3, followed by supported high-demand areas and finally Lower priority. This ensured that cells with multiple infrastructure gaps were assigned to the more comprehensive gap category. The resulting variables were used only for post-model spatial interpretation and planning screening and were not entered into the ZINB models.

The classification should not be interpreted as an automatic intervention list. A priority cell identifies a location where observed activity and mapped infrastructure conditions warrant closer investigation. Detailed planning would still need to consider street width, pedestrian movement, land ownership, construction feasibility, local safety conditions and existing municipal projects.

3.14 Data Quality and Limitations

Quality checks ran throughout the workflow.

For the trip records:

- original and cleaned totals were compared;
- missing or unusable coordinates were checked;
- trip-origin and trip-destination feature counts were compared with the cleaned table;
- a sample of points was inspected visually.

For the temporal variables:

- month and weekday values were checked against the timestamps;
- time-class boundaries were inspected;
- weekday and weekend totals were compared with the complete dataset;
- distance and duration classes were compared with the continuous values.

For the buffer analyses:

all spatial layers were confirmed to use EPSG:3763;

- buffer distances were checked;
- dissolved and undissolved outputs were stored separately;
- selected-trip totals were inspected after each operation;
- binary fields were checked for null values;
- sample points were visually compared with the relevant buffers.

For infrastructure-level analysis:

- individual stop and parking identifiers were retained;
- locations with zero or exceptionally high activity were checked spatially;
- overlapping buffers were recognised during interpretation;
- infrastructure-level counts were not summed as unique trip totals.

For the grid:

- the initial and final cell totals were checked;
- actual area and area ratio were inspected;
- the 99 excluded fragments were identified;
- trip totals were compared before and after filtering;
- extreme count and distance values were reviewed spatially.

For the model dataset:

- dependent variables were checked as non-negative integers;
- zero-cell counts were confirmed for each model;
- explanatory variables were checked for missing values;
- demand-derived variables were excluded from the predictor set;
- Poisson, Negative Binomial and ZINB outputs were compared;
- the same explanatory-variable structure was used in all three models.

3.15 Chapter Summary

This chapter sets out the data and methods used to analyse shared e-scooter activity in Porto, Matosinhos, Vila Nova de Gaia and Espinho.

The original operator dataset held 142,476 records. After cleaning and spatial filtering, 125,874 valid trips were retained and converted into separate origin and destination layers, with temporal and trip-related variables created for weekday and weekend, month, season, time of day, trip distance and duration.

Public transport and designated parking were examined through complementary trip-level and infrastructure-level methods. Dissolved buffers measured the proportion of unique trips near the infrastructure networks, while individual buffers supported comparison between public transport stops and parking locations. Public transport proximity was treated as potential spatial interaction, and parking proximity as alignment rather than confirmed compliance.

A 300 m × 300 m grid was built to combine demand with transport, parking, cycle infrastructure, tourism, education, land use and socio-demographic characteristics. After removing 99 small boundary fragments, the final grid held 3,432 cells and 125,865 start trips.

Because the dependent variables showed excess zeros and strong overdispersion, Zero-Inflated Negative Binomial models were estimated for total, weekday and weekend trip starts, with public transport represented through separate bus, light rail/metro, railway, and tram counts alongside distance to the nearest public transport facility.

Finally, the statistical results were combined with GIS-based demand and infrastructure classifications to identify locations where observed activity and infrastructure provision appeared aligned or mismatched.

4

RESULTS

4.1 Overview of the Analysed Trips

This chapter presents the results of the trip-level, infrastructure-level and grid-level analyses of shared e-scooter activity in Porto, Matosinhos, Vila Nova de Gaia and Espinho. The results are organised into five main components. First, the characteristics of the cleaned trip dataset are described. Second, the temporal and spatial distributions of the trips are examined. Third, the proximity of e-scooter activity to public transport and designated parking is assessed. Fourth, trip-start demand is analysed using a 300 m × 300 m spatial grid. Finally, the ZINB model results are presented.

The cleaned trips had an average distance of 2.82 km and a median distance of 2.04 km. The mean trip duration was 15.34 minutes, while the median duration was 10 minutes. The main indicators of the cleaned dataset are summarised in Table 4.1 . The difference between the mean and median values indicates that the distribution was positively skewed, with a smaller number of comparatively long trips increasing the average distance and duration.

Table 4.1 - Summary of the cleaned e-scooter trip dataset.

Indicator	Value
Original trip records	142,476
Valid trips retained	125,874
Records removed	16,602
Observation period	1 January 2024–28 February 2025
Mean trip distance	2.82 km
Median trip distance	2.04 km
Mean trip duration	15.34 min
Median trip duration	10 min

The trip-level analysis used the full set of 125,874 cleaned trips. The descriptive grid analysis used 125,865 trip starts after the removal of nine points located in excluded boundary fragments. The statistical models used the model dataset supplied for the ZINB analysis, which contained 3,531 grid cells.

4.2 Temporal Distribution of Trips

The temporal analysis examines how shared e-scooter activity varied between weekdays and weekends, across the hours of the day and throughout the observation period. The cleaned dataset of 125,874 trips was used for the weekday, weekend and time-of-day analyses. Monthly results cover the full period from January 2024 to February 2025, while the seasonal comparison was restricted to the complete 2024 calendar year to ensure that all seasons were represented over comparable periods.

4.2.1 Weekday and Weekend Activity

Of the 125,874 trips, 87,714 occurred on weekdays and 38,160 occurred on weekends. Weekday trips, therefore, represented 69.68% of the dataset, compared with 30.32% on weekends. These values describe the total number of trips recorded in each day class; they do not account for the larger number of weekdays in the observation period. The results nevertheless show that shared e-scooter use was not limited to working days and remained substantial during weekends. The distribution of trips by day class is presented in Table 4.2.

Table 4.2 - Distribution of trips by day-class

Day class	Number of trips	Share of trips (%)
Weekday	87,714	69.68
Weekend	38,160	30.32
Total	125,874	100.00

The higher weekday total should be interpreted carefully because the observation period contains more weekdays than weekend days. Each week contains five weekdays but only two weekend days. Therefore, the weekday and weekend totals do not represent equal numbers of calendar days.

Despite the larger weekday total, weekend use remained substantial as shown in Fig. 4.1. Almost one third of all trips occurred on Saturdays and Sundays, showing that the service was not used exclusively for regular weekday travel. Weekend activity formed an important part of the observed system and was examined separately in the grid-level models.

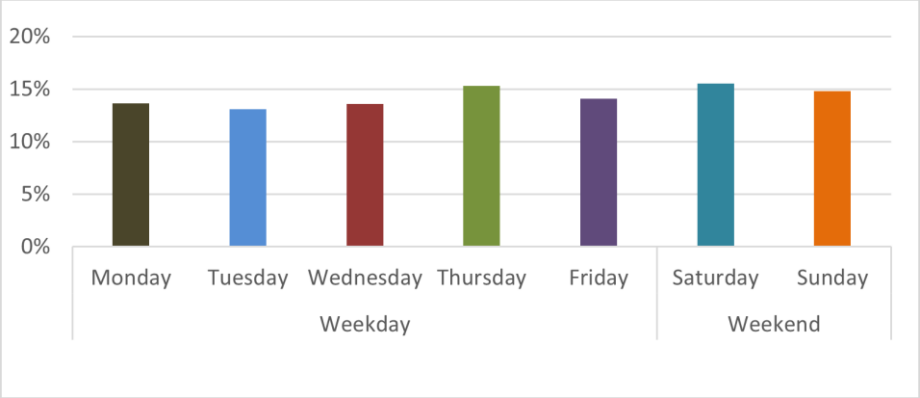


Fig. 4.1. Distribution of shared e-scooter trips by day of the week

4.2.2 Hourly and Time-of-Day Patterns

The hourly distribution shows a clear daily pattern. Trip activity was very low during the early-morning hours, particularly between midnight and approximately 06:00. Activity then

increased gradually during the morning and rose more strongly from late morning into the afternoon.

The largest hourly volume was recorded at approximately 17:00. Activity remained relatively high during the early evening before declining. A smaller rise was also visible during the later evening, around 22:00.

As shown in Fig.4.2,trip starts and trip ends followed closely aligned hourly profiles. This is expected because every completed trip contributes one origin and one destination, although the end of a journey occurs later than its start. The similarity between the two series should therefore be interpreted as similarity in the temporal profiles of trip departures and completions, not as proof that scooters were spatially balanced across the study area.

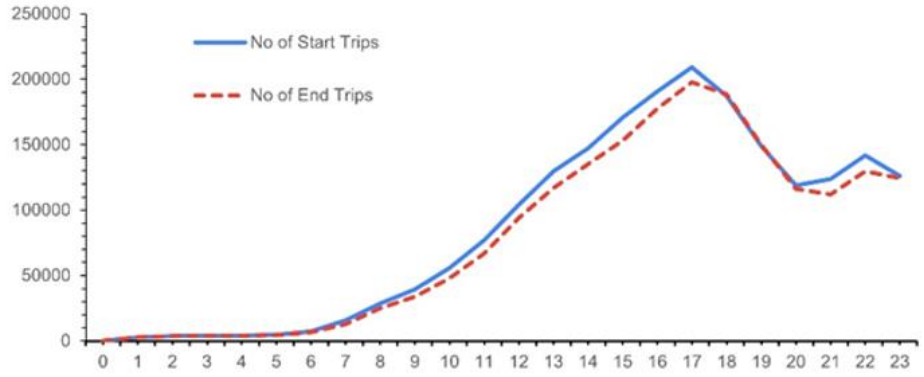


Fig. 4.2. Hourly distribution of trip starts and trip ends.

The hourly pattern should also be interpreted in relation to local operating conditions. In the Municipality of Porto, shared micromobility services are normally permitted to operate between 06:00 and 22:00, with the municipality able to restrict or extend this period in justified situations. The Municipality of Matosinhos establishes an equivalent 06:00 to 22:00 operating window, likewise subject to possible municipal exceptions. For Vila Nova de Gaia and Espinho, no equivalent shared-micromobility regulation establishing the same operating window was identified in this study, and no metropolitan-wide rule covering all four municipalities was found. The dataset therefore covers four municipalities with partially differing regulatory contexts. Recorded activity outside the documented operating windows should not be

interpreted solely as evidence of night-time travel demand. The observed night-time records were therefore retained in the descriptive analysis but interpreted with caution.

The four time-of-day categories were defined to distinguish periods with distinct mobility functions rather than to divide the day into intervals of equal length. The morning peak (06:00 to 09:59) and evening peak (17:00 to 20:59) were defined around typical commuting periods, each covering four hours. Midday (10:00 to 16:59) covers the seven-hour period between the two peaks, when leisure, tourism and errand-related travel can be expected to dominate. Night (21:00 to 05:59) is a nine-hour residual period of low expected activity, which partly overlaps the period outside Porto's standard operating window. Because the categories differ in duration, the shares reported in Table 4.3 reflect both demand level and window length. To account for this, Table 4.3 also reports trips per hour of the defined interval.

Midday contained the largest number of journeys, with 46,691 trips, corresponding to 37.09% of the dataset. Evening activity represented 37,618 trips, or 29.89%, while the night period accounted for 32,399 trips, or 25.74%. Morning contained the smallest share, with 9,166 trips, or 7.28%.

Table 4.3 - Distribution of trips by time-of-day category

Time-of-day category	Number of trips	Share of trips (%)	Trips per hour of interval
Morning peak (06:00–09:59)	9,166	7.28	2,292
Midday (10:00–16:59)	46,691	37.09	6,670
Evening peak (17:00–20:59)	37,618	29.89	9,405
Night (21:00–05:59)	32,399	25.74	3,600
Total	125,874	100.00	

4.2.3 Monthly and Seasonal Variation

Monthly trip activity varied considerably over the observation period from January 2024 to February 2025. During 2024, the lowest number of trips was recorded in January, with 4,956 trips. Activity then increased gradually through spring and early summer, reaching its highest level in July, when 13,187 trips were recorded. August followed closely with 12,921 trips.

Trip activity remained relatively high in September, with 11,505 trips, before declining in October. A further increase was observed in November, followed by a moderate reduction in December. January and February 2025 recorded 6,734 and 7,638 trips, respectively, both higher

than the corresponding months in 2024. The monthly trip totals over the full observation period are summarised in Table 4.4 and illustrated in Fig. 4.3.

Table 4.4 - Monthly number of trips, January 2024–February 2025

Month	Number of trips	Share of full dataset (%)
January 2024	4,956	3.94
February 2024	5,160	4.10
March 2024	5,503	4.37
April 2024	7,090	5.63
May 2024	8,109	6.44
June 2024	10,880	8.64
July 2024	13,187	10.48
August 2024	12,921	10.27
September 2024	11,505	9.14
October 2024	9,847	7.82
November 2024	12,149	9.65
December 2024	10,195	8.10
January 2025	6,734	5.35
February 2025	7,638	6.07
Total	125,874	100

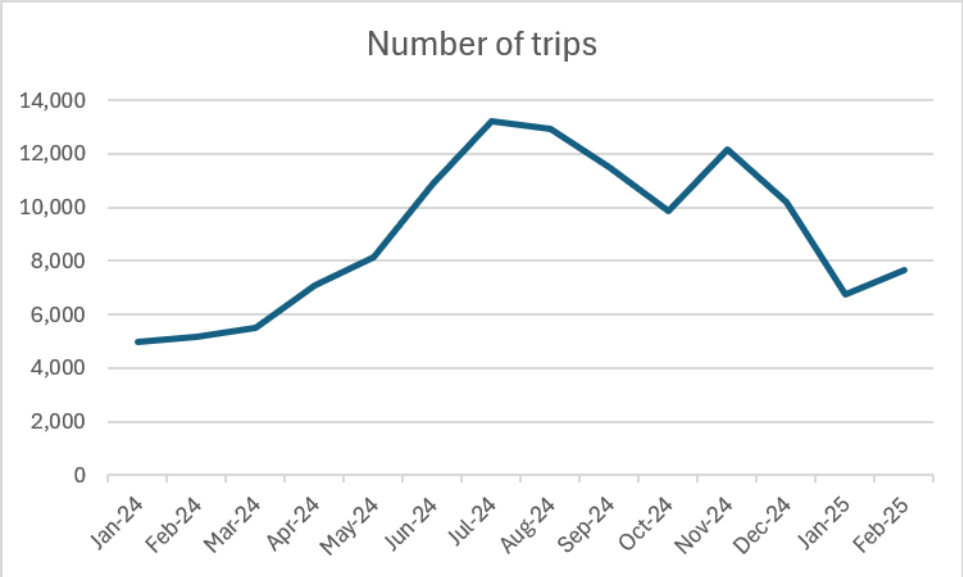


Fig. 4.3. Monthly number of shared e-scooter trips from January 2024 to February 2025.

The combined number of trips recorded in January and February increased from 10,116 in 2024 to 14,372 in 2025, representing an increase of approximately 42.1%. A direct comparison between January and February 2024 and the corresponding months in 2025 is presented in Table

4.5. January increased by approximately 35.9%, while February increased by approximately 48.0%.

Table 4.5 - Comparison of January and February trip totals in 2024 and 2025.

Period	January	February	Combined total
2024	4,956	5,160	10,116
2025	6,734	7,638	14,372
Change	+1,778	+2,478	+4,256
Percentage change	+35.9%	+48.0%	+42.1%

For a like-for-like comparison, the combined number of trips in January and February increased from 10,116 in 2024 to 14,372 in 2025, an increase of approximately 42.1%. This increase should not be interpreted as proof of a continuing long-term growth trend. The dataset does not establish whether fleet size, service coverage, operator practices, weather conditions or other operational factors remained unchanged between the two years.

To examine seasonal variation without giving winter additional weight, the seasonal analysis was restricted to the complete 2024 calendar year. A total of 111,502 trips were recorded during 2024. Summer contained the largest share, with 36,988 trips, representing 33.17% of the annual total. Autumn followed with 33,501 trips, or 30.05%. Spring and winter recorded similar but substantially lower totals, accounting for 20,702 and 20,311 trips, respectively. The seasonal distribution of trips during the complete 2024 calendar year is summarised in Table 4.6 and illustrated in Fig. 4.4.

Table 4.6 - Seasonal distribution of trips during 2024.

Season	Number of trips	Share of 2024 trips
Winter	20,311	18.22%
Spring	20,702	18.57%
Summer	36,988	33.17%
Autumn	33,501	30.05%
Total	111,502	100.00%

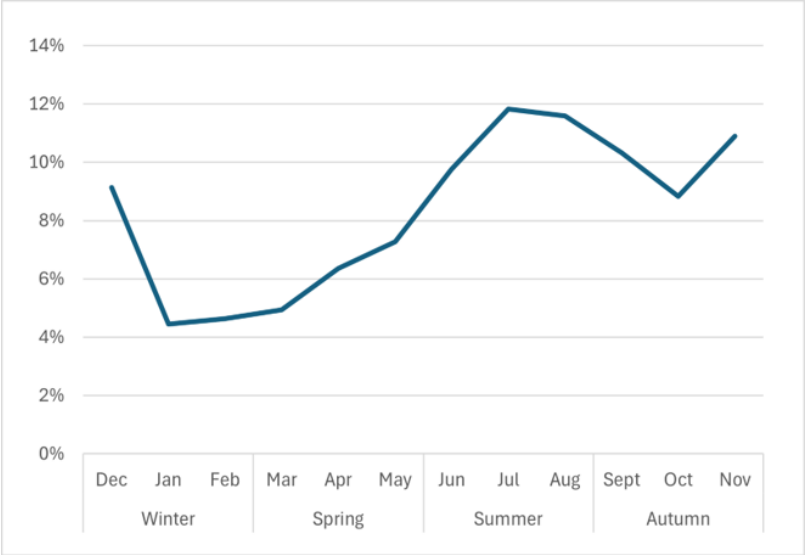


Fig. 4.4.Seasonal variation in shared e-scooter trips during 2024.

The larger summer and autumn totals are consistent with stronger activity during warmer periods and months with greater outdoor and visitor activity. However, weather was not included directly in this part of the analysis and cannot be treated as the sole explanation. Tourism, fleet availability, service management, holidays and local events may also have contributed to the observed pattern.

4.2.4 Trip-Distance Classes

As shown in Table 4.7, medium-distance trips formed the largest group in the dataset. A total of 59,429 trips, or 47.21%, were between 1 km and 3 km. Long trips of at least 3 km accounted for 41,288 trips (32.80%), while 25,157 trips (19.99%) were shorter than 1 km. The results show that e-scooter use in the study area was not confined to very short journeys: almost one third of the recorded trips covered at least 3 km.

Table 4.7 - Distribution of trips by distance class.

Trip class	Distance range	Number of trips	Share of trips (%)
Short	<1 km	25,157	19.99
Medium	1–2.999 km	59,429	47.21
Long	≥3 km	41,288	32.80
Total		125,874	100.00

4.3 Spatial Distribution of Trips

The spatial analysis examined how shared e-scooter trips were distributed across the four municipalities and their parishes. Trip origins and destinations were analysed separately to identify where journeys began and ended. Both layers showed a strong concentration of activity in Porto and in the adjoining coastal areas of Matosinhos, while more peripheral parts of the study area recorded substantially lower activity, as illustrated in Fig. 4.5 .

4.3.1 Distribution by Municipality

As shown in Table 4.8, shared e-scooter activity was unevenly distributed across the four municipalities. Porto accounted for 96,554 trips, representing 76.71% of all observations when municipalities were assigned from the spatial location of the trip points. Matosinhos contained 15,534 trips (12.34%), Vila Nova de Gaia 12,268 trips (9.75%), and Espinho 1,518 trips (1.21%). The result confirms that the service was used mainly within the denser metropolitan core, although meaningful activity was also present in Matosinhos and Vila Nova de Gaia.

Table 4.8 - Distribution of trips by municipality.

Municipality	Number of trips	Share of trips (%)
Porto	96,554	76.71
Matosinhos	15,534	12.34
Vila Nova de Gaia	12,268	9.75
Espinho	1,518	1.21
Total	125,874	100.00

Average trip characteristics also differed across municipalities, as shown in Table 4.9. Based on trip origins, Matosinhos had the longest mean distance at 3.38 km, followed by Vila Nova de Gaia at 3.01 km, Porto at 2.73 km and Espinho at 2.32 km. Mean trip duration was highest for trips starting in Vila Nova de Gaia (17.32 minutes) and Matosinhos (16.96 minutes), while trips starting in Porto averaged 14.94 minutes and those in Espinho 11.94 minutes. Destination-based values were similar, although Matosinhos had a slightly higher mean distance and duration when classified by trip end. These differences may reflect the geography and spatial extent of activity within each municipality, but they do not by themselves explain why users travelled farther.

Table 4.9 - Mean trip distance and duration by origin municipality.

Municipality	Mean distance (km)	Mean duration (min)
Porto	2.73	14.94
Matosinhos	3.38	16.96
Vila Nova de Gaia	3.01	17.32
Espinho	2.32	11.94

4.3.2 Distribution by Parish

The municipal totals conceal a much stronger concentration at parish level. The union of parishes Cedofeita, Santo Ildefonso, Sé, Miragaia, São Nicolau e Vitória recorded 44,553 trip starts, accounting for 35.39% of the full dataset. It was followed by Aldoar, Foz do Douro e Nevogilde with 20,444 trips (16.24%), Lordelo do Ouro e Massarelos with 14,788 trips (11.75%), and Matosinhos parish with 11,285 trips (8.97%).

Together, the ten most active parishes shown in Table 4.10 accounted for approximately 94% of all trip starts. This demonstrates that shared e-scooter activity was concentrated within a relatively small part of the wider four-municipality study area.

As shown in Fig. 4.5, the strongest concentration occurred in central Porto, where tourism, commercial activity, employment, public transport and urban services overlap. High activity also extended westwards towards Foz do Douro and northwards into Matosinhos.

The presence of Santa Marinha and Canidelo among the most active parishes indicates that activity in Vila Nova de Gaia was concentrated mainly near the Douro riverfront and in areas closest to Porto.

Table 4.10 - Ten parishes with the highest number of trip starts.

Rank	Parish	Trip starts	Share of all trips (%)
1	Cedofeita, Santo Ildefonso, Sé, Miragaia, São Nicolau e Vitória	44,553	35.39
2	Aldoar, Foz do Douro e Nevogilde	20,444	16.24
3	Lordelo do Ouro e Massarelos	14,788	11.75
4	Matosinhos	11,285	8.97
5	Santa Marinha	7,554	6.00
6	Paranhos	5,294	4.21
7	Bonfim	5,243	4.17
8	Ramalde	5,145	4.09
9	Leça da Palmeira	2,049	1.63
10	Canidelo	1,989	1.58

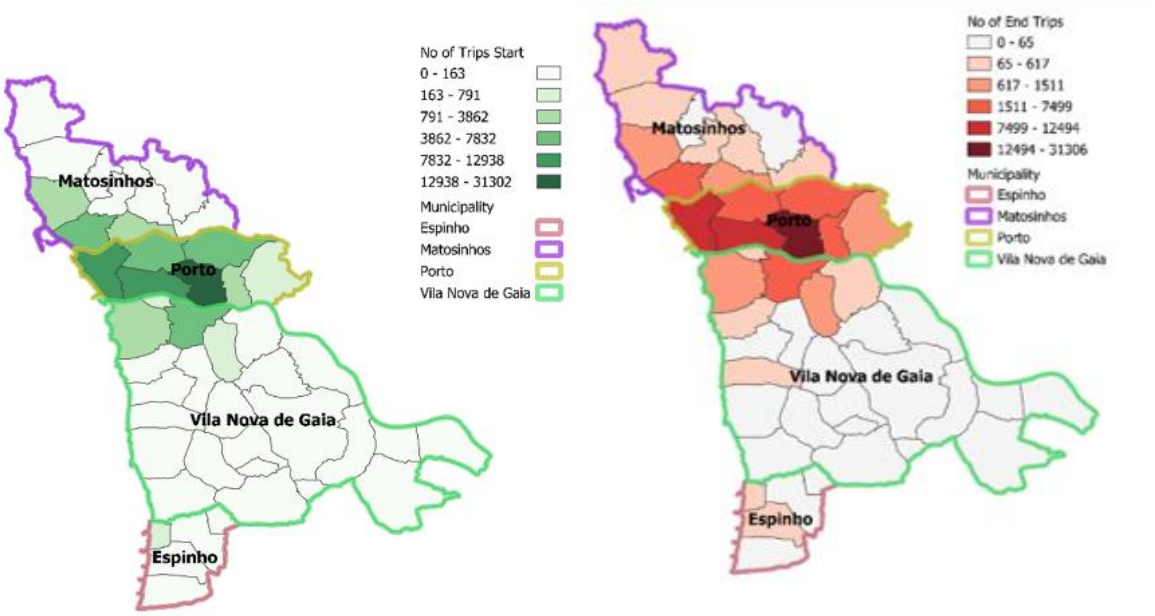


Fig. 4.5.Spatial distribution of trip starts (a) and trip ends (b) by parish.

4.3.3 Origin–Destination Movement Between Municipalities

As shown in Table 4.11, most shared e-scooter trips ended within the same municipality in which they started. Internal municipal movements clearly dominated the observed travel pattern, while cross-municipal trips accounted for only a small proportion of the classified journeys.

Approximately 98% of trips originating in Porto also ended in Porto, while around 2% ended in Matosinhos. For trips originating in Matosinhos, almost all ended within Matosinhos, with only a very small proportion ending in Porto. All classified trips originating in Espinho and Vila Nova de Gaia ended within their respective municipalities.

The main cross-municipal connection, therefore, occurred between Porto and Matosinhos. This is consistent with the spatial continuity between the two municipalities, particularly along the western and coastal urban corridor. Nevertheless, the origin–destination results describe recorded movements only and do not explain the reasons for travel or the routes followed by users.

Table 4.11 - Origin–destination matrix of trips between municipalities

Origin \ Destination	Porto	Matosinhos	Espinho	Vila Nova de Gaia
Porto	98%	2%	–	–
Matosinhos	0%	100%	–	–
Espinho	–	–	100%	–
Vila Nova de Gaia	–	–	–	100%
All origins (destination shares)	77%	12%	1%	10%

The overall destination distribution shown in the matrix also reflects the concentration of e-scooter activity across the study area. Approximately 77% of the classified trips ended in Porto, followed by 12% in Matosinhos, 10% in Vila Nova de Gaia and 1% in Espinho. These values further confirm the dominant role of Porto in the observed shared e-scooter system.

4.4 Public Transport Proximity and Stop-Level Interaction

The public transport analysis examined the spatial proximity of shared e-scooter trip locations to public transport stops. Two distance thresholds were considered: 100 m, representing immediate proximity, and 400 m, representing a broader walkable catchment. The analysis used dissolved buffer layers so that each trip point was counted only once, even where the catchments of several public transport stops overlapped.

The results describe spatial proximity between e-scooter activity and public transport infrastructure. They do not confirm that users transferred between an e-scooter and a public transport service.

4.4.1 Overall Proximity to Public Transport

As shown inTable 4.12, a total of 100,965 trip points were located within 100 m of a public transport stop, corresponding to 80.21% of all analysed trips. The remaining 24,909 trip points, or 19.79%, were located outside the 100 m catchment.

At the wider 400 m threshold, 125,126 trip points were located within reach of a public transport stop, representing 99.41% of the complete dataset. Only 748 trip points, or 0.59%, were located more than 400 m from the nearest public transport stop.

Table 4.12 - Overall proximity of e-scooter trip points to public transport stops.

Buffer distance	Within buffer	Outside buffer	Share within buffer
100 m	100,965	24,909	80.21%
400 m	125,126	748	99.41%

The results show that shared e-scooter activity was strongly concentrated near public transport infrastructure. As illustrated in Fig. 4.6, more than four-fifths of all trip points were located within immediate proximity of a public transport stop, while almost the entire dataset was located within the broader 400 m catchment.

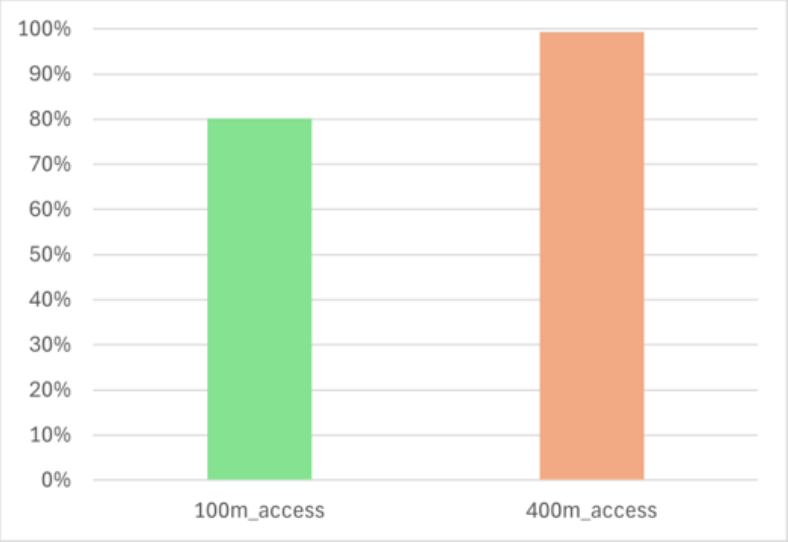


Fig. 4.6.Share of e-scooter trip points within 100 m and 400 m of public transport stops.

However, this high level of proximity should not be interpreted as evidence of actual interchange. E-scooter trips and public transport stops may be concentrated in the same dense urban areas without users necessarily combining the two modes during the same journey.

4.4.2 Differences Between Municipalities

As shown in Table 4.13, the level of proximity to public transport differed considerably between municipalities at the 100 m threshold. Porto recorded the highest immediate proximity, with 84,392 of its 96,554 trip points located within 100 m of a public transport stop. This corresponded to 87.40% of all trip points in the municipality.

Vila Nova de Gaia recorded 7,310 trip points within the 100 m catchment, representing 59.59% of its total. Matosinhos followed closely, with 8,748 trip points, or 56.32%. Espinho had the lowest immediate proximity, with 515 trip points located within 100 m of a stop, corresponding to 33.93%.

At the 400 m threshold, the differences between municipalities became much smaller. All trip points in Porto were located within 400 m of a public transport stop. The corresponding shares were 99.28% in Matosinhos, 95.92% in Espinho and 95.32% in Vila Nova de Gaia.

Table 4.13 - Public transport proximity by municipality.

Municipality	Within 100 m	Share within 100 m	Within 400 m	Share within 400 m
Porto	84,392	87.40%	96,554	100.00%
Matosinhos	8,748	56.32%	15,422	99.28%
Vila Nova de Gaia	7,310	59.59%	11,694	95.32%
Espinho	515	33.93%	1,456	95.92%
Total	100,965	80.21%	125,126	99.41%

The results indicate that immediate access to public transport was strongest in Porto. In Matosinhos, Vila Nova de Gaia and Espinho, a larger share of e-scooter trip points fell outside the 100 m catchment, although nearly all were still located within 400 m of a stop.

This suggests that public transport coverage was extensive throughout the active e-scooter service area, but the strength of direct spatial overlap differed between municipalities, as illustrated in Fig. 4.7.

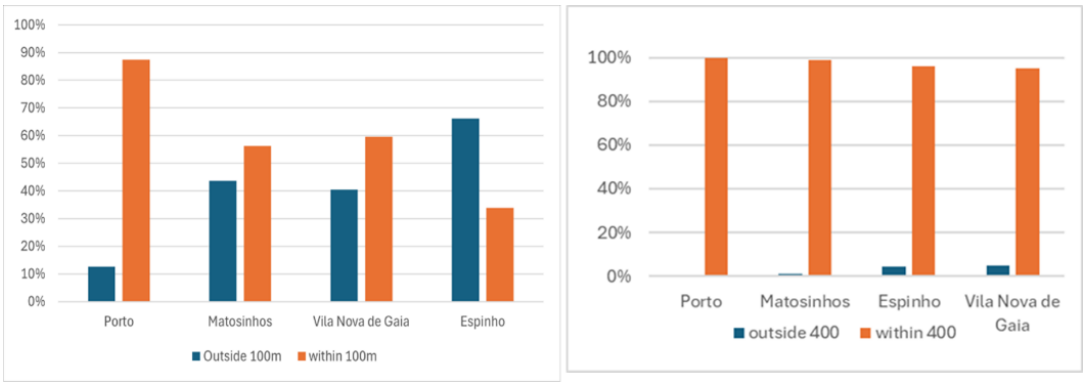


Fig. 4.7. Public transport proximity of shared e-scooter trip points by municipality: (a) within and outside 100 m; and (b) within and outside 400 m.

4.4.3 Stop-Level Interaction

The second part of the analysis examined interaction around individual public transport stops. Unlike the dissolved-buffer method, this analysis retained a separate buffer around every stop and counted the trip origins and destinations located nearby.

As shown in Table 4.14, the stop-level results showed that e-scooter activity was distributed unevenly across the public transport network. At the 400 m threshold, 2,042 public transport stops, approximately 38% of the analysed stops had no nearby e-scooter activity. At the 100 m threshold, approximately 60% of stops had no associated trip activity.

These results appear different from the trip-level finding that approximately 99% of trips were within 400 m of public transport. The two findings are not contradictory. Most e-scooter trips occurred near at least one public transport stop, but those trips were concentrated around only part of the complete stop network. A large number of stops, particularly in less active or peripheral areas, had little or no nearby e-scooter activity.

Table 4.14 - Public transport stops without nearby e-scooter activity.

Buffer distance	Stops with no nearby activity	Share of stops
100 m	3222	Approximately 60%
400 m	2,042	Approximately 38%

Because individual stop buffers overlap, one trip point may be associated with more than one stop. The stop-level counts should therefore not be summed to estimate the number of unique e-scooter trips near public transport. Instead, they indicate the relative intensity of surrounding e-scooter activity at each stop.

The spatial pattern suggests that stops with stronger interaction were concentrated primarily in central Porto and other high-activity areas. By contrast, many stops in peripheral parts of the study area had limited nearby e-scooter activity, even where public transport infrastructure was available.

4.5 Parking Proximity and Parking-Location Interaction

Designated e-scooter parking locations were defined by each municipality and were available to the operators active during the study period. The parking analysis examined how closely recorded e-scooter activity aligned spatially with this infrastructure.

A 100 m buffer was applied around designated parking locations to represent short-distance proximity and to accommodate limited positional differences between recorded trip coordinates and mapped infrastructure. Two complementary approaches were used. First, a trip-level analysis classified trip origins and destinations separately according to whether they were located within 100 m of at least one designated parking location. Second, an infrastructure-level analysis retained an individual buffer around every parking location and examined the trip activity occurring nearby.

The results represent spatial proximity and local interaction intensity rather than confirmed parking compliance. A trip point located within 100 m of a designated parking location cannot be assumed to correspond to use of the marked parking space itself.

4.5.1 Overall and Municipal Parking Proximity

The trip-level analysis showed that 30,585 trip starts were located within 100 m of a designated parking location, corresponding to 24.30% of all analysed trips. The remaining 95,289 trip starts, or 75.70%, occurred outside the 100 m parking catchment. This indicates that only about one quarter of observed trip starts were closely aligned with designated parking infrastructure.

Parking proximity varied substantially between municipalities, as shown in Table 4.15. Matosinhos recorded the highest share of trip starts within 100 m of parking, with 7,504 starts or 48.31% of its total. Espinho followed, with 449 starts or 29.58%. In Porto, 21,947 trip starts were located within the parking buffer, corresponding to 22.73% of all starts in the municipality. Vila Nova de Gaia showed the weakest alignment, with only 685 trip starts, or 5.58%, occurring within 100 m of designated parking.

Although Porto had the largest absolute number of starts near parking, this reflects its much larger overall trip volume. In proportional terms, Matosinhos showed the strongest parking alignment, while Vila Nova de Gaia showed the weakest. These differences suggest that designated parking infrastructure was not equally aligned with observed e-scooter demand across the metropolitan area.

Table 4.15 - Trip-start proximity to designated parking by municipality.

Municipality	Within 100 m	Outside 100 m	Total trip starts	Share within 100 m
Porto	21,947	74,607	96,554	22.73%
Matosinhos	7,504	8,030	15,534	48.31%
Vila Nova de Gaia	685	11,583	12,268	5.58%
Espinho	449	1,069	1,518	29.58%
Total	30,585	95,289	125,874	24.30%

Trip ends were also examined independently using the destination coordinates and the same 100 m dissolved-buffer method. Of the 125,874 trip destinations, 30,585 (24.30%) were located within 100 m of a designated parking location, while 95,289 (75.70%) were outside the 100 m catchment. The overall proportion was therefore identical to that observed for trip starts. This indicates a similar level of spatial alignment between designated parking and both scooter availability at trip origins and trip completion at destinations. Trip ends are conceptually more relevant to parking behaviour because they represent where users completed their journeys. However, the result should still not be interpreted as a direct parking-compliance rate. A trip ending within 100 m of a designated parking location does not confirm that the scooter was left inside the designated facility, while a trip ending outside the buffer does not necessarily demonstrate non-compliance because the result is affected by the selected distance threshold, positional accuracy and the completeness of the mapped parking data.

4.5.2 Variation by Trip and Temporal Characteristics

To understand whether parking proximity varied across different types of travel, the trip-start analysis was also compared by trip-distance class, time of day, weekday/weekend, and season.

As shown in Table 4.16, only limited differences were observed across trip-distance classes and time-of-day categories. Approximately 26% of short trips started within 100 m of designated parking, compared with 24% of medium-distance trips and 25% of long trips. This suggests that parking proximity was broadly similar across the three trip-length categories, with no

strong evidence that shorter or longer trips were systematically more likely to begin near designated parking.

A somewhat clearer difference appeared across the daily time periods. Night trips recorded the highest parking proximity, with around 27% of trip starts occurring within 100 m of parking. Midday trips followed at 24%, while evening-peak trips recorded 23%. Morning-peak trips showed the lowest parking proximity, at around 21%. The difference was not dramatic, but it suggests that parking alignment was slightly stronger during the night than during the morning.

By contrast, weekday/weekend and seasonal variation were minimal. Around 24% of weekday trips and 25% of weekend trips began within 100 m of designated parking. Seasonal differences were similarly small: approximately 24% of trip starts were near parking in spring, summer and autumn, compared with 25% in winter. These results suggest that parking proximity was a relatively stable feature of the system rather than one that changed strongly with season or day type.

Trips starting near parking were also slightly longer and lasted slightly more time on average, although the difference was very small. The mean trip distance increased from 2.812 km outside the parking buffer to 2.862 km within it, while mean trip duration increased from approximately 15 minutes to 16 minutes. These differences are descriptive only and do not indicate that parking proximity had a meaningful effect on trip length.

Table 4.16 - Share of trip starts within 100 m of designated parking by trip class and time of day.

Analysis dimension	Category	Share within 100 m
Trip-distance class	Short	26%
	Medium	24%
	Long	25%
Time of day	Morning peak	21%
	Midday	24%
	Evening peak	23%
	Night	27%

4.5.3 Interaction Around Individual Parking Locations

The trip-level proximity analysis shows whether a trip started near any designated parking location, but it does not reveal how activity was distributed across the individual parking network. To address this, a second analysis examined the number of trip starts associated with each specific parking location using undissolved 100 m buffers. This allowed each parking

location to retain its identity and made it possible to assess whether the interaction with the designated parking network was evenly or unevenly distributed.

Throughout this section, the term interaction refers to the number of trip starts recorded within the individual 100 m buffer of each designated parking location, counted through a spatial summary join. An interaction level therefore describes how much observed e-scooter pick-up activity surrounds each facility, and not whether riders made use of the parking facility itself. Because individual buffers can overlap, the same trip start may be counted in the interaction count of more than one parking location; the interaction counts are therefore used to compare relative intensity across locations rather than summed as unique trip totals.

The average number of nearby trip starts per designated parking location also varied across municipalities. Porto recorded the highest average, with approximately 315 nearby trip starts per location, followed by Matosinhos with 215. Much lower averages were observed in Espinho and Vila Nova de Gaia, with 43 and 34 nearby trip starts per location, respectively.

Across the complete parking network, the mean was approximately 230 interactions per location, while the median was only 39. The large difference between the mean and median indicates a strongly right-skewed distribution, in which most parking locations had relatively low interaction and a small number accounted for a much larger share of nearby activity.

Parking locations were classified into five interaction levels based on the number of nearby trip starts, as summarised in Table 4.17.

Table 4.17 - Interaction-level classification used for designated parking locations.

Interaction level	Number of nearby trip starts
No interaction	0
Low	1–199
Medium	200–799
High	800–1,999
Very high	2,000 or more

The parking-location analysis revealed a clearly uneven spatial pattern. Only a limited number of designated locations were associated with high or very high levels of nearby trip-start activity, while many others fell within the low or no-interaction categories. Interaction with the designated parking network was therefore concentrated around a relatively small number of locations.

The distribution of parking locations across the interaction classes by municipality is illustrated in Fig. 4.8. Porto was the only municipality in which parking locations appeared across the full range of interaction classes, including the very high category. This indicates that some locations in Porto were closely aligned with major concentrations of e-scooter activity. Matosinhos also showed substantial interaction, particularly in the low and medium classes. By contrast, parking locations in Vila Nova de Gaia and Espinho were concentrated mainly within the low or no-interaction categories.

These results indicate that the issue is not simply the number of designated parking locations provided, but also their spatial placement. Some locations were positioned close to major concentrations of trip-start activity, while many others were associated with little or no nearby activity.

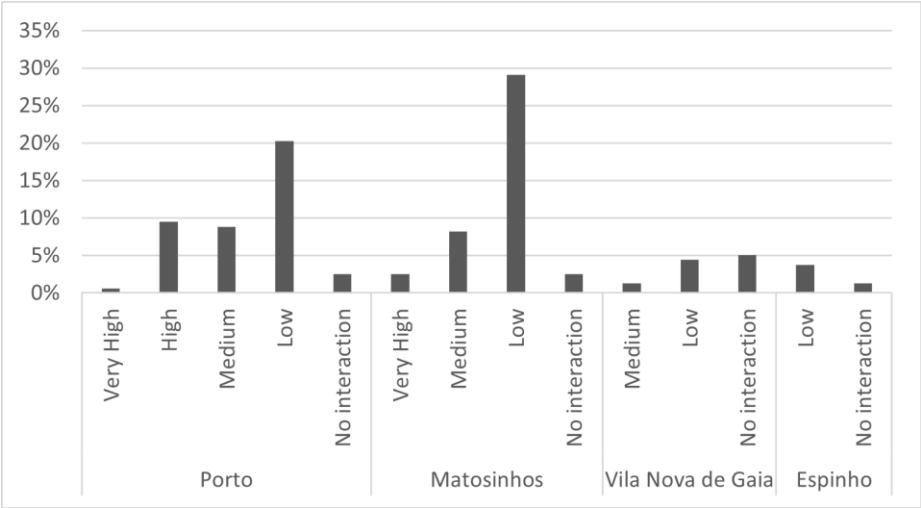


Fig. 4.8.Distribution of designated parking locations by trip-start interaction level across municipalities within a 100 m buffer.

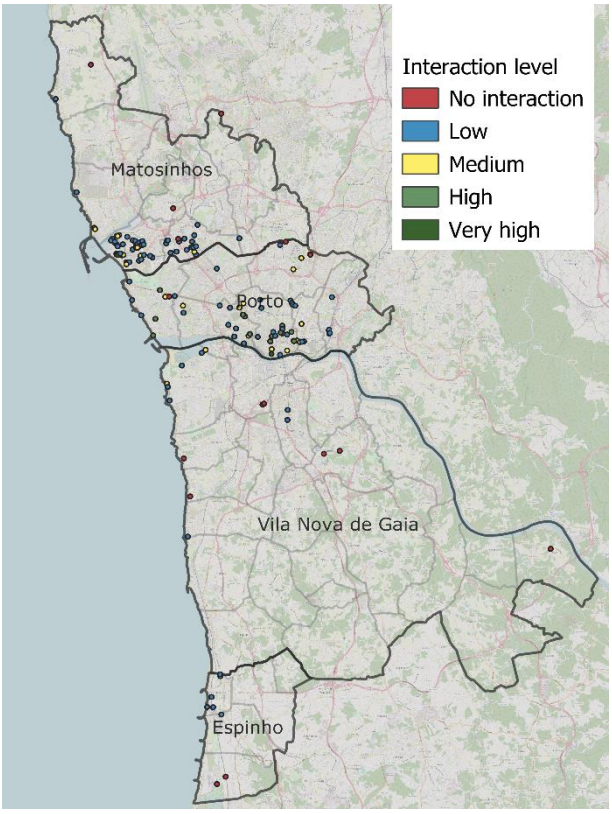


Fig. 4.9. Spatial distribution of designated parking locations classified by nearby trip-start interaction level within a 100 m buffer across the study area.

Fig. 4.9 shows that parking locations with higher surrounding trip-start activity, that is, higher interaction levels as defined above, were concentrated mainly in Porto and parts of Matosinhos, particularly within the central and coastal urban corridor. Parking locations in Vila Nova de Gaia and Espinho were more frequently classified within the low or no-interaction categories, meaning that few or no trip starts were recorded within 100 m of those facilities. The spatial pattern, therefore, reinforces the municipality-level results and shows that the alignment between parking provision and observed trip-start demand varied considerably across the study area.

Because individual parking buffers overlap, a single trip start may fall within the 100 m catchment of more than one parking location. The interaction counts should therefore be interpreted as measures of local activity intensity around each location rather than as unique trip totals that can be summed across the parking network.

4.6 Grid-Level Spatial Distribution of E-Scooter Demand

The grid-level analysis provided a more detailed spatial representation of trip-start demand. A regular 300 m × 300 m grid was used to aggregate trip starts and contextual variables, including public transport, designated e-scooter parking, cycle infrastructure, tourism, education, land use and socio-demographic characteristics.

The area-ratio-filtered descriptive grid contained 3,432 cells and 125,865 trip starts. The average trip-start density across the retained grid was approximately 474 trips per km².

The grid-based distribution showed a pronounced spatial concentration of e-scooter trip starts. Of the 3,432 cells included in the analysis, 2,682 recorded no trip starts. Therefore, approximately 78% of the retained grid cells contained no observed origin activity during the study period.

For descriptive mapping, grid cells were classified according to the number of trip starts as: no activity (0 starts), low activity (1–30), moderate activity (31–300), high activity (301–1,000), and very high activity (more than 1,000 starts).At the opposite end of the distribution, only 35 cells were classified as very-high-activity areas, yet these cells accounted for 62,508 trip starts, representing approximately half of all recorded origins.

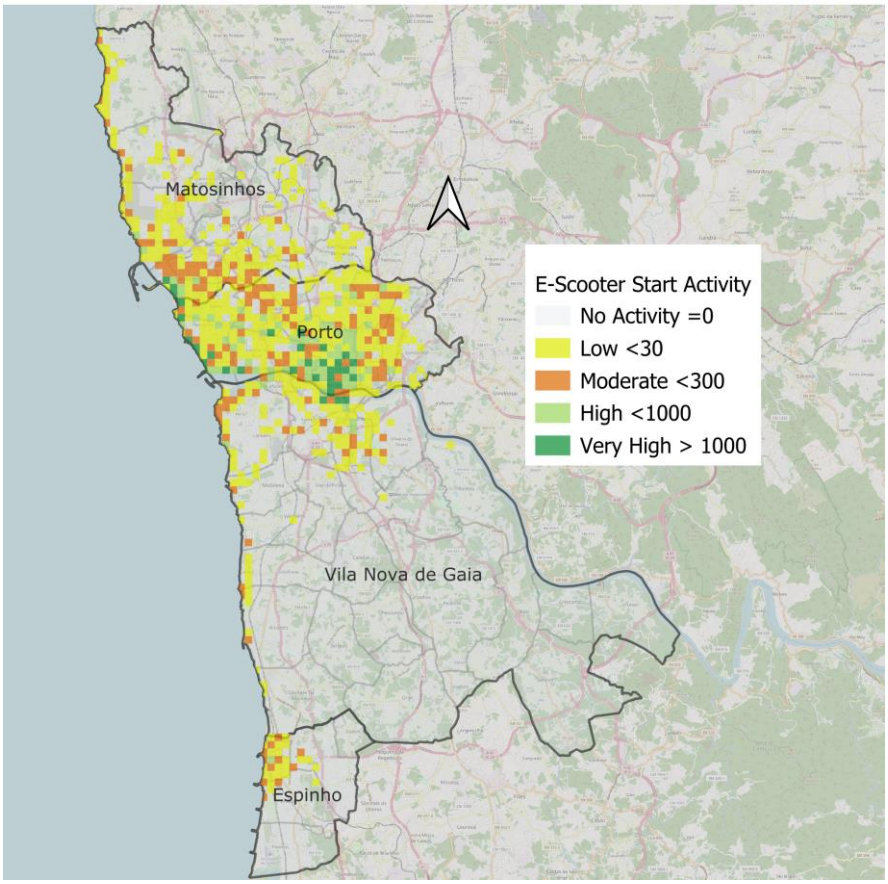


Fig. 4.10. Spatial distribution of e-scooter trip-start activity across the 300 m grid.

Fig. 4.10, shows that high- and very-high-activity cells were located predominantly in Porto and along the adjoining coastal corridor of Matosinhos. Within Porto, activity formed a relatively continuous concentration across the central and western urban areas, including the historic centre, commercial districts, the riverfront and areas extending towards the Atlantic coast.

Matosinhos formed the second main concentration of e-scooter activity. Its most active cells were located primarily in the southern part of the municipality, close to the boundary with Porto and along the coastal corridor. Activity became progressively less continuous towards the northern and inland parts of Matosinhos.

Vila Nova de Gaia showed a more fragmented spatial pattern. Active cells were concentrated mainly near the Douro riverfront and along selected parts of the western coastal corridor, while much of the municipality's inland area recorded low or no activity. Espinho contained a smaller concentration of active cells around its central and coastal urban area.

The grid-level results also indicate differences in the spatial concentration of activity between municipalities. Porto recorded the highest mean trip-start density, at approximately 2,589 starts per km², and was the only municipality with a median trip-start count greater than zero. In Matosinhos, Vila Nova de Gaia and Espinho, the median trip-start count was zero, indicating that at least half of the grid cells in each municipality contained no recorded trip starts.

Overall, the grid results show that observed e-scooter activity was concentrated mainly in Porto and adjoining parts of Matosinhos, while large parts of the more peripheral study area recorded little or no trip-start activity. The relative contribution of urban density, public transport, designated parking, cycling infrastructure, land use and other contextual characteristics is examined in the statistical model presented in the following section.

4.7 ZINB Model Results

Three Zero-Inflated Negative Binomial models were estimated for:

- total trip starts (total start model);
- weekday trip starts (weekday model);
- weekend trip starts (weekend model).

The models examined the conditional association between trip-start demand and municipality, demographic characteristics, parking, public transport, cycle-lane infrastructure, tourism, education and land-use variables.

The explanatory variables included in all three models were: municipality; population density; young-population share; working-age population share; designated e-scooter parking count; distance to designated e-scooter parking; bus-stop count; light-rail/metro-stop count; railway-station count; tram-stop count; distance to public transport; cycle-lane length; tourism presence; education presence; and commercial, industrial and residential land use. Vila Nova de Gaia was used as the reference municipality.

The model-selection diagnostics reported in Table 3.10 (Section 3.11) support the ZINB specification over the standard Negative Binomial model. This section therefore focuses on the estimated coefficients and their interpretation. Table 4.18, shows the results of the three models.

Table 4.18 - ZINB coefficient estimates for total, weekday and weekend trip starts.

Variable group	Variable	Total starts	Weekday starts	Weekend starts
Municipality	Constant	2.189***	1.794***	1.065***
	Espinho	0.639***	0.694***	0.530***
	Matosinhos	1.413***	1.389***	1.120***
	Porto	2.599***	2.603***	2.207**
Demographics	Population density	2.827***	2.636***	2.094***
	Young-population share	−5.779***	−5.845***	−4.224***
	Working-age share	−0.664	−0.393	−0.364
Parking	Parking count	0.596***	0.584***	0.666***
	Distance to parking	−7.933***	−7.963***	−6.353***
Public transport	Bus count	0.122***	0.127***	0.107***
	Light-rail/metro count	0.035	0.039	0.031
	Railway count	0.660*	0.651*	0.526
	Tram count	0.966***	0.916***	1.010***
	Distance to public transport	−6.679***	−6.667***	−5.316***
Cycle infrastructure	Cycle-lane length	5.100***	4.861***	4.060***
Activity and land use	Tourism presence	2.177***	1.901***	2.173***
	Education presence	0.289	0.306	0.249
	Commercial presence	0.835***	0.931***	0.539***
	Industrial presence	−0.567***	−0.528***	−0.467***
	Residential presence	−0.327***	−0.316***	−0.274***

Note: Vila Nova de Gaia is the reference municipality. ***, ** and * indicate significance at the 1%, 5% and 10% levels, respectively.

4.7.1 Municipality and Demographic Characteristics

Vila Nova de Gaia was used as the reference municipality. Having Vila Nova de Gaia as a reference, the coefficients for Espinho, Matosinhos and Porto were positive and statistically significant in the total, weekday and weekend models.

Porto recorded the strongest municipality coefficient in all three specifications. Its coefficient was 2.599 in the total-start model, 2.603 in the weekday model and 2.207 in the weekend model. Matosinhos showed the second-largest positive association, followed by Espinho.

These results indicate that, after controlling for the included infrastructure, land-use and demographic variables, grid cells in Porto were still associated with higher expected trip-start counts than comparable cells in Vila Nova de Gaia. This remaining difference may represent location-specific characteristics not fully captured by the model, such as urban morphology, operator deployment decisions, street connectivity, visitor concentration and the broader mobility culture.

Population density was positive and statistically significant in all three models. Its coefficient was 2.827 for total-start model, 2.636 for weekday model and 2.094 for weekend model. Denser grid cells were therefore generally associated with higher expected e-scooter demand.

Young-population share was negative and statistically significant across all models. The coefficient was −5.779 for total starts, −5.845 for weekdays and −4.224 for weekends. This result should not be interpreted as evidence that younger people used e-scooters less frequently. The variable represents the residential share of people aged 15–24 within each spatial unit rather than the age characteristics of actual users.

High-demand cells in Porto were often located in commercial, tourism and central activity areas that attract workers, visitors and non-residents. These users are not necessarily represented by the residential demographic composition of the grid cell.

Working-age share was not statistically significant in any model. After accounting for population density, municipality, infrastructure and urban activity variables, the residential proportion of people aged 25–64 did not show an independent association with grid-level trip starts.

4.7.2 Parking Availability and Accessibility

The count of designated e-scooter parking locations count was positive and statistically significant across all three models. Its coefficient was 0.596 in the total model, 0.584 during weekdays and 0.666 during weekends. The slightly larger weekend coefficient indicates that parking availability had a somewhat stronger association with weekend demand.

Distance to designated e-scooter parking was the largest negative coefficient in all three models. It was −7.933 for total starts, −7.963 for weekday starts and −6.353 for weekend starts. Grid cells located farther from designated parking locations, therefore, tended to record substantially lower expected trip-start counts.

This was one of the clearest statistical findings of the grid analysis. It is especially important because only 111 grid cells, approximately 3.2% of the study area, contained designated e-scooter parking infrastructure.

The result should nevertheless be interpreted as an association rather than a causal effect. Parking locations may have been placed in areas where operators or municipalities already expected high activity. Similarly, high-demand areas may have received more parking provision because of their existing importance.

4.7.3 Public Transport Variables

The public transport results differed according to mode.

Bus-stop count was positive and statistically significant in all models. The coefficient was 0.122 for total starts, 0.127 for weekday starts and 0.107 for weekend starts. The weekday coefficient was slightly larger, suggesting a stronger association between bus accessibility and weekday activity.

Tram-stop count showed the largest positive coefficient among the individual public transport modes. It was 0.966 in the total model, 0.916 on weekdays and 1.010 at weekends. The weekend coefficient was therefore the strongest. This pattern is spatially consistent with Porto's historic tram routes, which pass through the riverfront and coastal corridors that also contain tourism and leisure activity.

Railway count showed a weak positive association in the total and weekday models but was not statistically significant during weekends. This pattern may reflect the stronger weekday role of

railway-station areas, although the model does not identify the specific purpose of the associated e-scooter trips.

Light-rail or metro count was not statistically significant in any of the three models. This does not mean that metro accessibility was unrelated to the broader spatial pattern of demand. Metro stations are generally located in dense, accessible and commercially active areas, and those surrounding characteristics were already represented by other model variables. Consequently, the metro-stop count did not show a separate independent association once the broader urban context was controlled.

Distance to public transport remained strongly negative and statistically significant in all models. Its coefficient was −6.679 for total starts, −6.667 on weekdays and −5.316 at weekends. Cells farther from public transport generally recorded lower expected e-scooter activity.

This result indicates spatial co-location between e-scooter demand and accessible, activity-intensive urban environments. It does not demonstrate that individual e-scooter trips were used to transfer to or from public transport.

4.7.4 Cycle-Lane Infrastructure

Cycle-lane length was positive and statistically significant in all three models. The coefficient was 5.100 for total starts, 4.861 during weekdays and 4.060 during weekends.

The positive direction was consistent across all periods, indicating that cells containing more cycle-lane infrastructure generally recorded higher expected trip-start demand. The slightly larger weekday coefficient may reflect the role of dedicated infrastructure in supporting regular or utilitarian travel during working days.

The coefficient should not be interpreted as proving that cycle lanes directly generated e-scooter trips. Cycle lanes may also be more common in central, accessible or mobility-supportive urban environments where e-scooter demand is already high.

4.7.5 Tourism, Education and Land Use

Tourism presence was positive and statistically significant in every model. Its coefficient was 2.177 for total starts, 1.901 during weekdays and 2.173 during weekends. The weekend coefficient was therefore close to the total effect and larger than the weekday value, indicating a stronger weekend association with tourism-related areas.

Commercial presence was also positive and significant across all models. The association was strongest during weekdays, with a coefficient of 0.931 compared with 0.539 at weekends. This suggests that commercial districts were more strongly associated with weekday trip generation, indicating a stronger weekday association with commercial areas.

Education presence was not statistically significant in any model. After controlling for municipality, population density, transport accessibility, tourism and commercial activity, the presence of education facilities did not show an independent relationship with trip-start demand.

Industrial presence showed a negative and statistically significant coefficient in all models. It was −0.567 for total starts, −0.528 during weekdays and −0.467 at weekends.

Residential presence was also negative and significant, with coefficients of −0.327, −0.316 and −0.274. These results suggest that, after controlling for the other included characteristics, cells dominated by industrial or residential functions were associated with lower trip-start counts than more commercially active or tourism-oriented environments.

4.7.6 Comparison Between Weekday and Weekend Results

The direction of the principal relationships remained broadly stable between weekday and weekend models. Population density, parking count, bus count, tram count, cycle-lane length, tourism presence and commercial presence were positively associated with trip starts in both periods.

Distance to parking and distance to public transport remained negative and statistically significant throughout. Industrial and residential presence also remained negatively associated with demand.

Several differences were nevertheless visible.

Weekday demand showed a stronger association with:

- population density;
- bus-stop count;
- cycle-lane length;
- commercial presence;
- railway count.

Weekend demand showed a relatively stronger association with:

- parking count;
- tram-stop count;
- tourism presence.

This distinction shows that weekday demand had relatively stronger associations with population density, commercial presence, bus and railway variables, and cycle-lane length, whereas weekend demand had relatively stronger associations with parking count, tram-stop count and tourism presence. These differences are useful for interpretation but should not be treated as evidence that weekday and weekend travellers had specific trip purposes.

5
DISCUSSION

5.1 INTRODUCTION

The results show that shared e-scooters have become part of the mobility system in the Porto Metropolitan Area, but their role is not as simple as describing them as a first- and last-mile solution. Their use varied considerably by location, time of day, day of the week, municipality and surrounding land use. The service was most active in central and destination-rich areas, particularly Porto and the southern and coastal parts of Matosinhos, while activity was much weaker and more fragmented in Vila Nova de Gaia and Espinho.

The findings also show that proximity to infrastructure does not automatically reveal how a scooter was used. Many trips occurred close to public transport, but this does not prove that passengers transferred between the two modes. Similarly, the presence of a designated parking facility near a trip origin or destination does not prove that the scooter was correctly parked in the designated facility. The results should therefore be understood as evidence of spatial relationships and potential interaction, rather than direct evidence of individual travel behaviour.

This distinction is important because the existing literature does not present e-scooters as a single-purpose mode. Depending on the city, location and time, they may complement public transport, replace a short transit trip, substitute for walking or cycling, or function as an independent mode. Previous research also shows that spatial proximity is useful for identifying potential connections, but it cannot establish the purpose of a trip without information about the wider journey (Badia & Jenelius, 2023; Li et al., 2024; Yin et al., 2024).

The discussion therefore focuses on what the results can reasonably demonstrate, what they cannot demonstrate, and what they imply for planning in Porto, Matosinhos, Vila Nova de Gaia and Espinho.

5.2 Spatial and Temporal Pattern of E-Scooter Use

The trip characteristics broadly support the view of shared e-scooters as a short-distance urban mode, although the results also show that their use extends beyond very short journeys. The mean trip distance was 2.82 km and the mean duration was 15.34 minutes. The median distance was 2.04 km and the median duration was 10 minutes, indicating that the distribution was positively skewed. Most journeys were relatively short, but a smaller number of longer trips increased the average.

Almost half of the trips were between 1 and 3 km, while nearly one-third were at least 3 km and trips below 1 km represented only around one-fifth of the total. This is important because it challenges the idea that shared e-scooters are used predominantly for very short connections, as previous studies have shown that e-scooters can also serve a broader range of urban trips and may complement or substitute other transport modes depending on the local context (Wang et al., 2023; Aarhaug et al., 2023).The results do not show whether these longer trips replaced walking, public transport, car travel, taxis, ride-hailing or cycling. They only show that e-scooters were being used for journeys that extended beyond very short-distance travel; the data do not establish whether walking would have been a practical alternative.

This finding is consistent with research showing that e-scooters can occupy an uncertain position between active travel and motorised transport. They may serve trips that are too long, steep or inconvenient for walking, while still being shorter than journeys normally made by car or conventional public transport. Previous research has similarly found that e-scooters may complement or substitute several modes, depending on local conditions and the purpose of the journey (Wang et al., 2023; Aarhaug et al., 2023).

The physical geography of Porto may also help explain why journeys of 2 or 3 km are attractive. Slopes, indirect street connections and changes in elevation can make walking or conventional cycling less convenient. Electric assistance may reduce the effort required for these trips. However, this remains a contextual interpretation rather than a measured finding. The available

data identify trip origins and destinations, but they do not include the routes taken, gradients experienced or the travel modes that would otherwise have been used.

The daily pattern gives a clearer indication of when the service was being used. Only 7.28% of trips were recorded in the morning period, while more than 92% occurred from midday through the evening and night. Activity increased gradually during the day and reached its highest level at approximately 17:00. More than one-quarter of trips occurred after dark.

This pattern is broadly consistent with studies that identify stronger afternoon and evening demand. Foissaud et al. (2022) reported afternoon peaks across several European cities, while Shah et al. (2023) identified a mixture of daytime errands, social activity, entertainment and utilitarian trips in Nashville. At the same time, the Porto results differ from studies that found a clearer two-peak weekday pattern associated with morning and evening commuting, such as Abouelela et al. (2023).

The absence of a strong morning peak should not be interpreted as evidence that commuting was absent. The afternoon peak may include journeys from work or education, but it may also reflect shopping, tourism, social activity, leisure, or increased scooter availability after morning redistribution. The data do not include trip purpose, employment status or the mode used before the scooter journey. Therefore, it would be too strong to label the morning and evening periods as commuting periods simply because they occur at times commonly associated with work travel.

Night-time activity is particularly relevant in Porto. The city centre contains restaurants, hotels, tourist attractions, nightlife and cultural destinations, and these uses may help explain why demand remained high after dark. Nevertheless, a night-time trip cannot automatically be classified as leisure, just as a morning trip cannot automatically be classified as commuting. The temporal data show when people travelled, not why they travelled.

The weekday and weekend results require similar care. Weekdays accounted for 69.68% of all trips, while weekends accounted for 30.32%. However, these totals should be interpreted in relation to the number of days in each category. During the study period, there were 305 weekdays and 120 weekend days. This corresponds to an average of approximately 288 trips per weekday and 318 trips per weekend day. Therefore, although the total number of weekday trips was substantially higher, average daily e-scooter activity was about 10.6% higher on

weekends. This indicates that weekend use was more substantial than the aggregate totals alone suggest.

This is consistent with the possibility that shared e-scooters served both routine and discretionary travel, although the dataset does not identify individual trip purposes. The service remained important during the weekend, when commuting is generally less dominant and tourism, leisure and social activities become more visible in the urban environment. Matosinhos recorded a comparatively strong weekend contribution, which is consistent with its coastal areas, beaches, restaurants and recreational destinations. This does not prove that individual trips were made for leisure, but the spatial and temporal pattern makes that interpretation plausible.

Seasonal variation provides further evidence that e-scooter activity was influenced by the wider urban environment. Summer recorded the highest share of activity in 2024, followed by autumn, while winter and spring were lower. This is consistent with research showing that weather, temperature, rainfall and seasonal outdoor activity influence shared micromobility demand (Foissaud et al., 2022; Abouelela et al., 2023; Garus et al., 2025).

However, the seasonal pattern cannot be attributed to weather alone because weather variables were not included in the analysis. Tourism, holidays, changes in fleet size, service expansion, pricing, local events and operator decisions may also have affected the monthly totals. The 42.1% increase between January and February 2024 and the same period in 2025 should therefore not be described as evidence of long-term growth. It shows that more trips were recorded in the later period, but it does not demonstrate that demand increased independently of changes in service conditions.

The spatial distribution was even more uneven than the temporal distribution. Porto accounted for approximately three-quarters of all recorded activity, while Matosinhos was the second most active municipality. Vila Nova de Gaia and Espinho recorded substantially lower levels of use. At the parish level, the most active areas were concentrated in central Porto, western Porto and the southern and coastal parts of Matosinhos.

This result is consistent with the wider literature. Studies in Washington, D.C., several United States cities and other urban areas have found that shared e-scooter activity is usually concentrated in central districts, commercial areas, university locations, tourist destinations and mixed-use neighbourhoods (McKenzie, 2019; Huo et al., 2021; Abouelela et al., 2023). These

places bring together employment, tourism, public transport, services, shops and leisure destinations within a relatively small area.

The concentration in Porto is consistent with these characteristics, but it should not be interpreted as evidence that the urban environment alone caused the pattern. Porto also appears to have received more vehicles, more frequent redistribution and stronger operational support. The positive municipality coefficient for Porto remained strong after the variable's population density, parking, public transport, tourism, commercial activity and cycle infrastructure were included in the model. This suggests that the variables used in the analysis did not fully capture the differences between Porto and Vila Nova de Gaia.

The remaining difference may include street connectivity, pedestrian activity, destination density, visitor numbers, fleet availability, service visibility, geofencing and user familiarity with the service. This is an important distinction between realised demand and potential demand. The trip records show where journeys took place under the operator's existing conditions. They do not show how much demand might have existed if scooters had been more widely available in peripheral areas.

The origin and destination patterns also indicate that the service operated mainly within municipal boundaries. The strongest cross-boundary connection was between Porto and Matosinhos, which reflects the physical continuity of the western and coastal urban corridor. The weak cross-river and longer-distance flows may relate to the Douro, bridge conditions, trip length, geofencing or different municipal rules. However, the data cannot identify which of these explanations is most important.

Overall, the spatial and temporal results describe a mixed-purpose service concentrated around the most active parts of the metropolitan area. It supported short and medium-distance journeys, was used more heavily from midday onwards, remained relevant at weekends and at night, and followed the geography of centrality and destination intensity. At the same time, the pattern was shaped by the operator's decisions about where scooters were available. It should therefore not be read as a complete map of latent metropolitan demand.

5.3 PUBLIC TRANSPORT AND PARKING: PROXIMITY, OPPORTUNITY AND MISMATCH

The relationship between shared e-scooters and public transport appears strong when measured through spatial proximity. Approximately 80.21% of trip points were located within 100 m of a public transport stop, while 99.41% were within 400 m. These figures show that e-scooter activity occurred mainly in parts of the metropolitan area that were already well served by public transport. They also identify locations where e-scooters could potentially support access to or egress from public transport.

The 400 m result must nevertheless be interpreted carefully. When almost all trip points fall within this distance of a stop, the measure begins to describe the general accessibility of the urban area rather than a specific relationship between an e-scooter journey and public transport. In a dense metropolitan area with a large number of stops, many trips in central districts will fall within a 400 m catchment even when the journey is connected to a workplace, shop, restaurant, hotel, residence or tourist destination rather than to a public transport transfer.

The results, therefore, support the possibility of first- and last-mile interaction, but they do not support the stronger claim that most e-scooter journeys were multimodal. A trip located close to a public transport stop may have involved a transfer, but it may also have been an independent journey occurring near the same urban destination. This distinction is central to the wider literature. Studies have shown that shared e-scooters can provide access and egress to public transport in particular situations, but they can also operate independently or compete with public transport (Aarhaug et al., 2023; Gödde & Scheiner, 2025; Currie et al., 2025).

User-validated research has also shown that buffer-based methods can overestimate the number of trips that are genuinely connected to public transport (Yin et al., 2024). Distance thresholds are useful for analysing large operational datasets consistently, but they cannot reveal the purpose of a trip or the mode used before or after the e-scooter journey. The Porto results should therefore be understood as evidence of spatial opportunity, not confirmed travel behaviour.

The municipal results add an important qualification. Immediate proximity was highest in Porto, where 87.40% of trip points were within 100 m of a public transport stop. It was lowest in Espinho, at 33.93%. At the wider 400 m threshold, however, every municipality exceeded 95%, with Porto reaching 100%, Matosinhos 99.28%, Vila Nova de Gaia 95.32% and Espinho 95.92%.

This difference suggests that the municipalities offered different levels of immediate access to public transport, even though the wider public transport catchment was extensive throughout the study area. In Porto, the dense stop network created a high level of direct spatial overlap. In Matosinhos, Vila Nova de Gaia and Espinho, a greater proportion of trips were within a broader walking distance of public transport without being located immediately beside a stop.

The stop-level results make the integration question more complex. Approximately 60% of public transport stops had no nearby e-scooter activity within 100 m, and around 38% had no activity within 400 m. These results are not inconsistent with the high trip-level proximity figures because the two measures describe different aspects of the system. Trip-level proximity asks whether scooter journeys occurred near public transport. Stop-level analysis asks whether the public transport network as a whole was surrounded by e-scooter activity.

The distinction is important. E-scooter trips were concentrated around a limited number of stops in already active urban areas, while much of the wider public transport network recorded little or no nearby scooter activity. This suggests that shared e-scooters were embedded in locations that already had strong public transport, commercial activity, tourism and destination intensity. The results therefore do not indicate that e-scooters were functioning as feeders to the public transport network as a whole.

The grid analysis supports the same interpretation. Only 106 cells were classified as a Good Match between high scooter demand and public transport accessibility. These cells represented approximately 3% of the analytical grid and had a mean start-trip density of 12,863 trips per km². In contrast, 2,861 cells, or approximately 83% of the grid, were classified as Underused PT-accessible cells, with an average of only 12 starts per km². No cells were classified as public transport accessibility gaps.

The absence of public transport gap cells indicates that high e-scooter demand did not occur in areas with weak public transport access. At the same time, the large number of underused PT-accessible cells shows that public transport access alone did not generate substantial e-scooter activity. Public transport was therefore an important part of the urban context, but it was not sufficient to explain demand without the presence of centrality, destinations, commercial activity, tourism, parking and scooter availability.

The mode-specific results require similar caution. Bus counts were positively associated with demand in all three models. Tram counts showed an even stronger positive relationship,

particularly at weekends. Railway counts were weakly significant in the total and weekday models, while light rail or metro counts were not statistically significant on their own. These results do not mean that tram stops were inherently more important to e-scooter users than metro stations. Different modes operate through different types of urban environments, and the surrounding land use may be partly responsible for the observed relationships.

Bus stops are widely distributed and may partly represent general urban connectivity. Areas with several bus stops are also likely to contain more destinations, services, pedestrian activity and commercial land uses. The positive bus coefficient may therefore capture both public transport access and the wider intensity of the surrounding area.

The weekend tram relationship may reflect the character of Porto's historic, riverfront and tourist corridors as much as actual transfers between trams and e-scooters. Although tourism was included in the model, a simple presence variable cannot fully represent visitor numbers, leisure activity or the intensity of use along a particular corridor. Similarly, the weak railway relationship may reflect the small number of railway stations and their association with regional or weekday travel. The non-significant metro relationship does not mean that metro stations were irrelevant. It may indicate that their influence overlapped with other variables such as density, commercial activity and general accessibility.

The public transport results therefore neither confirm nor reject the first- and last-mile role of shared e-scooters. They demonstrate clear spatial overlap and identify locations where multimodal travel was possible. However, the concentration around a small number of stops, the large Underused PT-accessible category and the influence of broader urban characteristics all argue against treating proximity as proof of integration. E-scooters in Porto may have fed public transport on some journeys, replaced short public transport trips on others and operated independently in the same central areas. The available data cannot determine the proportion belonging to each category.

Parking presents a different and more uneven relationship with demand. Only 24.30% of trip starts were located within 100 m of a designated parking facility, considerably lower than the 80.21% of trip points located within the same distance of public transport. This indicates that designated parking was much less closely aligned with observed scooter activity than the public transport network.

The municipal differences were substantial. Matosinhos had the highest proportion of trip starts within 100 m of designated parking, at 48.31%, followed by Espinho at 29.58%, Porto at 22.73% and Vila Nova de Gaia at 5.58%. These results suggest a particularly weak spatial relationship between observed scooter starts and designated parking in Vila Nova de Gaia.

These percentages should not be described as parking compliance rates. A trip start shows where a scooter was available for a new journey. It does not necessarily show where the previous rider ended the trip, whether the operator redistributed the vehicle, or whether the scooter was left inside a designated facility. The 100 m buffer also allows a considerable distance around the mapped parking location. The measure, therefore, describes spatial alignment between scooter availability and designated parking, not confirmed parking behaviour.

The trip-end analysis produced the same overall 24.30% proximity rate as the trip-start analysis, suggesting that designated parking showed a similar level of spatial alignment with both scooter availability and trip completion. Because trip ends more directly represent where journeys were completed, this result is more relevant to parking behaviour, although it remains a proximity measure rather than verified compliance.

This distinction is consistent with previous research. Parking compliance is influenced by the location and convenience of facilities, sidewalk width, legally parkable space, street design, GPS accuracy and the position of natural trip-end destinations (Hemphill et al., 2022; Karlsen et al., 2025; Meng et al., 2025). A parking facility may exist but still have limited influence if it is poorly located, difficult to reach, not visible to users or too far from the destination.

The stronger proportional alignment in Matosinhos does not necessarily mean that it has a better parking policy in every respect. Its demand is more concentrated along particular urban and coastal corridors, which may make it easier for designated parking to correspond with trip activity. Porto has a much larger and more complex demand pattern, so a lower proportion may partly reflect the fact that activity is spread across a dense central area. Similarly, the very low figure in Vila Nova de Gaia may reflect sparse facilities, limited operational coverage, inaccurate infrastructure data or a mismatch between designated parking and the locations where activity actually occurs. The present analysis cannot distinguish between these explanations.

Parking proximity changed little across trip-distance classes, weekdays and weekends or seasons. Night trips showed slightly stronger proximity to designated parking than morning trips, but the difference was limited. This relative stability suggests that parking alignment was mainly a fixed spatial characteristic of the network rather than a relationship that changed substantially according to trip length or season.

Interaction around individual parking locations was highly uneven. Some facilities were close to large concentrations of trip starts, while others recorded little or no nearby activity. This supports research showing that the location and distribution of parking facilities may be more important than the total number of spaces. Well-positioned facilities can attract substantially more activity than a larger network that is poorly located (Sandoval et al., 2021; Meng et al., 2025).

These findings do not mean that every underused facility should be removed or that every demand gap requires a new parking space. Some facilities may serve other operators, regular bicycles, future demand or public-space management objectives. Persistent underuse should nevertheless lead to a closer review of visibility, access, location and capacity. In some cases, relocation may be more effective than simply increasing the total number of facilities.

The model results reinforce the importance of parking location. Parking count was positively associated with trip starts, while distance to parking had the strongest negative coefficient in the model. This indicates that demand was concentrated near the designated parking network. The direction of the relationship remains uncertain, however. Convenient parking may make scooters easier to find and use, but municipalities and operators may also have placed parking in areas where demand was already high. The observed relationship may therefore reflect both the potential influence of parking provision and the possibility that parking was located in areas where demand was already high.

The grid-based parking classification shows the same pattern. Good Match cells had the highest mean activity density, at 15,074 starts per km². The 21 parking-gap cells also recorded substantial activity, with a mean of 7,440 starts per km². This indicates that some high-demand locations were generating considerable scooter activity despite weak or limited access to designated parking.

The parking-gap cells should be treated as locations for further investigation rather than as an automatic list of new facilities. A gap may be caused by a facility located just outside the grid

boundary, incomplete mapping, a lack of suitable public space, operator redistribution or a genuine shortage of parking. Street-level inspection is therefore necessary before deciding whether the appropriate response is a new facility, relocation, improved visibility, greater capacity or a change in operating rules.

The comparison between public transport and parking is one of the clearest findings of the study. Public transport accessibility was widespread across the study area, but it did not explain demand by itself. Designated parking was more limited and unevenly distributed, but where it was close to active locations, it showed a stronger spatial relationship with scooter activity. Public transport formed a broad urban backdrop for e-scooter use, while parking acted as a more selective operational factor whose location appeared to matter considerably.

The overall conclusion is therefore cautious but useful. The evidence supports the possibility that shared e-scooters contributed to multimodal travel in Porto, but it does not prove that most trips were connected to public transport. It also shows that parking provision was not simply a matter of increasing the number of facilities. The effectiveness of both systems depended on where infrastructure was located, what activities surrounded it and how the operator and municipalities managed the service.

5.4 URBAN CONTEXT AND THE FACTORS ASSOCIATED WITH DEMAND

The ZINB models show that shared e-scooter demand in the Porto Metropolitan Area was associated with a combination of population density, accessibility, parking, public transport, tourism, commercial activity and cycle infrastructure. This broadly supports the established view that shared e-scooters are more active in dense and destination-rich urban environments. However, these relationships are context-dependent and should not be transferred directly from one city to another.

Throughout this section, the model coefficients are interpreted as conditional spatial associations rather than causal effects. The explanatory variables often occur together within the same urban areas, and the models cannot establish that changing one characteristic would independently cause e-scooter demand to change. The discussion therefore focuses on the spatial relationships identified by the models and how they compare with previous research.

Population density was positively associated with trip starts in the total, weekday and weekend models. This is consistent with studies linking higher e-scooter activity to population density,

employment concentration, intersection density and proximity to central areas (Huo et al., 2021; Bai & Jiao, 2020; Tuli et al., 2021). Dense areas contain more potential origins and destinations within short distances and are often supported by stronger public transport, commercial activity and pedestrian movement.

Density alone, however, did not explain the spatial pattern. Porto, Matosinhos and Espinho remained positively associated with trip starts relative to Vila Nova de Gaia after population density, infrastructure, tourism and land use were included in the models. These municipality coefficients indicate that local characteristics associated with higher observed activity were not fully represented by the selected variables. Possible factors include street connectivity, destination density, visitor numbers, fleet availability, service visibility, geofencing and operator deployment.

Tourism was positively associated with demand in all three models and showed a relatively stronger relationship at weekends. This is consistent with research showing that tourist and local activity can respond differently to destinations, transport facilities and cycling infrastructure (Christoforou et al., 2023). The result also fits the concentration of activity observed in Porto's historic centre, riverfront and coastal areas.

Commercial presence was also positively associated with demand, with a stronger relationship in the weekday model. Previous studies have similarly found higher e-scooter activity in commercial, mixed-use and employment areas (Huo et al., 2021; Hosseinzadeh et al., 2021; Tuli et al., 2021). Weekday demand showed relatively stronger associations with population density, commercial activity, bus and railway access and cycle infrastructure, whereas weekend demand showed relatively stronger associations with tourism, parking and tram presence. These differences suggest that the same urban areas may support different mobility patterns across the week, although the dataset does not identify individual trip purposes.

The demographic results differed from some previous studies. The share of residents aged 15 to 24 was negatively associated with demand, while the working-age share was not statistically significant. Education presence was also not significant in any of the three models. These findings differ from studies that have identified younger populations and university areas as important locations for e-scooter use (Huo et al., 2021; Dias et al., 2024).

The negative young-population coefficient should not be interpreted as evidence that younger people used e-scooters less. The variable represents the age structure of residents within each

grid cell rather than the characteristics of actual users. Central Porto attracts students, tourists, workers and other visitors who may live elsewhere in the metropolitan area. Evidence from Portugal also shows that private-car travel is common among younger children travelling to school and that home–school distance influences active travel (Rodrigues et al., 2018). Residential age structure therefore does not necessarily represent the population moving through an area during the day.

The non-significant education variable should also be interpreted in relation to how it was measured. The binary indicator records only whether an education facility is present and does not distinguish between the type, size or intensity of use of those facilities. Education locations may also overlap spatially with population density, public transport and commercial activity. These measurement limitations are discussed further in the limitations section.

Industrial and residential land uses were negatively associated with demand. Industrial areas often contain fewer closely located destinations, larger blocks and lower levels of pedestrian activity. The residential result may appear inconsistent with the positive relationship identified for population density, but the two variables measure different aspects of the urban environment. Population density measures how many people live in an area, while residential land use reflects its functional character. A dense mixed-use area may contain residents, shops, tourism, offices and services, whereas a predominantly residential area may contain fewer destinations and less passing activity. The results therefore suggest that demand was stronger in dense, mixed and activity-rich areas rather than in locations that were mainly residential.

Cycle-lane length was positively associated with demand in all three models, consistent with research linking cycling infrastructure with more supportive environments for micromobility (Christoforou et al., 2023; Hosseinzadeh et al., 2021). However, cycle infrastructure is also concentrated in central and accessible areas containing destinations, public transport and other forms of urban investment, so the coefficient may partly reflect the wider characteristics of those locations.

The GIS results provide an important complement to the model. A total of 73,821 trip starts occurred in high-demand cells without mapped cycle support, compared with 41,649 starts in high-demand cells with cycle infrastructure. This is not inconsistent with the positive model coefficient. The model indicates that cells with more cycle infrastructure tended, on average, to

have higher expected demand after other variables were considered, while the GIS analysis shows that the existing network does not cover all locations where demand is already high.

This distinction has practical importance. A high-demand cell without mapped cycle infrastructure should not automatically be treated as a location requiring a new cycle lane. It may contain a pedestrian street, low-speed road, steep route, infrastructure immediately outside the grid boundary or a route-continuity problem. The planning question is therefore not only whether cycle infrastructure is present, but whether safe and convenient connections exist between important destinations and neighbouring high-demand areas.

Overall, the ZINB results indicate that e-scooter demand was stronger in dense, accessible and destination-rich areas. No single variable explains the observed pattern in isolation. Instead, demand appears to reflect the combined spatial context of urban centrality, land-use intensity, tourism, commercial activity, transport accessibility, parking provision, cycle conditions and operator supply. Residential demographic characteristics should therefore not be treated as a direct representation of e-scooter users, and differences between cities are likely to depend on how these urban and operational factors combine locally.

6

INFRASTRUCTURE INTERVENTION PLANNING

6.1 INTRODUCTION

This chapter translates the statistical findings of Chapter 4 into spatial planning information for the Porto Metropolitan Area. The grid-level statistical models identified several infrastructure variables associated with e-scooter trip-start activity, particularly distance to designated e-scooter parking, distance to public transport and cycle-lane length. The GIS classifications presented here were developed after the statistical modelling to examine where observed e-scooter activity coincided with different levels of infrastructure support. They were used for spatial interpretation and planning screening and were not included as explanatory variables in the ZINB models, as described in Chapter 3.

For the public transport and designated-parking analyses, grid cells were classified into four relationship categories: Good Match, Gap, Underused and Mixed. The detailed thresholds and classification rules are defined in the methodology section 3.13.1. In this chapter, these categories are used to interpret where observed e-scooter activity aligns with, or differs from, the spatial distribution of supporting infrastructure.

These categories describe spatial correspondence between observed activity and infrastructure accessibility and should not be interpreted as evidence that the infrastructure caused the observed demand.

6.2 PUBLIC TRANSPORT ACCESSIBILITY AND E-SCOOTER DEMAND

Using the demand–accessibility classification defined in Section 3.13.1, the public transport analysis compared grid-level e-scooter trip-start activity with accessibility to public transport. Three of the four relationship categories were present in the final grid: Good Match, Mixed and Underused. No cells were classified as a public transport accessibility Gap. Under the applied criteria, this means that all high- and very-high-activity cells were located in areas with high or moderate public transport accessibility. Table 6.1 summarises the distribution of grid cells across the public transport relationship categories.

Table 6.1 - Grid-level relationship between e-scooter demand and public transport accessibility.

Public transport relationship	Grid cells	Share of grid	Mean start-trip density
Good Match	106	3%	12,863 trips/km²
Mixed	465	14%	492 trips/km²
Underused	2,861	83%	12 trips/km²
Total	3,432	100%	474 trips/km²

Good Match cells represented only 106 cells, or approximately 3% of the analytical grid, but recorded a mean start-trip density of 12,863 trips/km². These cells were concentrated mainly in central Porto and adjoining parts of southern Matosinhos, as shown in Fig. 6.1.

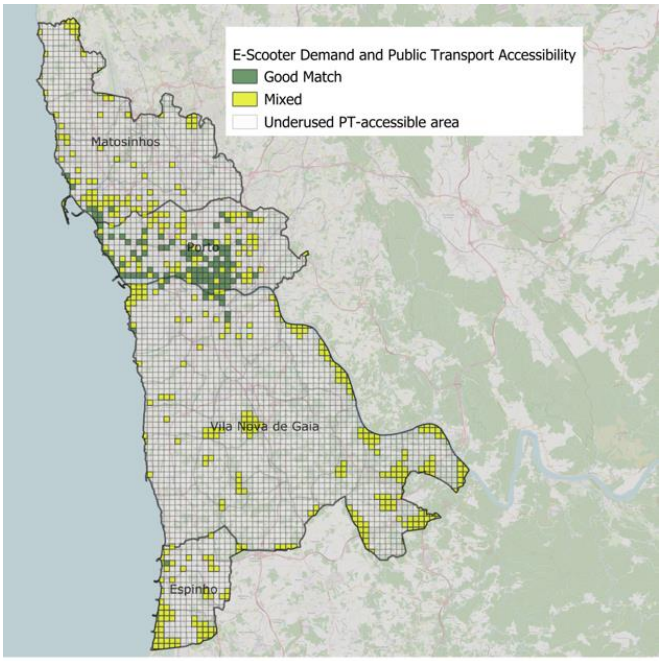


Fig. 6.1.Relationship between e-scooter trip-start activity and public transport accessibility across the analytical grid.

The Mixed category contained 465 cells, equivalent to approximately 14% of the grid, with a mean start density of 492 trips/km². Underused PT-accessible areas formed the largest category, with 2,861 cells, or approximately 83% of the grid, but recorded an average of only 12 starts/km².

These results show that public transport accessibility was widespread across the study area, while high e-scooter activity remained strongly concentrated in a relatively small number of locations. The absence of a Gap category indicates that the most active e-scooter cells were not located in areas classified as poorly accessible to public transport. This is consistent with the ZINB model, in which distance to public transport was negatively associated with trip starts.

However, the Good Match classification should not be interpreted as evidence that users transferred between e-scooters and public transport. It indicates spatial co-location between high e-scooter activity and public transport accessibility, rather than confirmed intermodal behaviour.

6.3 PARKING ACCESSIBILITY AND E-SCOOTER DEMAND

Using the demand–accessibility classification defined in Section 3.13.1, the designated-parking analysis compared grid-level e-scooter trip-start activity with accessibility to designated e-scooter parking. Unlike the public transport analysis, all four relationship categories were present: Gap, Good Match, Mixed and Underused. Table 6.2 summarises the distribution of grid cells across the parking relationship categories.

Table 6.2 - Grid-level relationship between e-scooter demand and designated-parking accessibility.

Parking relationship	Grid cells	Share of grid	Mean start-trip density
Gap	21	1%	7,440 trips/km²
Good Match	43	1%	15,074 trips/km²
Mixed	3,304	96%	248 trips/km²
Underused	64	2%	80 trips/km²
Total	3,432	100%	474 trips/km²

The spatial distribution of the parking relationship categories is shown in Fig. 6.2.

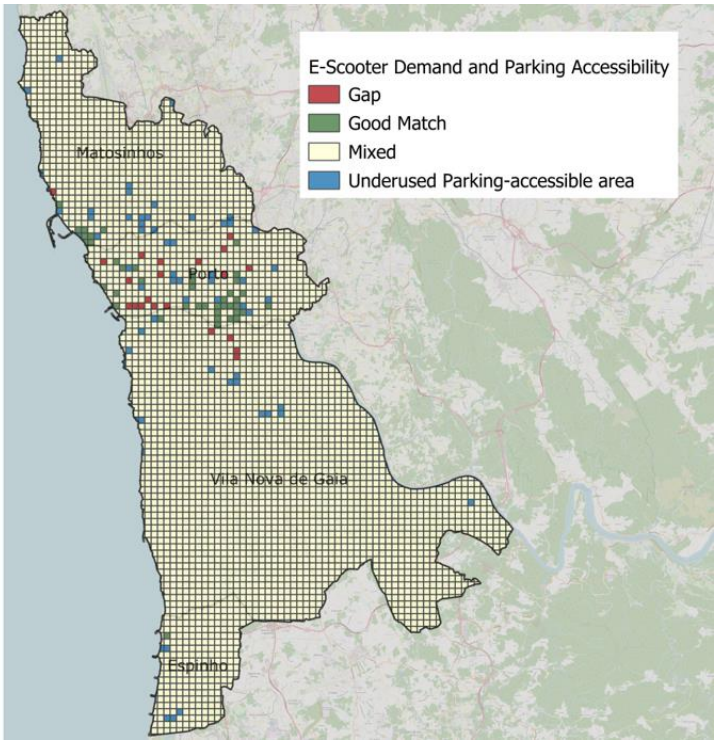


Fig. 6.2.Relationship between e-scooter trip-start activity and designated-parking accessibility across the analytical grid.

Good Match cells represented 43 cells, or approximately 1% of the analytical grid, and recorded the highest mean start-trip density, at 15,074 trips/km². These cells combined high or very high e-scooter activity with relatively good accessibility to designated parking.

A further 21 cells were classified as parking gaps. Although they represented less than 1% of the analytical grid, their average start density was 7,440 trips/km², substantially above the study-area average of 474 trips/km². These cells, therefore, represented locations where intensive activity occurred despite comparatively weak access to designated parking.

The Mixed category contained 3,304 cells, or approximately 96% of the grid. Its mean density was only 248 trips/km². This large category reflected the highly concentrated nature of demand and the fact that many cells contained neither high demand nor the specific accessibility combination required for the other categories.

The Underused category contained 64 cells, representing approximately 2% of the grid, and recorded a mean density of 80 starts/km². These were locations with relatively good parking accessibility but limited scooter activity.

The sharp difference between Good Match and Gap cells is consistent with the statistical model. The count of designated e-scooter parking locations was positively associated with trip starts, while distance to designated parking was negatively associated with demand in the ZINB models. However, these relationships do not establish that parking provision caused demand. Parking infrastructure may also have been placed in locations where high activity was already expected.

6.4 CYCLE-INFRASTRUCTURE READINESS

Using the cycle-infrastructure readiness classification defined in the chapter 3 in Section 3.13.2, the analysis compared grid-level e-scooter trip-start activity with the presence of mapped cycle-lane infrastructure. Four categories were considered: high demand with cycle support, high demand without cycle support, cycle infrastructure with low demand, and mixed conditions. Table 6.3 summarises the distribution of e-scooter activity across these categories.

Table 6.3 - E-scooter activity by cycle-infrastructure readiness category.

Cycle-readiness category	Share of grid	Start trips	Total trip activity	Mean total-activity density
Cycle infrastructure with low demand	7%	416	832	48 trips/km²
High demand with cycle support	2%	41,649	83,298	21,464 trips/km²
High demand without cycle support	3%	73,821	147,642	17,261 trips/km²
Mixed	88%	9,979	19,958	77 trips/km²
Total	100%	125,865	251,730	949 trips/km²

The spatial distribution of the cycle-readiness categories is shown in Fig. 6.3**.**

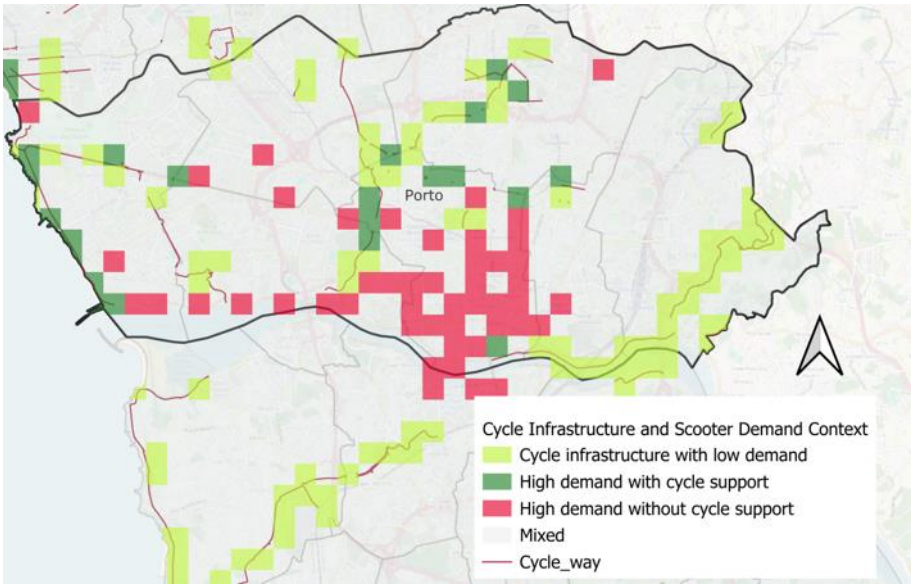


Fig. 6.3. Cycle-infrastructure readiness based on e-scooter activity and cycle-lane presence in Porto.

High-demand cells represented only a small proportion of the analytical grid but contained most of the observed e-scooter activity. Cells classified as high demand with cycle support accounted for approximately 2% of the grid and contained 41,649 trip starts. Their mean total-activity density reached 21,464 trips/km², the highest among the four categories.

High-demand cells without cycle support represented approximately 3% of the grid but contained 73,821 trip starts, corresponding to approximately 58.7% of all trip starts. Their mean total-activity density was 17,261 trips/km². Together, the two high-demand categories accounted for 115,470 trip starts, or approximately 91.7% of all origins, despite occupying only around 5% of the analytical grid.

The difference between the two high-demand categories is important for infrastructure assessment. Cells with cycle support identify locations where intensive e-scooter activity coincided with mapped cycling infrastructure, while cells without cycle support identify high-activity locations where mapped cycle-lane provision was absent. These cells therefore provide a useful starting point for more detailed street-level assessment.

Cells classified as cycle infrastructure with low demand represented approximately 7% of the grid but contained only 416 trip starts. Their mean total-activity density was 48 trips/km². This does not mean that the existing cycle infrastructure was unnecessary or ineffective, because the analysis considers shared e-scooter activity only and does not include conventional bicycle use or other forms of micromobility.

The spatial pattern indicates that many high-demand cells without cycle support were concentrated in central Porto and the riverside urban area. High-demand cells with cycle support appeared more selectively in western and northern Porto and along parts of the coastal corridor. This pattern is consistent with the ZINB model, in which cycle-lane length was positively and significantly associated with trip starts.

However, the classification does not establish that cycle infrastructure caused higher e-scooter demand. It also does not evaluate cycle-lane quality, continuity, width, physical separation, intersection safety or surface condition. It should therefore be interpreted as an initial infrastructure-coverage assessment rather than a complete measure of safe riding conditions.

6.5 INTEGRATED PLANNING-PRIORITY CLASSIFICATION

Using the integrated planning-priority classification defined in **Section 3.13.3**, the analysis combined high e-scooter activity with designated-parking gaps, cycle-lane support and public transport accessibility. The five resulting categories were Priority 1: Parking and cycle-lane gap, Priority 2: Parking gap, Priority 3: Cycle-lane gap, Supported high demand near public

transport, and Lower priority. Table 6.4 summarises the distribution of grid cells and trip starts across these categories.

Table 6.4 - Summary of the integrated planning-priority classification.

Priority class	Grid cells	Start trips	Share of starts	Mean parking count	Mean PT count
Lower priority	3,326	22,037	18%	0.031	1.45
Priority 1: Parking and cycle-lane gap	14	10,000	8%	0	9.36
Priority 2: Parking gap	7	4,018	3%	0	3.29
Priority 3: Cycle-lane gap	53	57,355	46%	0.472	4.49
Supported high demand near PT	32	32,455	26%	0.906	4.97

A total of 106 grid cells, approximately 3% of the analytical grid, were included in the four high-demand planning categories. Together, these cells contained 103,828 trip starts, corresponding to approximately 82.5% of all origins. The remaining 3,326 cells were classified as Lower priority and contained 22,037 trip starts, or approximately 17.5% of all origins. Lower priority therefore does not mean that a cell recorded no activity; it indicates only that the cell did not meet the high-demand conditions used for the four planning categories.

The spatial distribution of the planning-priority categories is shown in Fig. 6.4.

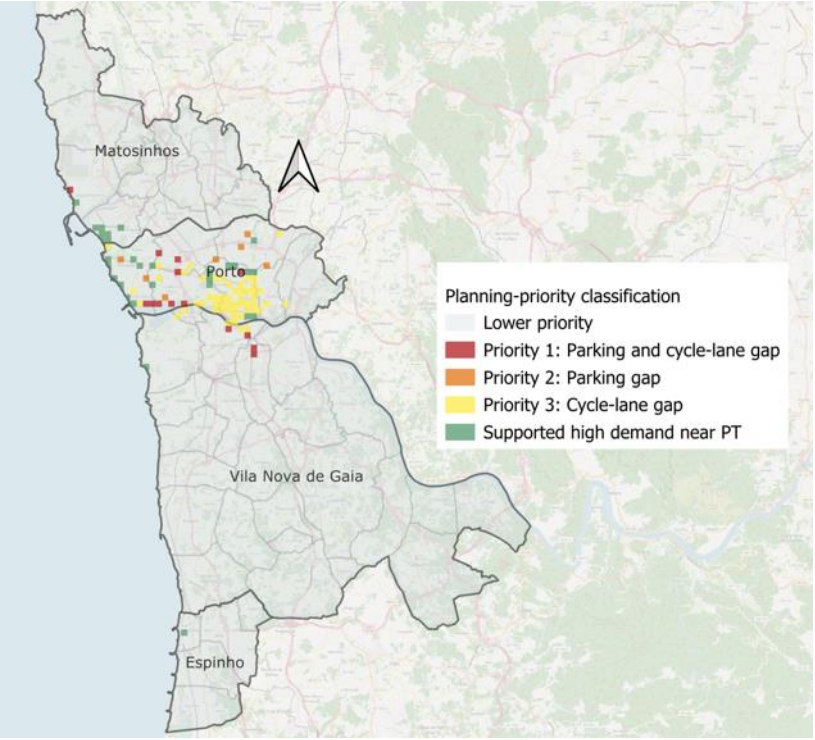


Fig. 6.4.Integrated planning-priority classification for e-scooter-supporting infrastructure.

Priority 1 contained 14 cells with high e-scooter demand, a parking gap and no mapped cycle-lane support. These cells generated 10,000 trip starts, representing approximately 8% of all origins. Their mean public transport count was 9.36 stops per cell, the highest among the high-demand planning categories. These cells therefore represent locations with substantial activity and public transport accessibility but with gaps in both designated parking and mapped cycle infrastructure.

Priority 2 contained seven cells with high demand and cycle-lane support but a parking gap. Together, they generated 4,018 trip starts, corresponding to approximately 3% of all origins. These cells identify locations where strong e-scooter activity and cycle infrastructure were present, but designated-parking accessibility remained weak. They therefore provide suitable locations for reviewing parking provision, subject to detailed local assessment.

Priority 3 was the largest high-demand gap category, containing 53 cells and 57,355 trip starts, equivalent to approximately 46% of all origins. These cells had high e-scooter activity but no mapped cycle-lane support. Their mean parking count was 0.472 per cell, while the mean public transport count was 4.49. The spatial pattern shows that many of these cells were concentrated

in central Porto. The main planning relevance is that substantial e-scooter activity was already occurring in these locations without mapped cycle support.

A further 32 cells were classified as Supported high demand near public transport. These cells generated 32,455 trip starts, representing approximately 26% of all origins. They recorded the highest mean parking count among the high-demand categories, at 0.906 per cell, and a mean public transport count of 4.97. These locations indicate where strong e-scooter demand coincided with public transport accessibility and the supporting micromobility infrastructure considered in the classification.

Overall, the integrated classification shows that high e-scooter activity was concentrated in a small number of cells with differing infrastructure conditions. Of the 106 high-demand cells, 74 showed a parking gap, a cycle-lane gap or both, while 32 were classified as supported high-demand locations near public transport. The classification should therefore be interpreted as a planning-screening tool rather than a direct intervention list. Gap cells identify locations where more detailed street-level assessment may be useful, while supported high-demand cells show where observed demand and supporting infrastructure already coincide spatially.

6.6 FROM CLASSIFICATION TO PLANNING IMPLICATIONS

The planning implications of this study arise from the combined relationship between e-scooter demand, infrastructure and urban context rather than from any single model coefficient. Demand was strongly concentrated, public transport accessibility was widespread, parking alignment varied across the study area, and substantial activity occurred in locations without mapped cycle infrastructure. These findings support a targeted planning approach rather than uniform infrastructure provision across Porto, Matosinhos, Vila Nova de Gaia and Espinho.

The priority cells identified in Section 6.5 should be interpreted as screening areas for further investigation rather than automatic intervention sites. A high-demand cell without mapped cycle infrastructure may still contain a low-speed street, pedestrian area, steep road or suitable route immediately outside the grid boundary. Street-level assessment should therefore consider factors such as route continuity, crossings, traffic speed, slope, pedestrian movement, available public space and connections to major destinations.

For cycle infrastructure, particular attention may be given to high-demand cells without mapped cycle-lane support. However, the positive association between cycle-lane length and e-scooter

demand does not demonstrate that additional cycle infrastructure would necessarily increase usage. Previous studies suggest that cycling infrastructure may provide more suitable riding conditions for shared e-scooters, while also reflecting wider characteristics such as centrality and urban investment (Christoforou et al., 2023; Hosseinzadeh et al., 2021).

Public transport accessibility should also be interpreted selectively. The spatial overlap between high e-scooter activity and public transport does not confirm modal transfer, but it can help identify locations where further investigation of multimodal potential may be useful. This distinction is consistent with previous research showing that spatial proximity alone cannot reliably identify trip purpose or confirm public transport transfer behaviour (Li et al., 2024; Yin et al., 2024).

Parking-gap cells should likewise be reviewed to determine whether designated parking is absent, poorly located, insufficiently visible or inadequate for the observed level of activity. Previous research indicates that the location, density and convenience of parking facilities can influence parking behaviour and compliance, rather than the total number of spaces alone (Hemphill et al., 2022; Meng et al., 2025).

Municipal coordination is particularly relevant along the Porto–Matosinhos corridor, where the strongest cross-boundary movements were observed. Compatible parking rules, geofencing, operator reporting and cycle-route continuity could help reduce discontinuities across administrative boundaries, while Vila Nova de Gaia and Espinho may require more locally adapted approaches reflecting their lower and more dispersed observed activity.

Overall, the classification is most useful as the first stage of an iterative planning process: identifying priority locations, assessing them at street level, implementing proportionate measures where justified, and monitoring subsequent changes in demand, parking behaviour and safety. More specific recommendations are presented in Chapter 7.

7

CONCLUSIONS AND RECOMMENDATIONS

7.1 MAIN CONCLUSIONS

This dissertation examined how shared e-scooter activity was distributed across Porto, Matosinhos, Vila Nova de Gaia and Espinho, and how that activity related to public transport, designated parking, cycle infrastructure and the surrounding urban environment. The analysis combined trip-level records, infrastructure-proximity measures, facility-level interaction analysis, a regular spatial grid, Zero-Inflated Negative Binomial models and GIS-based planning classifications. Together, these methods show that shared e-scooter activity in the study area was highly concentrated and associated with a combination of urban, infrastructure and operational conditions.

The first conclusion is that e-scooter use was not limited to a single type of journey. Most trips were short or medium in length, although a substantial share exceeded 3 km. Activity was relatively low during the morning and substantially stronger from midday through the evening. Weekend activity was also higher when compared on a per-day basis. These patterns are consistent with a mixture of urban travel purposes rather than a clearly dominant morning-commuting pattern. However, because the dataset does not include trip purpose, the analysis cannot determine whether individual journeys were made for commuting, shopping, tourism, leisure or other activities.

The second conclusion is that demand was strongly concentrated spatially. Porto formed the main activity core, with additional concentration extending into Matosinhos, while Vila Nova de Gaia and Espinho recorded substantially lower and more dispersed activity. This pattern is

consistent with the concentration of destinations, tourism, commercial activity, public transport and population density in the central urban area. Nevertheless, the observed distribution represents realised activity under existing operating conditions. Fleet availability, redistribution, service boundaries and operator deployment may also have contributed to the concentration of trips in Porto.

The third conclusion concerns public transport. Approximately 80% of trip origins were located within 100 m of the public transport network and more than 99% within 400 m. Greater distance from public transport was also negatively associated with trip-start demand in the statistical models. These findings show that most e-scooter activity occurred in areas with strong public transport accessibility.

However, spatial proximity does not demonstrate first- or last-mile integration. Many public-transport-accessible locations recorded little or no e-scooter activity, and many individual stops had no nearby scooter interaction. The results therefore identify spatial opportunity for interaction rather than confirmed transfers between modes. This distinction is consistent with previous research showing that proximity-based measures cannot by themselves establish complete travel chains (Aarhaug et al., 2023; Li et al., 2024; Yin et al., 2024).

The fourth conclusion concerns designated parking. Approximately one-quarter of both trip origins and destinations occurred within 100 m of a designated parking facility, with substantial differences between municipalities. Matosinhos showed the strongest proportional alignment, while Vila Nova de Gaia showed the weakest. Activity was also concentrated around a relatively small number of parking locations, while many facilities recorded little or no nearby interaction.

The analysis of trip ends is particularly relevant because destinations more directly represent where users complete journeys. Nevertheless, even an endpoint located within 100 m of a designated facility does not demonstrate that the scooter was physically parked inside that facility. The parking results should therefore be interpreted as measures of spatial alignment rather than confirmed parking compliance. The analysis also cannot establish whether parking infrastructure generated demand or was installed in response to existing demand.

The fifth conclusion is that e-scooter demand was associated with several characteristics of the urban environment. Population density, designated-parking accessibility, selected public transport modes, cycle-lane length, tourism and commercial activity showed significant

relationships with trip-start demand. Greater distance from designated parking and public transport was consistently associated with lower activity.

At the same time, some findings differed from expectations based on previous studies. The residential share of young people was negatively associated with demand, while the education variable was not statistically significant. These findings should not be interpreted as evidence that younger people or students use e-scooters less. Residential demographic characteristics describe who lives in an area rather than who travels through it, while the education variable measured the presence of education-related locations rather than student population, enrolment, attendance or actual trip purpose.

Cycle-lane length was positively associated with trip-start demand, but the GIS analysis also identified substantial high-demand activity in cells without mapped cycle infrastructure. This means that mapped cycle infrastructure and e-scooter activity frequently coincided, while important infrastructure gaps remained in locations where scooters were already heavily used. The statistical association does not demonstrate that constructing additional cycle infrastructure would itself cause demand to increase.

The integrated GIS classification brought these findings together. Only 106 cells, approximately 3% of the analytical grid, accounted for about 82.5% of all trip starts. Of these high-demand cells, 74 showed a designated-parking gap, a cycle-infrastructure gap or both, while 32 were classified as supported high-demand locations near public transport. This concentration supports a targeted rather than uniform approach to infrastructure assessment.

Overall, shared e-scooter activity in the Porto Metropolitan Area was associated with the interaction of urban centrality, destination concentration, transport accessibility, micromobility infrastructure and service operation. No single variable explains the observed spatial pattern. The most defensible interpretation is therefore one of spatial association and infrastructure alignment rather than direct causation, confirmed modal integration or verified parking behaviour.

7.2 Contribution of the Study

The main contribution of this dissertation lies in bringing together forms of evidence that are often examined separately. Trip-level analysis described when and where individual journeys occurred. Infrastructure-level analysis examined activity around public transport stops and

designated parking locations. Grid-based modelling then related demand to population, land use, tourism, commercial activity, transport infrastructure and cycle provision.

This multi-scale structure is important because each level answers a different question. Trip-level analysis preserves the detail of individual journeys. Facility-level analysis shows whether activity is concentrated around particular infrastructure locations. Grid-level analysis allows demand to be compared with the wider urban environment. Treating these measures as interchangeable would create confusion, but using them together provides a more complete account of the system.

A second contribution is the clear distinction between proximity and behaviour. Trips close to public transport were not automatically classified as multimodal transfers, and trips close to parking were not treated as evidence of compliance. This is consistent with concerns in the wider literature that distance-based methods can identify spatial opportunity without identifying user intention or complete travel chains (Li et al., 2024; Yin et al., 2024).

A third contribution is the separation of public transport by mode. Bus, tram, railway and light rail or metro facilities did not have identical relationships with demand. Treating all public transport as one variable would have concealed these differences and produced a less informative interpretation of how e-scooter activity relates to the transport network.

A fourth contribution is the use of Zero-Inflated Negative Binomial models to address the large number of zero-demand cells and the strong variation between areas. Estimating separate total, weekday and weekend models also showed that the broad spatial structure remained stable while the relative importance of tourism, commercial activity, parking and transport context changed during the week.

A fifth contribution is the translation of the statistical results into an infrastructure intervention planning framework, presented in Chapter 6. The analysis did not stop at reporting coefficients. It identified a limited number of cells where high observed demand coincided with missing or weak infrastructure, creating a practical connection between statistical analysis and planning, while still recognising that final decisions require fieldwork, local knowledge and consultation.

The framework can be adapted to other cities where operational micromobility data and infrastructure information are available. Its transferability does not depend on applying the exact thresholds used in Porto. Its broader value lies in combining several spatial scales, separating opportunity from behaviour and using transparent classifications to guide further

investigation. Parts of this research were developed within the URBAN-NET project and have resulted in two scientific articles, one accepted for publication and one under review, as described in Section 1.2.

7.3 LIMITATIONS

The most important limitation is that the analysis is based on records from a single shared e-scooter operator. The results therefore describe the activity of one service operating under particular fleet, redistribution, geofencing and deployment conditions. They do not represent all shared or privately owned e-scooters, conventional bicycles or other micromobility modes.

Related to this, the study measures realised trips rather than latent demand. A low number of trips in a particular area may reflect genuinely low demand, limited scooter availability or both. Without detailed fleet-availability and redistribution information, these explanations cannot be separated. This is particularly relevant when comparing central Porto with lower-activity areas such as Vila Nova de Gaia and Espinho.

The dataset also lacks individual behavioural information. It does not include user age, residence, income, occupation, trip purpose or the mode used before or after the scooter journey. Temporal patterns therefore cannot establish whether trips were made for commuting, tourism, leisure or another purpose. Similarly, the negative association between residential young-population share and trip demand does not demonstrate that younger people used e-scooters less, because census variables describe residents rather than necessarily the people travelling through each location.

The education variable has an additional measurement limitation. It represents the presence or count of mapped education-related locations within grid cells but does not measure student enrolment, attendance, campus population, opening hours or actual education-related travel. Its non-significant statistical relationship should therefore not be interpreted as evidence that education-related activity is unrelated to e-scooter use.

The public transport analysis is also constrained by the use of Euclidean distances. Straight-line buffers do not account for the street network, crossings, station entrances, bridges, slope, physical barriers or route directness. The 100 m and 400 m results should therefore be interpreted as measures of spatial opportunity rather than actual travel accessibility. They also cannot demonstrate whether a user transferred between e-scooters and public transport.

The parking analysis included both trip origins and destinations, but neither provides a direct measure of legal parking compliance. Trip ends are conceptually closer to the user's parking decision, while trip starts may additionally reflect operator redistribution and fleet management. An endpoint within 100 m of a designated facility does not confirm that the scooter was physically parked within that facility, while an endpoint outside the buffer does not necessarily establish non-compliance. GPS uncertainty, facility dimensions, incomplete mapping and the selected threshold can all affect the classification.

The quality and completeness of the spatial datasets provide another limitation. OpenStreetMap-derived infrastructure and land-use data may be incomplete, outdated or unevenly maintained. This could affect public transport, parking, cycle infrastructure, tourism, education and land-use indicators. Cycle-lane length also provides only a limited description of riding conditions because it does not distinguish between protected and unprotected infrastructure or measure continuity, surface quality, safety, slope or connectivity.

The 300 m × 300 m grid provided a consistent unit of analysis, but the results remain sensitive to grid size, alignment and boundary definition. A different spatial unit could alter the number and location of high-demand or infrastructure-gap cells. Conditions within each cell are also heterogeneous, reflecting the Modifiable Areal Unit Problem (Openshaw, 1984).

The descriptive/GIS analysis and the statistical modelling also used slightly different grid datasets. The final descriptive spatial analysis used the 3,432-cell grid after removing 99 very small boundary fragments, while the ZINB models correspond to the pre-filtered 3,531-cell grid. Because the removed fragments contained only a very small number of trip starts, their effect on overall demand is limited; nevertheless, a sensitivity analysis using identical grids would provide an additional robustness check.

Individual public transport and parking buffers can overlap, meaning that the same trip may contribute to the local interaction count of more than one facility. Facility-level interaction counts should therefore not be interpreted as unique trip totals.

The ZINB models are observational global models. Relationships may vary spatially between central Porto, coastal Matosinhos, Vila Nova de Gaia and Espinho. The models also omit variables such as weather, fleet availability, fares, promotions, special events, enforcement, geofencing changes, slope, street safety and temporary traffic conditions. Consequently, the

estimated coefficients represent conditional associations under the observed operating conditions rather than causal effects.

Finally, the GIS planning classifications depend on the thresholds used to define demand, accessibility and infrastructure support. Alternative thresholds could change the number and location of priority cells. The classifications should therefore be regarded as transparent screening tools rather than a definitive ranking of infrastructure needs.

7.4 RECOMMENDATIONS

The detailed location-specific planning implications are presented in Chapter 6. The recommendations here therefore focus on broader measures that follow from the analysis as a whole.

First, municipalities and operators should strengthen the sharing of anonymised operational information, including trip starts and ends, vehicle availability, redistribution activity, parking events and geofencing changes. Trip counts alone cannot distinguish low demand from limited vehicle supply. Improved operational data would allow municipalities to interpret low-activity areas more reliably.

Second, the infrastructure classifications developed in this study should be updated periodically. Demand patterns can change with season, tourism, fleet size, regulations and infrastructure provision. A parking or cycle-infrastructure gap identified during one period may no longer remain a priority following an intervention or operational change. Monitoring should therefore form part of an ongoing planning cycle rather than a one-time assessment.

Third, the priority classifications, proximity indicators and statistical models should be used as screening and decision-support tools rather than substitutes for local assessment. Street-level inspection, accessibility considerations, consultation with operators and users, and knowledge of planned municipal projects should be considered before implementing infrastructure changes.

7.5 FUTURE RESEARCH

Future research should combine operational trip records with information that can explain user behaviour more directly. Surveys, travel diaries and interviews could identify trip purpose, user

characteristics, previous and subsequent modes, reasons for choosing an e-scooter and perceptions of parking or route quality. These data would help distinguish commuting, leisure, tourism, independent scooter trips and actual public transport connections.

Linked public transport and micromobility records, where legally and ethically feasible, would provide stronger evidence of first- and last-mile integration. The existing literature shows that buffer-based estimates may overstate the number of e-scooter trips genuinely connected to rail or public transport. Future studies should therefore combine spatial data with travel sequences, user reports or linked ticketing information where appropriate (Yin et al., 2024; Li et al., 2024).

Fleet availability and redistribution data should also be incorporated. This would help distinguish locations with genuinely weak demand from places where few journeys occur because scooters are rarely available. Before-and-after studies of newly installed or relocated parking facilities could provide stronger evidence about whether infrastructure changes influence demand and parking behaviour. Such designs would be more informative than relying only on cross-sectional associations. Future research could extend the trip-end parking analysis using smaller distance thresholds, mapped facility boundaries, geofencing records or operator parking-event data to assess parking compliance more directly.

Accessibility should be measured through the street network rather than only through straight-line distance. Network-based analysis could account for crossings, station entrances, bridge access, disconnected streets, slope and route directness. Route or trajectory data would also make it possible to examine actual path choice, cycling conditions and the effect of topography in Porto and Vila Nova de Gaia. Network-based approaches have been recommended in previous research because Euclidean buffers can simplify the actual experience of reaching public transport or parking facilities (Oeschger et al., 2025; Yin et al., 2024). Spatial count models, Geographically Weighted Regression and Geographically and Temporally Weighted Regression could additionally examine whether the estimated relationships differ between Porto, Matosinhos, Vila Nova de Gaia and Espinho, since a single coefficient for the entire study area may conceal meaningful local differences.

Weather, special events, prices, promotions, enforcement and regulatory changes should be added to future temporal models. Their inclusion would help explain daily and monthly fluctuations that cannot be attributed solely to population, land use or infrastructure. The sensitivity of the results to grid size and alignment should also be tested using alternative spatial

scales. A longer observation period would help distinguish genuine changes in demand from temporary operational variation.

Future studies should also compare several operators and, where possible, include privately owned e-scooters, conventional cycling and other shared micromobility services. The present study describes the activity of one shared e-scooter system. A broader comparison would place those trips within the wider mobility system and provide a stronger basis for evaluating substitution, complementarity, equity and infrastructure demand.

7.6 FINAL STATEMENT

Shared e-scooters form part of the contemporary mobility system of the Porto Metropolitan Area, but their role is more complex than that of a simple first- or last-mile service. Their activity occurs within a wider system of destinations, public transport, designated parking, cycle infrastructure, municipal boundaries and operator decisions, and varies substantially across both space and time.

This dissertation demonstrates that operational e-scooter data can provide valuable evidence for urban and infrastructure planning when the limits of those data remain explicit. Spatial proximity can identify opportunity but not intention. Statistical modelling can identify association but not causation. GIS classifications can identify where closer investigation may be justified, but not prescribe the intervention itself.

The main practical value of the study therefore lies in combining these forms of evidence to identify where e-scooter activity is concentrated, where infrastructure and demand appear aligned, and where potential gaps warrant more detailed assessment. Used together with street-level observation, operational data and local planning knowledge, this approach can support more targeted and evidence-based micromobility planning across the Porto Metropolitan Area.

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APPENDIX

A.1 VARIABLE DICTIONARY

Variable name	Description	Type/unit	Source or derivation	Used in
Trip identification				
trip_id	Unique trip identifier	Identifier	Operator dataset	Data validation, all trip-level analysis
user_id	Anonymised user identifier, where available	Identifier	Operator dataset	Data cleaning checks
Spatial fields — origin and destination				
start_longitude	Longitude of trip origin	Decimal degrees	Operator dataset	Origin-layer creation
start_latitude	Latitude of trip origin	Decimal degrees	Operator dataset	Origin-layer creation
end_longitude	Longitude of trip destination	Decimal degrees	Operator dataset	Destination-layer creation
end_latitude	Latitude of trip destination	Decimal degrees	Operator dataset	Destination-layer creation
start_municipality	Municipality containing the trip origin	Categorical	Spatial join (origin point × municipal boundary)	Municipal-level analysis
start_parish	Parish containing the trip origin	Categorical	Spatial join (origin point × parish boundary)	Parish-level analysis
end_municipality	Municipality containing the trip destination	Categorical	Spatial join (destination point × municipal boundary)	Origin–destination analysis
end_parish	Parish containing the trip destination	Categorical	Spatial join (destination point × parish boundary)	Parish-level analysis
Temporal fields				

ride_started_at	Recorded start timestamp	Date and time	Operator dataset	Temporal analysis
ride_completed_at	Recorded completion timestamp	Date and time	Operator dataset	Duration and end-time analysis
date	Calendar date of trip	Date	Derived from ride_started_at	Daily and monthly aggregation
start_hour	Hour of trip start	Integer, 0–23	Derived from ride_started_at	Hourly distribution
end_hour	Hour of trip completion	Integer, 0–23	Derived from ride_completed_at	Hourly distribution
weekday	Day of the week	Categorical	Derived from date	Day-of-week comparison
day_class	Weekday or weekend	Categorical (2 levels)	Derived from weekday	Weekday/weekend comparison
time_class	Morning peak, midday, evening peak or night	Categorical (4 levels)	Derived from start_hour,	Time-of-day comparison
month	Calendar month	Categorical	Derived from date	Monthly analysis
season	Winter, spring, summer or autumn	Categorical (4 levels)	Derived from month, 2024 only	Seasonal analysis
Trip-characteristic fields				
cleaned_distance	Cleaned journey distance	Metres (reported in km)	Derived from operator distance field, post-cleaning	Distance analysis, all trip-level tables
trip_duration	Journey duration	Minutes	ride_completed_at − ride_started_at	Duration analysis
trip_class	Short (<1 km), medium (1–2.999 km) or long (≥3 km)	Categorical (3 levels)	Derived from cleaned_distance, per Table 3.3	Distance-class comparison
Public transport proximity — trip level				
PT100_start	Origin within 100 m of any PT stop (dissolved buffer)	Binary	Buffer intersection, origin × dissolved 100 m PT buffer	PT proximity, overall and by municipality
PT100_end	Destination within 100 m of any PT stop (dissolved buffer)	Binary	Buffer intersection, destination × dissolved 100 m PT buffer	PT proximity

PT400_start	Origin within 400 m of any PT stop (dissolved buffer)	Binary	Buffer intersection, origin × dissolved 400 m PT buffer	PT proximity, overall and by municipality
PT400_end	Destination within 400 m of any PT stop (dissolved buffer)	Binary	Buffer intersection, destination × dissolved 400 m PT buffer	PT proximity
Public transport interaction — stop level				
stop_id	Unique identifier for each PT stop or station	Identifier	OpenStreetMap-derived PT layer	Stop-level interaction
stop_mode	Bus, light rail/metro, railway or tram	Categorical (4 levels)	OpenStreetMap-derived PT layer	Mode-specific grid counts
nearby_start_count_PT	Trip starts within the individual 100 m/400 m buffer of a given stop	Count	Spatial summary join, undissolved buffer	Stop-level interaction
nearby_end_count_PT	Trip ends within the individual 100 m/400 m buffer of a given stop	Count	Spatial summary join, undissolved buffer	Stop-level interaction
Designated parking proximity — trip level				
parking100_start	Origin within 100 m of any designated parking (dissolved buffer)	Binary	Buffer intersection, origin × dissolved 100 m parking buffer	Parking proximity
parking100_end	Destination within 100 m of any designated parking (dissolved buffer)	Binary	Buffer intersection, destination × dissolved 100 m parking buffer	Parking proximity
Parking interaction — location level				

parking_id	Unique identifier for each designated parking location	Identifier	OpenStreetMap-derived parking layer	Parking-location interaction
nearby_start_count_parking	Trip starts within the individual 100 m buffer of a given parking location	Count	Spatial summary join, undissolved buffer	Parking-location interaction
nearby_end_count_parking	Trip ends within the individual 100 m buffer of a given parking location	Count	Spatial summary join, undissolved buffer	Parking-location interaction
interaction_level	No/Low/Medium/High/Very high interaction class	Categorical (5 levels)	Derived from nearby_start_count_parking,	Parking classification

A.2 GRID-LEVEL VARIABLES

Variable	Definition	Unit/coding	Processing	Model role
Grid identification and geometry				
grid_id	Unique grid-cell identifier	Identifier	Generated in QGIS (300 m × 300 m polygon grid, EPSG:3763)	Spatial reference
cell_area	Actual retained cell area after boundary clipping	m²	Geometry calculation	Density calculation
area_ratio	Ratio of actual cell area to a complete 90,000 m² cell	Proportion, 0–1	cell_area ÷ 90,000 m²	QA / cell-inclusion filter (Eq. 3.5; cells ≤0.10 excluded)
Dependent variables				
total_starts	Total trip origins per cell	Count	Count points in polygon	Dependent
weekday_starts	Weekday trip origins per cell	Count	Count points in polygon	Dependent
weekend_starts	Weekend trip origins per cell	Count	Count points in polygon	Dependent
Municipality				

Espinho	Cell falls within Espinho	1/0	Municipality dummy	Explanatory
Matosinhos	Cell falls within Matosinhos	1/0	Municipality dummy	Explanatory
Porto	Cell falls within Porto	1/0	Municipality dummy	Explanatory
Vila Nova de Gaia	Reference municipality (not separately coded)	Omitted category	Baseline against which Espinho, Matosinhos and Porto coefficients are read	Reference
Demographics				
population_density	Resident population per unit area	Normalised, 0–1 (min–max, Eq. 3.7)	INE data aggregated to grid	Explanatory
young_share	Share of residents aged 15–24	Proportion, 0–1	INE data aggregated to grid	Explanatory
working_age_share	Share of residents aged 25–64	Proportion, 0–1	INE data aggregated to grid	Explanatory
Parking				
parking_count	Number of designated parking locations inside the cell	Count	Point aggregation	Explanatory
distance_parking	Distance from cell centroid to nearest parking location	Normalised Euclidean distance, 0–1	Nearest-hub calculation, then min–max normalised	Explanatory
Public transport				
bus_count	Bus stops inside the cell	Count	Point aggregation	Explanatory
metro_count	Light-rail/metro facilities inside the cell	Count	Point aggregation	Explanatory
railway_count	Railway stations inside the cell	Count	Point aggregation	Explanatory
tram_count	Tram stops inside the cell	Count	Point aggregation	Explanatory
distance_PT	Distance from cell centroid to nearest public transport facility (any mode)	Normalised Euclidean distance, 0–1	Nearest-hub calculation, then min–max normalised	Explanatory
Cycle infrastructure				
cyclelane_length	Total length of mapped cycle lanes/cycleways inside the cell	Normalised metres, 0–1	Line intersection with grid, length	Explanatory

			summed, then min–max normalised	
Activity and land use				
tourism_presence	At least one tourism point of interest present in the cell	1/0	Spatial aggregation	Explanatory
education_presence	At least one education facility present in the cell	1/0	Spatial aggregation	Explanatory
commercial_presence	Commercial land use present in the cell	1/0	Spatial overlay	Explanatory
industrial_presence	Industrial land use present in the cell	1/0	Spatial overlay	Explanatory
residential_presence	Residential land use present in the cell	1/0	Spatial overlay	Explanatory

A.3 Summary of the Reviewed Literature

Spatial and Temporal Patterns of Shared E-Scooter Use

Reference	Study area / data	Contribution to this thesis
McKenzie — "Spatiotemporal comparative analysis of scooter-share and bike-share usage patterns in Washington, D.C."	Washington, D.C.; trip data	Comparative basis for temporal profiles; distinguishes scooter-share from bike-share commuting
Li et al. — "Integrating shared e-scooters as the feeder to public transit: 124 European cities"	124 European cities; comparative	Feeder potential of e-scooters to first/last-mile public transport
Wang et al. — "What travel modes do shared e-scooters displace?"	Review	Mode-substitution discussion — walking, cycling, PT or car trips
Orozco-Fontalvo et al. — "Dockless electric scooters: A review of a growing micromobility mode"	Review	Broad background on development, adoption and usage patterns
Sanders et al. — "To scoot or not to scoot: benefits and barriers for riders and non-riders"	Survey	User-perception evidence to complement operational trip data
Caggiani et al. — "A geofencing-based methodology for speed limit regulation and user safety"	Methodology	Geofencing, operational boundaries, safety and regulatory constraints
Abouelela et al. — "Understanding the landscape of shared e-scooters in North America"	North America; multi-city	Weekday, weekend, temporal and weather-related demand comparison
Shah et al. — "Why do people take e-scooter trips?"	Nashville; detailed trip data	Trip classification — work, school, errands, social, night, utilitarian
Badia & Jenelius — "Shared e-scooter micromobility: Review of use patterns, perceptions and environmental impacts"	Review	Broad framework for use patterns, users, substitution, environment

Guo & Zhang — "Factors influencing shared e-scooter usage and impact on auto mode substitution"	Regression	Car-trip substitution and conditions for reducing private-car use
Heumann et al. — "Factors influencing the usage of shared micromobility: Implications from Berlin"	Berlin	Weather and contextual factors as influences on demand
Foissaud et al. — "Free-floating e-scooter usage in urban areas: A spatiotemporal analysis"	Paris, Málaga, Bordeaux, Hamburg	Trip duration, afternoon peaks, tourist vs. local activity
Garus et al. — "Urban Micromobility in Practice: Full-Year Analysis, Tel Aviv"	Tel Aviv; full year	Importance of a full annual observation period for seasonal patterns

BUILT ENVIRONMENT AND URBAN CONTEXT

Reference	**Study area / data**	**Contribution to this thesis**
Huo et al. — "Influence of the built environment on E-scooter sharing ridership: A tale of five cities"	5 US cities; trip data + regression	Links demand to population, employment, intersection density, land-use mix, centrality, age structure
Bai & Jiao — "Dockless E-scooter usage patterns and urban environments: Austin, TX vs. Minneapolis, MN"	2 US cities; comparative regression	Downtown/campus concentration; land-use diversity; city-specific effects
Christoforou et al. — "Neighborhood characteristics encouraging micromobility"	Bordeaux; trip-position + payment-card data	Separates tourist vs. resident activity; centrality, PT, cycling infra
Adorean et al. — "Mobility patterns of shared and own e-bikes and e-scooters in Iberian cities"	Iberian/Portuguese cities	Shared vs. private micromobility serve different functions
Hosseinzadeh et al. — "E-scooters and sustainability"	Louisville; regression	Land use, Walk Score, Bike Score as demand indicators
Jin & Sui — "Spatial determinants of e-bike and e-scooter sharing link flows"	Comparative	Demand depends on origin–destination connectivity, not density alone
Kubik — "Energy Consumption of Electric Scooters Used in the Polish Shared Mobility Market"	Poland; operational + energy data	Frames topography/terrain as a limitation not directly modelled here

Jiao & Bai — "Understanding the shared e-scooter travels in Austin, TX"	Austin; descriptive/spatial	Additional single-city case study of spatial/temporal patterns
Tuli, Mitra & Crews — "Factors influencing the usage of shared E-scooters in Chicago"	Chicago; regression	Built-environment and demographic factors
Dias, Ribeiro & Arsenio — "Determinants of shared e-scooter usage... Braga, Portugal"	Braga, Portugal; survey	Portuguese-context comparison for Porto findings

PUBLIC TRANSPORT INTERACTION

Reference	Study area / data	Contribution to this thesis
Li et al. — "Integrating shared e-scooters as the feeder to public transit"	124 European cities	Feeder potential; spatial fit between stops, destinations, walking access
Yin et al. — "Shared micromobility as a first- and last-mile transit solution?"	Spatiotemporal analysis	Access, egress, independent trips; variation by location, time, transit type
Oeschger, Caulfield & Carroll — "Measuring the integration of micromobility and public transport"	Network-analysis tool	Advanced network-based integration measure, beyond simple buffers
Gödde & Scheiner — "Spatiotemporal patterns of shared-e-scooter-usage: access, egress and complementary trips"	Spatiotemporal	Separation of origins/destinations; access, egress or independent travel
Fearnley, Johnsson & Berge — "Patterns of E-Scooter Use in Combination with Public Transport"	Combined-trip analysis	E-scooters as part of multimodal PT journeys, not universally
Vinagre Díaz et al. — "Blind classification of e-scooter trips according to their relationship with public transport"	Rome; unsupervised clustering	Complementary, auxiliary, substitute and other trip–PT relationships
Reynolds et al. — "Exploring shared e-scooter trip patterns and links to public transport service level"	Trip-pattern analysis	Whether e-scooters fill gaps from lower PT service levels

Javadiansr et al. — "Coupling shared E-scooters and public transit: spatial and temporal analysis"	Spatial/temporal coupling	Framework for spatial and temporal overlap between scooter and PT demand
Aarhaug, Fearnley & Johnsson — "E-scooters and public transport: Complement or competition?"	Comparative	Balanced view — complement on some journeys, competitor on others
Ziedan et al. — "The impacts of shared e-scooters on bus ridership"	US cities; ridership impact	Extends discussion from proximity to actual bus-ridership effects
Oeschger, Carroll & Caulfield — "Micromobility and public transport integration: current state of knowledge"	Review	Review-level foundation for defining micromobility–PT integration

PARKING INFRASTRUCTURE AND TRIP-END BEHAVIOUR

Reference	**Study area / data**	**Contribution to this thesis**
Hemphill et al. — "Congested sidewalks: effects of the built environment on e-scooter parking compliance"	Portland, Oregon; GIS	Parking outcomes depend on sidewalk width, street space, nearby destinations
Meng et al. — "Cities with dense networks of shared scooter parking have higher parking compliance"	Multiple cities	Parking-network density and its relationship to compliance
Shoshany-Tavory & Bar-Gera — "Pardon me but your e-scooter is in my space"	Big-data policy analysis	Effects of parking regulations and policy interventions
Karlsen et al. — "Clutter from parked e-scooters: Effects of dedicated spaces"	Dedicated-space analysis	Pedestrian-space impacts, user convenience, walking distance to parking
Sandoval et al. — "Data driven methods for effective micromobility parking"	Nashville; data-driven siting	Using trip data to identify strategically located parking facilities

Hurlet, Manout & Diallo — "Policy implications of shared e-scooter parking regulation: an agent-based approach"	Agent-based simulation	How alternative parking-regulation designs affect system outcomes

SPATIAL UNITS AND ANALYTICAL APPROACHES

Reference	Study area / data	Contribution to this thesis
Nardin et al. — "GIS-based analysis of the new three-operator-only e-scooter sharing system of Rome"	Rome; GIS	Multi-operator system analysis and spatial comparison methods
Van Wee & Banister — "How to Write a Literature Review Paper?"	Methodological guidance	Transparency and structure of the literature-review process
Noh, Mohamad & Hamid — "Acceptable walking distance accessible to the nearest bus stop"	Walking-distance analysis	Walking-distance thresholds and PT catchment definitions
Tennøy, Knapskog & Wolday — "Walking distances to public transport in Norwegian cities"	Norwegian cities	Acceptable walking distance varies by city size and context
Zou et al. — "Exploratory Analysis of Real-Time E-Scooter Trip Data in Washington, D.C."	Real-time trip data	Exploratory, data-driven approaches to spatial/temporal patterns
Arias-Molinares et al. — "Uncovering spatiotemporal micromobility patterns through space–time cubes and GIS"	GIS methodology	Advanced spatiotemporal GIS methods for micromobility activity