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Data-driven inference approach for integration between shared micro-mobility and public transit with empirical analysis

Master's thesis in Infrastructure and Environmental Engineering

HAO LI
LOUIS INKUMSAH

DEPARTMENT OF ARCHITECTURE AND CIVIL ENGINEERING

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LOUIS INKUMSAH

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Urban Mobility Systems Group
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HAO LI
LOUIS INKUMSAH

Supervisor: Ruo Jia, Department of Architecture and Civil Engineering
Examiner: Kun Gao, Department of Architecture and Civil Engineering

Master's Thesis 2024
Department of Architecture and Civil Engineering
Division of Urban Mobility
Urban Mobility Systems Group
Chalmers University of Technology
SE-412 96 Gothenburg
Telephone +46 31 772 1000

Cover: E-scooters parked in front of the architecture and civil engineering faculty building, with one hanging from a tree branch.

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LOUIS INKUMSAH
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Abstract

E-scooters are here to stay, as we see promising growths of about 10% annually by 2030. The industry is envisioned as a prospect to promote environmental and socio-economic sustainability. Integrating it with other forms of public transit since it is a more flexible form of transit, for the first- and last-mile seems to be the most promoted desire presently. However, the challenge lies in the fact that there are very few policies to govern them and also very little research to fully understand the impact of e-scooter's integration with public transport. With our research aimed at using machine learning and a k-prototype technique to analyse the usage patterns, seasonal effect and effects on POI of the first- and last-mile trips within the city of Gothenburg. From that we found that the closer an e-scooter was to a stop it encouraged it's usage for integration, especially in the winter with about 62% decline in integrated trips as compared to 70% in non-integrated trips. Indicating that, there is a stronger desire for integrated trips in the winter than in the summer. We also found that the city had 80% of substituted and 20% complementary e-scooter trips with public transit, with the common day and time of usage being on Wednesdays and Thursdays between 12:00 and 14:00 or 14:00 and 16:00. In the city the high counts of integration was found to be in the centre of the city at locations with multi-modal transport and dense activities which included commercial, others and recreational areas but their integration rates mostly occurred in suburban areas which were less dense with less efficient transport. One location stood dominant in both integrated trip count and integration rate which was "Stenpiren". Finally we, found that the weather impact the number of trips but does not affect the perception of usage, with the integration patterns being similar.

Keywords: E-scooter, Bus Public Transport, First- and last-mile, Micro-mobility, Seasons, Point of interest, temporal, space, Integration, Gothenburg.

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List of Acronyms

Below is the list of acronyms that have been used throughout this thesis listed in alphabetical order:

CBD	Central Business District
CO_2	Carbon Dioxide
DBS	Dockless bike-sharing
DB-SCAN	Density-Based Spatial Clustering of Applications with Noise
E-scooter	Electric Scooter
EPSS	Electrically Powered Standing Scooter
E-scooter	Electric Scooter
GIS	Geographic Information System
GTFS	General Transit Feed Specification
GPS	Global Positioning System
ID	Identification
kg	Kilograms
KJ	Kilojoules
km	Kilometres
km/h	Kilometres per hour
LiDAR	Light Detection and Ranging
MARTA stations	Metropolitan Atlanta Rapid Transit Authority
OD	Origin-Destination
PCA	Principal Component Analysis
POI	Point of interest
UITP	International Association of Public Transport
USA	United States of America
USD	United State Dollars
SDG	Sustainable Development Goals
SEK	Swedish Kronors
SKF	Svenska Kullagerfabriken
sqm	Square metres
%	Percent

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1

Introduction

Transportation serves as an essential element of infrastructure and a foundation for the structure of modern society. The sector involves the organised movement of people and goods across different geographical locations via a variety of modes (Kacher & Singh, 2021). The significance of transport extends beyond its immediate practicality in facilitating human mobility and trade. It plays an important role in promoting cultural connections and unity, which are essential for global peace and collaboration.

The industry, however, faces significant challenges. In 2019, the Intergovernmental Panel on Climate Change (IPCC, 2022) demonstrated a significant influence of transportation on climate change. They revealed that transportation alone accounts for approximately one-quarter of worldwide carbon dioxide (CO_2) emissions, with the road transport sector being responsible for the majority of these emissions, amounting to approximately three-quarters. The predominance of road transport in contributing to this contribution reflects the world's dependence on vehicles powered by fossil fuels, with continuous economic advancement and urbanisation leading to a surge in personal vehicle ownership. As a result, road transport has become a primary target for combating climate change.

1.1 Background

Over time, developed cities have had an increased demand for innovative modes of travel (Kamargianni et al., 2016), resulting in the creation of shared passenger transport. This has resulted in a more expansive notion known as shared mobility, which refers to a wide range of transport services used by several people, either one after another or at the same time. The idea encompasses a range of transportation options, including public transport, micro-mobility (such as bikes and scooters), automobile-based modes like car-sharing and trips on demand, as well as commuter-based modes (Kersten Heineke et al., 2023). In service-based terminology, they are commonly labelled as ride-sharing, car-sharing, bike-sharing, and scooter-sharing and viewed as a subset of the "sharing economy", a continuously evolving concept that eliminates focus on individual ownership and runs parallel with technological developments (Shaheen et al., 2015).

The advent of technology, especially the widespread adoption of GPS-enabled smartphones, revolutionised urban mobility. The capability of individuals to access real-time transit information has spurred the development of applications that facilitate the optimisation of transport mode selection (Pakarinen et al., 2023). The birth of shared micro-mobility services gained traction because of this almost a decade ago with the introduction of bike-sharing programmes in various cities (Bloom et al., 2021). They were presented as a transformational and convenient urban transportation alternative since they are portable and can be ridden on streets and bicycle lanes, allowing riders to choose faster or shorter routes due to their flexibility (Ma et al., 2022). Particularly in areas where public transit routes may not adequately cover all neighbourhoods or align with users' schedules, the behaviour pattern depicted commuters patronising it as an alternative to complement the rather rigid public transit with first- and last-mile trips (Zuo et al., 2020). The elegant fusion of technology has progressively encouraged commuters to shift away from conventional private vehicles and combine trips with biking and public transport.

The idea that commuters can have all of their demands satisfied by a single mode of transportation is becoming less and less acceptable. The possibility of transport multi-modality to solve urban problems has drawn much attention in recent years, where several forms of transportation are integrated into a single system (UITP, 2023). A concept such as "Park and Ride" allowed commuters to park their vehicles at predetermined locations and continue their trip with public transportation (Meek et al., 2008). Although this strategy was meant to encourage public transport and lessen the number of personal vehicles entering crowded urban areas, its results were varied. The proximity of the transit station or stop to the commuter's point of origin also affects the use of flexible transportation options (Yang et al., 2024). Commuters are more inclined to use various transportation options, including walking, to reach their destination when public transportation is more readily available and reasonably close. Interestingly, the city of Gothenburg, through Västtrafik is carrying out a similar programme supported by "commuter parking" for vehicles and bicycles (Västtrafik, n.d.).

The e-scooter market was valued at about USD 37 billion in 2023 and is predicted to reach approximately USD 78 billion by 2030. It predicts that the industry has the potential to grow at a little under a 10% annual rate by 2030. An indicator that there is an increasing demand for this technology and more people are investing in it (Grand View Research, n.d.). Over almost a decade-long growth period, the micro-mobility cluster industry's contributions in Gothenburg (the second largest city in Sweden) from 2018 have been remarkable with growth in tourism activities, which reflected growth as well in micro-mobility services (Business Region Göteborg AB, 2022). The relationship between micro-mobility usage and tourism suggests they do not only support each other in growth but also reveal a gradual acceptance of micro-mobility services as an integral part of urban transportation.

Gothenburg's "The Bicycle City" project is a noteworthy investment indicator. The city has committed SEK 473 million to enhance and expand cycling infrastructure, which includes extending the existing 37,000 sqm lane and adding 3 km of lanes in 2022 (City of Gothenburg, 2022). This commitment shows the Gothenburg city authority's strategic approach to enhancing micro-mobility and e-scooter ridership as it makes specific infrastructure provisions for e-scooters. These are a clear indication of a global desire to continuously develop and invest in the industry.

1.2 Problem Statement

There is widespread concern about the safety, environmental impact, and service cost of e-scooters, but users generally have a more favourable view of it. Despite this, there is still a strong consensus on the need for stricter regulations and better support infrastructure (Wallgren et al., 2023). The comprehension of commuters' behavioural patterns and use of shared e-scooters is essential in moulding this, especially to assess whether it complements the traditional public transit systems or if it is perceived as used independently. In some cities, there is increasing recognition of the potential for shared mobility as a sustainable transport mode, with advocacy for its inclusion into urban strategies and to provide it with more appropriate infrastructure and regulatory support (Laa & Emberger, 2020).

Generally, micro-mobility services are considered important in attaining environmental sustainability as they help reduce congestion and potentially greenhouse gas emissions (Kjærup et al., 2021). With that, it is important to evaluate their influence on urban transportation (König et al., 2022; Krier et al., 2021), especially since there are no clearly defined laws to govern them now. An evaluation of their impacts on integration with public transport and first- and last-mile solutions is necessary to improve their overall efficacy (Cai & Liang, 2021; Saberi et al., 2018).

1.3 Objectives

The objective of this research is to develop data-driven algorithms using naturalistic data to analyse the integration patterns between shared micro-mobility and public transit in Gothenburg. The study aims to achieve the following objectives:

- Examine the present user patterns in the integration of Gothenburg's public transport system with shared micro-mobility services, with a particular emphasis on e-scooters.
- Analyse the patterns of bus and e-scooter integration between key seasons of the year.
- Assess the variations in user behaviour and preferences when integrating public transport and e-scooter services in locations with varied levels of activity.

1.3.1 Research Question

To align with the study's objectives, the following questions were developed to help in better understanding and shaping the research's focus:

1. How does the mixed use of shared micro-mobility with Gothenburg's public transport system impact connectivity and user choices?
2. How do seasonal and temporal variations affect the coordination between bus arrivals and e-scooter departures in areas with different integration levels?
3. How does the coordination of bus and e-scooter services affect public transport use in areas with different levels of activity?

1.4 Limitations

- The GTFS data was limited to buses only. We, however, observed stops interacting with other transport modes, which could/could not be a main contributor to the integration observed.
- The access and egress radius of 50 m for integrated trips and the 200 m buffer for POI were selected based on supposition.
- Hardware capacity limitations, specifically in memory and processing power, had a significant impact on the execution times of Python computations.

2

Literature Review

With a rapidly growing interest in emission-free transportation, scholars and policymakers are beginning to pay much attention to shared micro-mobility services and how to maximise their benefits in development. While there has been ample research on bike-sharing users and integration patterns, few studies have covered the field of shared e-scooters. As such, this chapter focuses on reviewing works that are related to micro-mobility as a service, the usage and integration patterns of shared micro-mobility, and related research methods used to assess them.

2.1 Micro-mobility as a Service (MaaS)

The introduction of rental e-scooters in several cities across the United States in 2017 was an important milestone in the evolution of urban transportation (Cittadini et al., 2022). They were easily accepted into urban life, as it made it much easier for people to travel short distances quickly and improved their ability to connect with larger public transportation systems when needed. Naturally, it was important in transforming the landscape and providing a practical alternative to traditional transport methods, (Shaheen et al., 2021), especially considering that most of them are electrically powered.

The industry on its own has proven to be highly efficient and flexible, particularly in facilitating short trips to and from public transport hubs. Often referred to as first-mile or last-mile solutions, function as connections supplementing journeys between different modes of transit (Kapuku et al., 2021; Wang & Shen, 2022). Although the idea and desire are that they are used in such a manner, the reality of usage isn't entirely so, as commuters don't always have fixed or pre-planned travel patterns.

Shared micro-mobility involves the collective use of low-speed, lightweight vehicles. Descriptively, commuters share them or access the vehicles temporarily for use instead of the traditional style of owning them outright (Shaheen et al., 2021). A more specific definition of micro-mobility considers them as a class of vehicles that are limited to a maximum weight of 350 kg and a top speed of 45 km/h. This restriction keeps the kinetic energy of these vehicles to just 27 KJ, which is considerably lower than that of a standard car travelling at high speeds, thereby reducing both energy consumption and the potential for harm (Haji et al., 2023). When defining micro-mobility, multiple factors are considered, including vehicle speed, weight, intended use, and size. Typically, its definition is rooted in the vehicle's characteristics and urban infrastructure that they best suit, plus they are mostly used in short-distance travel (Zarif et al., 2019). In the UK, the e-scooter is formally known as the Electrically Powered Standing Scooter (EPSS) and is practically described as a vehicle that resembles a traditional scooter but is designed for a single rider in a standing position. What sets the EPSS apart is its electric powertrain and the placement of propulsion controls on a handlebar, which enhance manoeuvrability and ease of use. Other single-rider vehicles, such as segways, electric skateboards, and self-balancing vehicles, are clearly classified and cannot be used on roads. This means that regulators can focus on safety and making sure that e-scooters work with existing infrastructure. (RoSPA, 2020)

2.2 Micro-mobility Safety and Policies

Urbanisation is a continuous process that has resulted in a significant increase in population density as people move to cities for improved economic prospects and a better quality of life. This phenomenon generally attracts a greater percentage of highly educated people. The increased adoption of e-scooters as a preferred mode of transportation has been linked to this trend (Heumann et al., 2021; Jiao & Bai, 2020) but the widespread acceptance of e-scooters is directly attributed to the convenience and accessibility they offer. Which, however, has not been without its challenges.

A notable consequence of the increased acceptance is the rise in safety-related incidents. (Blomberg et al., 2019), wrote about the worrying trend of accidents involving riders and pedestrians, with the number of life-threatening incidents surprisingly higher among pedestrians, with a rise in public health concerns and calls for urgent measures to address them. The behaviour of e-scooter users reveals diverse concerning patterns; among them is the fact that riders frequently ignored traffic signals and tended to increase their speed instead when approaching red lights, thereby exacerbating accident risks (Guo et al., 2014), and some also sped up to 27 km/h, with instances of exceeding this on downhill paths (Mayhew & Bergin, 2019). To mitigate these effects, regulatory bodies imposed restrictions. Some of them were focused on speed, location, and time. One example is setting speed limits to 20 km/h during the day and reducing them to 15 km/h at night (Pakarinen et al., 2023). Apart from the aforementioned characteristics, (James et al., 2019) identified other key contributors to injuries that included improper parking obstructing pedestrian traffic, leading to trips and falls, use during the night, and riding at excessive speeds. These are particularly problematic as they increase the risk of accidents but also contribute to urban clutter and pose a direct hazard to pedestrians (Knapp et al., 2014).

In addition to regulatory measures, technological solutions have been explored to enhance safety. One such innovation is "geo-fencing", implemented directly on the service provider's maps to restrict e-scooters from operating in certain areas or exceeding specific speeds within designated zones. Geo-fencing has been perceived by some, according to (Sharp, 2019), as more effective than traditional regulatory approaches. Geo-fencing is not perfect, though, because of problems with technology like GPS multi-path interference, which can make positioning wrong without the help of extra technologies like LiDAR or cameras (Miura & Kamijo, 2015). Incorporating all these technologies only increases the cost of service, which is often passed on to the users in the form of higher fees.

As part of a larger effort to address safety concerns, stricter regulatory and enforcement measures are required. Some noteworthy proposed strategies include implementing visible identification tags on shared e-scooters (Datava et al., 2022). The idea would allow bystanders and authorities to easily identify and/or report improper behaviour with the possibility of imposing direct fines on e-scooter companies (Lin et al., 2023). A pre-conceptualised way to incentivize companies to educate their users and manage their fleets more responsibly.

Another aspect influencing e-scooter safety is the purpose of their use. The recreational use of e-scooters often leads to a higher chance of injury as compared to commuting on foot (Coelho et al., 2021). Their distinction underscores the variability in rider behaviour and risk exposure based on how they are used, suggesting that safety measures need to be tailored to suit different use cases.

(Salas-Niño, 2022) pointed out the challenges many urban areas face in crafting effective guidelines that not only promote safety but also integrate e-scooters into the broader transport ecosystem in a sustainable manner. The difficulty lies in balancing unpredictable usage with public safety and urban design, necessitating a dynamic approach to policy-making that can adapt to the evolving nature of the industry.

Sweden, similar to many developed nations, places a high priority on safety across various facets of public life, particularly in the realm of transportation. The country is well-known for its dedication to road safety, which takes a proactive approach that always prioritises the well-being of all road users. The "Vision Zero" programme is a game-changer among Sweden's safety initiatives. It represents a paradigm shift in traffic safety philosophy, based on the belief that no loss of life or serious injury is acceptable, as opposed to traditional safety programmes, which frequently accept some level of risk. The programme contends that the road system should be inherently safe and that drivers should not bear sole responsibility for accidents and injuries. Instead, multiple stakeholders, including vehicle manufacturers, infrastructure planners, and policymakers, collaborate to ensure safety (Belin et al., 1997).

While some cities have implemented regulations to address these safety concerns, the effectiveness of such measures remains questionable. Enforcing speed limits and mandating helmet use for e-scooter riders are positive steps, but without strict enforcement and penalties for non-compliance, these regulations may not effectively mitigate the safety risks associated with e-scooter usage (Kleinertz et al., 2023).

We cannot ignore the safety risks that the increased use of e-scooters poses. The potential for conflicts, collisions, and injuries in urban environments should prompt a re-evaluation of the widespread use of e-scooters in transportation networks. The drawbacks of e-scooters for public safety may outweigh their advantages if there aren't extensive and effective safety measures in place.

2.3 E-Scooter and Sustainability

Transportation is a key component of urban development and It supports economic growth by facilitating trade and access to locations. Still, it must be managed to balance ecological impacts, such as emissions and land use, with social and economic benefits. Effective transport systems reduce travel time, enhance safety, and promote affordability, while poor planning can worsen social inequalities (City of Gothenburg, 2018). Through the United Nations' Agenda 2030, (Trafikverket, 2018)" highlighted the interconnected nature of safety and sustainability in transportation. The role of sustainable transportation in building a sustainable society is highlighted through it, with a framework outlining specific targets that aim to transform transportation systems worldwide. Specifically, sub-target 3.6 aimed to halve the cases of road traffic fatalities and serious injuries by 2020, a goal that underscored the urgency of addressing road safety issues. Additionally, sub-target 11.2 set forth the objective to ensure a safe, affordable, accessible, and sustainable transportation system for all by 2030, reflecting a holistic view of transportation that integrates environmental, social, and economic dimensions.

Even though Agenda 2030 sets clear goals, research by (Trane et al., 2023) has shown that the Sustainable Development Goals (SDGs) have mostly been focused on the environmental aspects, leaving the social aspects out of the picture. This gap is significant as social aspects such as equity, accessibility, and safety are integral to the holistic achievement of sustainability. Environmental sustainability in transportation often covers topics like reducing greenhouse gas emissions and promoting energy-efficient vehicles. In contrast, the social dimensions involve ensuring that transportation systems are designed to be inclusive, catering to the needs of all segments of society.

Recognising this imbalance, our research intends to adopt a more integrated approach by delving into both the environmental and social dimensions of the SDGs related to transportation. By examining literature that encompasses both of these aspects, we aim to provide a more comprehensive understanding of what truly constitutes sustainable transportation.

2.3.1 Environmental Impacts

The ease of use and environmental advantages of e-scooters are what is driving their rising urban popularity (Glenn et al., 2020). In busy cities, where commuters routinely grapple with traffic jams, high parking fees, and limited parking spaces, e-scooters emerge as a viable alternative. They allow users to weave through congested streets and reach their destinations swiftly and effectively. In contrast to traditional vehicles such as cars and taxis, e-scooters offer a nimble and adaptable means for covering short urban distances. They enable riders to easily navigate through traffic, sidestepping jam-packed roads and thus facilitating quicker arrivals at various destinations. This level of convenience renders e-scooters an attractive option for daily commutes, errand running, or urban exploration.

Throughout their life-cycle, e-scooters also have significant environmental impacts, encompassing the energy consumed during their production, transport, and the processes of charging and recharging, up to their disposal. These environmental impacts are mitigated when the energy sources used are eco-friendly (Neves et al., 2024). The e-scooter itself has no tailpipe emissions during operation, putting it in an environmentally friendly category. According to research, combining shared mobility services with public transportation can lead to fewer people owning cars and lower overall transportation costs. It can also lead to more people using public transit, which can encourage more environmentally friendly transportation habits (Koo & Choo, 2022; Stiglic et al., 2018; Yan, Zhao, Han, Van Hentenryck, & Dillahunt, 2019; Zhang & Zhang, 2018). While sharing physical items typically yields more substantial environmental benefits than sharing spaces or transportation services, the latter can sometimes be detrimental to the environment. Contrary to previous assumptions, peer-to-peer sharing does not always result in greater environmental benefits than centralised ownership models (Meshulam et al., 2024). An easy way to consider such statements is to use ride-hailing vs. public transport as an example. When an app is used to book a trip, it's presumed to be a more environmentally friendly alternative as compared to using a privately owned car. However, the deficiency of travelling long distances to pick up passengers in the case of public bus transport contributes to increased emissions and sometimes traffic congestion. On the other hand, using a personal vehicle is a fuel-efficient choice, and the trips are planned efficiently considering this flexibility.

Adding to that, it has been found that the current shared e-scooter systems emit more CO_2 per km than the transportation modes they replace, primarily due to their brief lifespans. Nonetheless, with ongoing investments aimed at innovation within the industry, there is optimism that future developments will enhance their environmental performance (Moreau et al., 2020).

2.3.2 Socio-Economic Impacts

E-scooter riders are mostly younger and more educated, especially in cities with lots of tech companies or universities (Gkartzonikas & Dimitriou, 2023). They like e-scooters because they offer quick, affordable mobility and are environmentally friendly.

E-scooters are great for navigating dense urban areas because of their compatibility and agility, which makes them easy to use in tight and crowded spaces. They are also a popular choice for urban residents who intend to cut down on commute time. A survey by (Lee et al., 2021) found that people heading to educational institutions often used e-scooters for their first- or last-mile trips. Higher-income individuals also tend to use them more, especially when public transport isn't as efficient.

Several factors influence e-scooter use, such as employment status, household size, and the perceived benefits of e-scooters (Gkartzonikas & Dimitriou, 2023). These factors shape how often people use e-scooters in urban areas. As cities get more crowded, more people are recognising the practicality and benefits of e-scooters for reliable, quick, and eco-friendly transportation.

2.4 Micro-mobility User Behaviour

Research on mobility patterns reveals that adults walk at an average speed of approximately 4.8 km per hour, translating to about 1.6 km every 20 minutes (Hullett & Bubnis, 2020). The typical distance a person is willing to walk is an average of 1.25 km. Surprisingly, the walking distance, elevation changes, and satisfaction levels had negligible effects on it (Manaugh & El-Geneidy, 2013). Dockless e-scooters have been the subject of several studies, notably in the United States, where they are primarily used for short trips. (Jiao & Bai, 2020) identified that the trips they used were an average of 1.24 km in distance and took about 7.55 minutes, with noticeable differences between weekday and weekend usage patterns. On weekdays, peak usage times range from 1 pm to 5 pm, starting earlier at 11 am, whereas weekends see consistent use throughout the afternoon. In a comparable study conducted by (Noland, 2019), the observations varied with a larger dataset, with an average travel distance of 2.14 km and a duration of 15.59 minutes, indicating slightly longer journeys. The highest level of e-scooter usage was observed on Saturdays between 12 pm and 3 pm. In another study on dockless e-scooters in four European cities, the patterns found were distinct, suggesting that the average travel time ranged from 10.2 to 13.8 minutes, with a distance range of 1.96 km to 3.02 km. The peak usage was during the afternoons on Fridays and Saturdays (Foissaud et al., 2022).

Comparative studies between American and European users suggest that Americans tend to use e-scooters for relatively shorter and quicker trips, which reflects differences in commuting patterns, underscoring the need for studies to be conducted based on considerations of their geographic locations (Bozzi & Aguilera, 2021). Walking and riding e-scooters both reflect typical usage of under 3 km. Given that the typical walking willingness is capped at around 1.25 km and the average e-scooter trip tends to be around or above this range, e-scooters seem to offer a convenient alternative for distances that are slightly out of comfortable walking range. This may specifically attract users who are seeking to save time or minimise physical effort. Both the USA and Europe show a noticeable pattern of heightened e-scooter utilisation on weekends, suggesting that e-scooters are preferred for recreational and non-work-related journeys. Scores of previous studies have focused on bike-sharing, the reason being that the shared e-scooter service market is relatively novel. Notwithstanding that it is easy to observe from findings that their usage patterns are not far apart, making it easy to cross-reference research on bike-sharing reflectively on shared e-scooter services.

The e-scooter is used for various trip purposes. In a study based in the USA, it was found that midday and evening weekday usage was confined to commercial and institutional areas like the CBD and universities, whereas the trip times on weekends are more dispersed (Tokey et al., 2022). Dockless bike-sharing (DBS) and e-scooters are mostly used for short trips on weekday afternoons, reflecting similar trends in other countries and indicating they mainly serve non-commuting needs. Differences between these services are evident: dockless bike-sharing peaks notably in the morning, particularly around university areas, suggesting its role in commuting to and from educational institutions. E-scooter usage was found to be primarily concentrated in city centres and around public transit hubs, and it connects commuters to public transportation or their final destination (Chicco & Diana, 2022). Another study by (Orvin & Fatmi, 2021) found that individuals living in neighbourhoods with varied amenities and extensive cycling infrastructure frequently engage in bike-sharing for recreational purposes. Higher economic status and possession of a private vehicle typically decrease the possibilities of utilising shared transportation modes. Critical elements that encouraged a positive adoption of sharing were mostly based on convenience and access to public transport, residential density, and the availability of cycle paths.

Weather conditions, such as rain or extreme temperatures, significantly influence the adoption and usage of shared micro-mobility services (Bi et al., 2021). The quantity of e-scooter users changes with the weather changes, with harsh weather like snow causing a reduction in the number of riders (Abouelela et al., 2023).

2.5 Integration between Shared Micro-Mobility and Public Transit

Understanding user behaviours and perceptions is critical for integrating e-scooters into urban transportation systems effectively. This understanding, along with steps to lower the risks involved, makes it easier to add the services to current transport systems (Useche et al., 2022). In developed regions, public transit systems typically showcase high reliability, with schedules prominently displayed at stops. However, seasoned transit users often possess deeper insights than what is merely displayed, which highlights the diversity in commuters and types of information needs among them (Larsen & Sunde, 2008). E-scooters can both compete with and complement existing transport modes, depending on the specific use case and location (Yan, Zhao, Han, Hentenryck, & Dillahunt, 2019).

The current focus on shared micro-mobility extensively explores its dynamics and interplay with conventional public transport systems. A pivotal aspect of this involves determining whether micro-mobility services complement or replace existing public transport. Using a regression model, (Radzimski & Dzięcielski, 2021) looked into this relationship and found that shared micro-mobility services are much more appealing and useful when public transport is reliable and easy to get to. These services are particularly preferred for short to medium trips within urban settings, especially in contexts where public transit is frequent and dependable. The inclination towards micro-mobility in densely populated urban areas often correlates with its ability to conveniently and efficiently fill the gaps left by traditional transit routes.

In such environments, bike-sharing may substitute public transport due to its convenience and speed, indicating why more micro-mobility solutions tend to be integrated when public transit is used more efficiently (Kong et al., 2020). In less dense areas, bike-sharing acts more as a complement to public transport by bridging the first- and last-mile gaps, aiding commuters in reaching transit stations that are otherwise too distant to walk to (Martin & Shaheen, 2014). It was concluded that people frequently prefer shared bikes to other modes of transportation when travelling to and from transit stations in areas with few public transportation options. The introduction of bike-sharing services influenced transportation choices significantly, with more than 44% of commuters modifying their mode of transport and between 27% and 40% supplementing their trips with public transit as a result of these services (Shaheen et al., 2021). Integration patterns between e-scooters, e-bicycles, and bicycles are very similar (van Kuijk et al., 2022). The suggestion is that the integration patterns observed are interchangeable. With that, bike-sharing services showed that their patrons were much more likely to integrate their trips with rail than with a bus (Yan, Zhao, Han, Hentenryck, & Dillahunt, 2019). We infer that the same patterns are associated with e-scooters.

The versatility of micro-mobility trips in urban transport is becoming increasingly recognised. (Vinagre Díaz et al., 2023) systematically categorised these trips into four distinct functions: serving as a complementary choice that coexists with traditional transport modes without displacing them, acting as an auxiliary tool enhancing first-mile or last-mile connectivity, or completely substituting for public transport when necessary. The concepts of Modal substitution, Modal integration, and Modal Complementing describe the various interactions between bike sharing or micro-mobility services and public transit. Modal Substitution occurs when a bike-sharing trip directly replaces a public transit journey, often when the bike route closely aligns with transit schedules and starts and ends near transit hubs with minimal need for transfers. Modal Integration involves using bike-sharing in conjunction with public transit, typically covering the journey to a station at the beginning (first mile) or from a station at the end (last mile) of travel, requiring proximity to transit stations and timely connections. Modal Complementing happens when bike-sharing addresses coverage deficiencies in areas poorly served by public transit, particularly when the bike trip's start or end points are remote from transit stations or when the transit routes necessitate multiple transfers (Koo & Choo, 2022). Distinctively, (Vinagre Díaz et al., 2023) separated the roles of first-mile and last-mile connectivity into unique functions, unlike (Kong et al., 2020), who viewed any bike-sharing activity facilitating access to or from nearby transit stations as a single integrated role. (Vinagre Díaz et al., 2023) further detailed a complementary role where micro-mobility coexists harmoniously with other modes of transportation without replacing them, contrasting sharply with Modal complementing, which focuses on filling service gaps in areas underserved by public transit rather than merely coexisting.

2.6 Related Research Methods Explored for Integration

To find a commonality to our research parameters, a similar study evaluated public transit coverage using threshold distances of 400 m for subways and buses and 800 m for railways (El-Geneidy et al., 2014; Jin et al., 2019). Considering how indicative this represents the parametric gaps between rail and bus transit, we will avoid direct comparisons to rail transport in the review but may only consider the process. E-scooters are relatively new compared to other micro-mobility modes, including bike sharing. Bike-sharing usage patterns have shown some patterns slightly similar to the e-scooter, as they are both used in short trips but show different usage patterns (McKenzie, 2019; Zhu et al., 2020), with that, we'll adapt some of the processes used in the analysis of bike-sharing services. Reading through most of the previous research, it is easy to notice that some processes and methods stand out.

Distances are used in buffering, and clustering is a critical metric for analysing datasets to derive meaningful conclusions and identify patterns (Sharma & Seal, 2020). A review of studies revealed that Euclidean distance is frequently used as a metric. However, the debate over which method is better, whether the Euclidean or Haversine, is still ongoing, as each method has advantages and constraints based on its specific application (Maria et al., 2020). The Euclidean method computes the linear distance, similar to the diagonal of a triangle, and is appropriate for small distances where the Earth's curvature can be disregarded. Although this method is simple and direct, it fails to take into account practical obstacles such as buildings or roads. The Haversine formula is frequently used in navigation to determine the arc distance between two points on the spherical Earth and provides precise measurements for longer distances (Ghilissen, 2020). Another approach, the Manhattan distance method, computes the total sum of the absolute differences in coordinates, which is particularly advantageous in urban settings characterised by a grid-like layout (Ghilissen, 2020). It also offers a direct and efficient approach to computation, and its distance efficiency renders it highly valuable in fields such as data clustering.

(Vinagre Díaz et al., 2023) conducted a notable study that was comparable to ours. Their research developed an unsupervised method to assess how e-scooters complement or substitute public transportation networks in Rome, Italy. They looked at how close the starting and ending points of e-scooter trips were to the nearest train or subway stations, using GTFS data to explore the relationship with public transit.

Unlike traditional methods, their approach didn't start with any assumptions about the distance from transit stations. Instead, it lets distance emerge as a parameter in the clustering process, taking into account factors like urban design and user behaviour. They first filter to ensure data quality and remove the outliers caused by the tracking devices, just as earlier emphasised in Section 2.2. For this, they calculated the travel distances, and the only data considered were a distance ranging from 0.1 km to 20 km, a duration between 30 seconds and 125 minutes, and an average speed not exceeding 25 km/h used in the proceeding analysis. It was reassuring to see how this was empirically supported. The approach avoids the limitations inherent in setting arbitrary distance thresholds by allowing intrinsic city parameters, such as user behaviour and the layout of the public transport network, to dictate the relationships between e-scooter trips and public transit. Their study used a natural approach, giving a clearer view of how e-scooters are used and their effect on the transport network. Instead of fixed metrics, they grouped trips based on patterns in the data. This method created clusters by examining the similarities among trips using various distance measures and the K-means clustering algorithm.

The K-means algorithm analyses the distances from the start and end points of each e-scooter trip to the nearest station (Capó et al., 2018). The steps included setting initial cluster centres, assigning trips to the nearest centres, recalculating the centres, and repeating until the clusters stabilised.

In analysing POI data, a typical reflection of an ideal method such as (Espinoza et al., 2019)'s was a great fit to adopt. Using specific coordinates for locations in Atlanta, like the stadium due to its size, had problems because the point location didn't match well with the e-scooter's parked location. To fix this, buffer points were added around key places such as the Georgia Aquarium (90 m), Mercedes-Benz Dome (140 m), MARTA stations (20 m), and neighbourhoods (140 m). Additionally, a ring of 16 buffers with a 290 m radius was added around neighbourhoods. Generally, it is indicated that the buffers used were not fixed but varied based on size and to logically match the purpose of the location.

After grouping the POIs, duplicate entries were addressed where, if searches such as "restaurant" and "bar" returned to the same place, only the primary type matching the query was kept. POIs with vague addresses were excluded. When different POIs shared the same location, they were combined into a single "multiple" POI.

With clean trip and POI data, the closest POI to each trip's start and end was found using a k-dimensional tree. All locations were converted to a Cartesian plane for accuracy. Trips were then linked to their nearest POIs, and distances between them were recorded to help infer trip purposes. If the same POI appeared for both the start and end, a new search was done for the start point, as it was inferred that riders have more control over their last-mile trip than their last-mile trip (Espinoza et al., 2019).
Other authors have also used a variety of methods that yield reliable results in addition to these elaborate methods, which examine e-scooter and public transport integration and their interactions with POIs. Their summaries are illustrated in Tables 2.1 to 2.8

2.6.1 Integration Analysis Processes

(Zuniga-Garcia et al., 2022) investigated the role of e-scooters in bridging the last-mile transportation gap in Austin, Texas, using a two-stage methodological framework. (Kong et al., 2020) examined this by classifying trips based on their proximity to public transit stations. (Cao et al., 2021) investigated the feasibility of commuter preferences by conducting a Stated Preference Survey and employing mixed logit models.

Author(s)	Study Focus	Details
Zuniga-Garcia et al. (2022)	Bridging last-mile transportation gap	Two-stage methodological framework
Kong et al. (2020)	Bike-sharing integration with public transportation	Scenario and trip duration analysis
Cao et al. (2021)	E-scooter as a substitute for conventional transport	Stated Preference Survey and mixed logit models

Table 2.1: Summary of Integration Analysis Processes

2.6.2 Data collection and categorisation

In their study, (Ma et al., 2021) collected data on E-Scooter user guidelines from 156 cities in the United States. They identified sixteen important characteristics and used different methods of categorization to emphasise differences in policies. Similarly, (Karimpour et al., 2023) collected two years' worth of e-scooter Origin-Destination (OD) trip data from Louisville, USA, and created maps of the service areas within specific traffic analysis zones. (Zuniga-Garcia et al., 2022) compiled data from approximately 1.7 million e-scooter trips and 9 million public transport trips in Austin, Texas, to examine the incorporation of e-scooters into the preexisting public transport system. (Hawa et al., 2021) also monitored the geographical positions of e-scooters in Washington, D.C., for six consecutive days by dividing the city into 1,671 grid cells, each measuring 0.07 square miles. In all processes, there was an obvious attempt to gather a large dataset, showing the need to get results as close to reality as possible.

Table 2.2: Summary of Data Collection Efforts

Reference	Location	Details
(Ma et al., 2021)	USA	E-Scooter user guidelines from 156 cities.
(Karimpour et al., 2023)	Louisville, USA	Two years' worth of e-scooter OD trip data.
(Zuniga-Garcia et al., 2022)	Austin, Texas	1.7 million e-scooter trips and 9 million public transport trips.
(Hawa et al., 2021)	Washington, D.C.	Monitored e-scooters in 1,671 grid cells over six days.

2.6.3 Data filtration and wrangling Methods

(Ziedan et al., 2021) excluded trips that had missing data, duration shorter than 60 seconds or longer than 120 minutes, distances greater than ten miles, and average speeds higher than 24 km/h. (Cao et al., 2021) excluded e-scooter trips that lasted less than 1 minute or more than 900 minutes. (Hawa et al., 2021) initially considered excluding fishnets from areas where locking is not permitted. Nevertheless, they ultimately opted to incorporate them into their analysis because of the significant prevalence of e-scooter trips.

Author(s)	**Criteria**	**Details**
Ziedan et al. (2021)	Trip duration, distance, average speed	Excluded trips with missing data: shorter than 60 seconds, longer than 120 minutes, distances over 10 miles, speeds over 24 km/h
Cao et al. (2021)	Trip duration	Excluded trips less than 1 minute or more than 900 minutes
Hawa et al. (2021)	Fishnets	Considered excluding non-permitted areas but included them due to high prevalence

Table 2.3: Summary of Data filtration and wrangling Methods

2.6.4 Buffer Ranges

(Cao et al., 2021) eliminated trips that were less than 1 minute or more than 900 minutes in duration, indicating that they focused on time-based rather than distance-based boundaries. (Kong et al., 2020) used clear buffer zones 100 m and 400 m from transit stations to divide trips into different scenarios. Section 2.6.5 goes into more detail about these scenarios. These zones clearly showed the locations where bike-sharing trips connect to public transport stops. (Hawa et al., 2021) employed fine-scale geographical grids, also known as fishnets, with a size of 0.07 square miles. These grids were used to establish buffer ranges within each grid cell.

Author(s)	**Buffer Criteria**	**Details**
Zuniga-Garcia et al. (2022)	Spatial analysis near transit stations	Integrated e-scooters with transit systems
Cao et al. (2021)	Trip duration	Focused on time-based rather than distance-based boundaries
Kong et al. (2020a)	Buffer thresholds	Established 100 and 400 m from transit stations
Hawa et al. (2021)	Geographical grids	Used 0.07 square mile fishnets

Table 2.4: Summary of Buffer Ranges

2.6.5 Scenario Analysis

(Kong et al., 2020) classified bike-sharing trips into four specific scenarios in order to examine the ways in which these trips interacted with public transportation. Scenario 1 involved first- or last-mile trips within a range of 100 m to 400 m from public transport stations, which are deemed adequately served by public transport but not close enough for convenient transfers, hence potentially replacing the use of public transport. Scenario 2 encompassed first-mile trips within a distance of 100 m and last-mile trips between 100 and 400 m, or vice versa. These journeys were regarded as instances of either transit-and-bike or bike-and-transit integration, where riders would likely utilise bike-sharing to minimise or eliminate transfers in public transportation or to access the nearest public transit stations. Scenario 3 encompassed first-mile trips within a 100-m radius and concluded beyond a 400 m distance, or vice versa. The trips held the potential for modal integration. Scenario 4 involved first-mile trips greater than 400 m that ended between 100 and 400 m away, or vice versa. The origin point or destination of these trips was either more than 400 m away from public transport or close to it. These trips were assumed to complement public transit rather than replace or integrate with it.

Scenario	Criteria	Details
1	100 to 400 m from stations	Potentially replacing the use of public transport
2	Within 100 m and ending 100–400 m, or vice versa	Transit-and-bike or bike-and-transit integration
3	Within 100 m to beyond 400 m, or vice versa	Facilitated seamless integration with public transportation
4	More than 400 m to 100-400 m, or vice versa	Complemented public transit rather than replaced or integrated

Table 2.5: Summary of Scenario Analysis

2.6.6 Data Analysis Methods

(Ma et al., 2021) utilised Chi-squared analysis to investigate the associations among various policy components. In addition, Principal Component Analysis (PCA) was employed to condense the dataset into its principal components. (Karimpour et al., 2023) employed PCA to decrease the number of variables used for analysis. (Cao et al., 2021) utilised mixed logit models to analyse data collected from stated preference surveys on usage patterns and user preferences. to investigate ways in which e-scooters were utilised for different trip purposes, such as minimising transit transfers and facilitating access to public transit stations. (Hawa et al., 2021) employed multilevel mixed effects linear regression models to assess the influence of different covariates on the distribution of e-scooters. (Ziedan et al., 2021) employed fixed-effects regression models to investigate the associations between e-scooter usage and bus ridership. The aim was to ascertain whether e-scooters functioned as substitutes or complements to bus transportation. Some of the more advanced statistical models used were the negative binomial count model and the zero-inflated negative binomial count model (Zuniga-Garcia et al., 2022).

Author(s)	**Method**	**Details**
Ma et al. (2021)	Chi-squared analysis, PCA	Investigated policy components, condensed dataset, Categorization and testing
Karimpour et al. (2023)	PCA	Reduced variables for analysis
Cao et al. (2021)	Mixed logit models	Analyzed usage patterns and user preferences
Hawa et al. (2021) Zuniga-Garcia et al. (2022)	Multilevel mixed effects linear regression Negative Binomial Count Model, Zero-Inflated Negative Binomial Count Model	Assessed influence of covariates on e-scooter distribution Analysed integration between e-scooter and public transit
Ziedan et al. (2021)	Fixed-effects regression	Investigated associations between e-scooter usage and bus ridership

Table 2.6: Summary of Data Analysis Methods

2.6.7 Methods of Machine Learning

The study by (Zuniga-Garcia et al., 2022) used gradient boosting regression to find and separate possible confounding factors that might affect the patterns of e-scooter and public transit use. These factors included weather, urban design, and personal preferences. (Karimpour et al., 2023) utilised a random forest regression model in their integration analysis.

Author(s)	**Method**	**Details**
Zuniga-Garcia et al. (2022)	Gradient boosting regression	Identified confounding factors affecting usage patterns
Karimpour et al. (2023)	Random forest regression	Investigated factors influencing e-scooter ridership and accessibility

Table 2.7: Methods for Machine Learning

2.6.8 Cluster Analysis and Data Visualisation

(Ma et al., 2021) employed k-means clustering to detect groups of cities that share similar e-scooter policies and then represented the data using spiral bubble plots.

(Karimpour et al., 2023) also utilised agglomerative hierarchical clustering to investigate the first and last mile effects of e-scooter trips, and their results were presented in a dendrogram visualisation. (Hawa et al., 2021) used precise geographical fishnet grids to measure and analyse the distribution of e-scooters in different areas.

Author(s)	**Method**	**Details**
Ma et al. (2021)	K-means clustering	Detected groups of cities with similar policies, represented with spiral bubble plots
Karimpour et al. (2023)	Agglomerative hierarchical clustering	Investigated first and last mile effects, presented results in a dendrogram
Hawa et al. (2021)	Geographical fishnet grids	Measured and analysed e-scooter distribution

Table 2.8: Summary of Cluster Analysis and Data Visualisation

2.7 Micro-mobility in Gothenburg

Shared micro-mobility services have become an important part of urban transportation in many cities, Gothenburg included. As the number of people seeking environmentally friendly and flexible transport options continues to grow, the service plays a role in meeting this demand. The illustration of micro-mobility vehicles in Sweden seen in Table 2.9, sourced from (Trafikverket, 2018) describes the industry. In Gothenburg, the regulatory framework for e-scooters is the same as that of bicycles, since the Swedish Transport Agency considers both to be in the same category. This categorisation facilitates the integration of e-scooters into the current road network system (Göteborgs Stad, n.d.).

In Gothenburg, the use of e-scooters had a typical duration of up to approximately 7 minutes and covered a distance of about 1.8 km. Their usage significantly diminishes on weekends, particularly around the evening but spikes on weekdays, particularly in the afternoon, with an uneven geographic distribution within the city. There is, however, a markedly higher concentration of trips in central Gothenburg compared to the city's more peripheral areas (Peci et al., 2022). In almost every way, these usage patterns are very similar to those observed for Europe, as depicted by (Foissaud et al., 2022) in Section 2.5. All aspects, except for the usage days, which were on weekends.

The developments of e-scooter regulations and infrastructure in Gothenburg reflect the effort to accommodate them; though, there is a discrepancy between the objective of decreasing car usage and the continued allocation of resources towards road capacity expansion (Bi et al., 2021).

Vehicle Type	Engine Capacity	Drive System	Speed	Type Approval	Helmet Requirements	Registration	Insurance	Competence
Bicycle	-	Tramp or crank device	(1)	No	Children <15 years (2)	No	No	No
E-assisted Bicycle	Max 250W	Tramp or crank device	(1)	No (EU's Machinery Directive applies)	Children <15 years (2)	No	No	No
Class II Moped	Max 1kW	Tramp or crank device	< 25 km/hr (1)	Yes (3)	Bicycle helmet (2)	No	Yes	Driving Proof for age 15 years
Class II Moped (6)	Max 1kW	Throttle lever	< 25 km/hr (1)	Yes (3)	Protective helmet	No	Yes	Driving Proof for age 15 years
Class I Moped (5)	Max 4 kW	(Throttle lever)	45 km/hr (1)	Yes (4)	Protective helmet	Yes	Yes	AM Driving license

Table 2.9: Specifications and requirements for different vehicle types

(Wang et al., 2021) identified inefficiencies in the utility of e-scooters, where 40% of the energy stored was not used properly. They suggested the adoption of comprehensive strategies that integrated e-scooters with public transport systems to increase patronage and, consequently, improve energy efficiency. Malin Månsson, a traffic planner in Gothenburg, stated in a 2020 publication by Trafik Göteborg, that the city deals with approximately 1,000 instances of e-scooters being illegally parked daily. The large quantity of e-scooters poses logistical challenges in its management even with the implementation of fees on companies for improper usage (Trafik Göteborg, 2020). The GeoSence project investigated the use of geo-fencing as a means to enhance the regulation (Malmström & Tunmarker, 2023). To ride e-scooters in the city, a person must be a minimum of 18 years old and must ride and park in specific designated areas. Additionally, there are restrictions on the use of e-scooters during nighttime hours on weekends (VOI Technology AB, n.d.).

2.8 Summary

To sum up, while several scholarly articles have explored the integration of micromobility options, such as e-scooters, with public transportation systems, definitive conclusions regarding this relationship remain elusive. The interaction between e-scooters and public transport is likely to vary based on a multitude of context-specific factors, including urban scale, the density and coverage of the public transport network, user demographics, climatic conditions, the occurrence of special events, and the proximity to POIs. For example, in urban areas where public transport faces significant congestion, e-scooters might attract a segment of public transport users, serving as an alternative mode of transit. Conversely, in different city contexts, e-scooters might be adopted as a complementary mode, enhancing multi-modal transportation systems. While several studies have focused on the geographical correlation between public transport stop locations and e-scooter usage, there is a notable gap in research concerning the impact of the characteristics of public transport services on e-scooter utilisation.

3
Methodology

The chapter provides an overview of the methodological processes and perspectives that support the credibility of the study. It includes important aspects such as research design, study area, data collection, data sample, and data cleaning. The data cleaning section emphasises the process of preparing data, which involves techniques for organising and validating bus transit data, managing e-scooter data, and implementing buffering procedures. The exploratory analysis section provides a comprehensive overview of the initial steps involved in examining data, particularly the methods used to prepare the input data for thorough analysis. This chapter also explains how to use K-prototype clustering for both categorical and numerical data, as well as how to look at points of interest (POI) to understand patterns and relationships in space.

3.1 Research Design

Our goal was to use Python to create machine learning algorithms to analyse the patterns between bus transportation GTFS and e-scooter usage data, as well as their specific connections to different Points of Interest (POIs). As part of our methodological approach, we followed these steps: A literature review, conceptualisation, building a method for data collection, Data Processing, analysis, verification, and conclusion, in a flow pattern as elaborated in Figure 3.1.

Using the methodology of (Vinagre Díaz et al., 2023) as a reference guide, we eliminated the outliers and utilised clustering techniques to further analyse the data. By utilising the technique, we were able to categorise e-scooter trips according to inherent patterns found in the data. (Maria et al., 2020) emphasised how important the haversine formula is for using longitude and latitude to figure out the distances between points (Equation (3.1)). This formula is used to calculate the length of an arc connecting two sets of geographical coordinates. Our methods used this in calculating all distances.

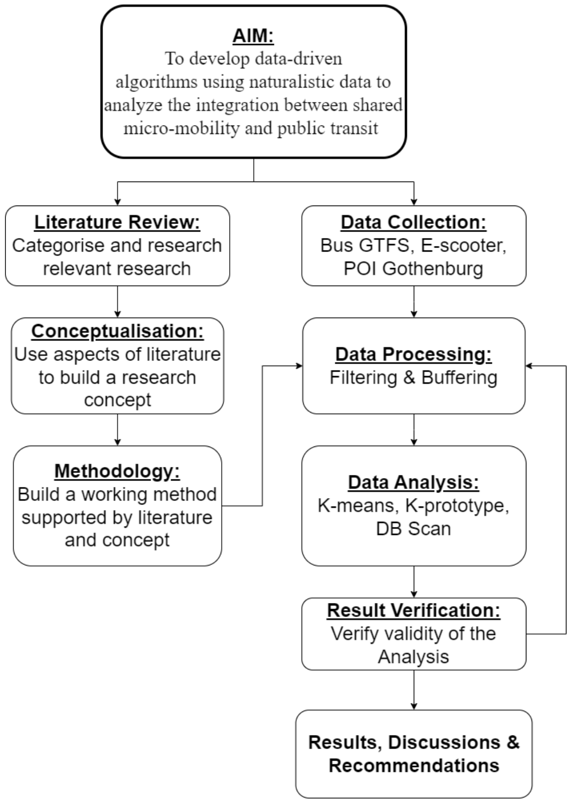


Figure 3.1: Illustration of Research Design

$$d = R \times c \tag{3.1}$$

where:

- d is the distance between the two points,
- R is the radius of the Earth (assumed to be approximately 6371 km),
- c is the central angle between the two points, calculated as:

$$c = 2 \times \tan^{-1} 2\left(\sqrt{a}\ \sqrt{1-a}\right) \tag{3.2}$$

where:

- a is calculated as:

$$a = \sin^2\left(\frac{\Delta lat}{2}\right) + \cos\left(lat_1\right) \times \cos\left(lat_{12}\right) \times \sin^2\left(\frac{\Delta lon}{2}\right) \tag{3.3}$$

where:

- Δ l a t is the difference in latitude between the two points $lat_2 - lat_1$
- Δ l o n is the difference in longitude between the two points $lon_2 - lon_1$

We also used, as a secondary aspect of our research, an empirical analysis which involved a thorough review of existing literature relevant to our study to bolster our findings and provide a solid academic foundation to support our observations and conclusions.

3.2 Study Area

Gothenburg is a city in the southwestern part of Sweden, with a land mass of over 440 sqm and a population of 596,841 and an annual growth rate of about 1.2% as of the end of 2022, which was the year the data used was assessed (Statistiska centralbyrån, n.d.). (Göteborgs Stad, n.d.) reported that the city's cycle network spans an impressive 813 km. The year 2021 marked a significant period of growth for micromobility in Gothenburg, particularly in e-scooter services. It saw the addition of three new service providers. By the peak of the summer, the number of e-scooters increased by 60% from the previous year, 2020. E-scooter trips more than doubled over the year, with close to 1,000,000 rides recorded in July alone (Trafikkontoret, 2022). The e-scooter companies currently operating in the city are four namely, VOI, Tier, Ryde, and Bolt, with Ryde being the new entrant (Göteborgs Stad, n.d.-b). Figure 3.2 shows the public transport layout of Gothenburg, Västtrafik also manages the city's public bus system, which as of 2022 was running on 121 bus lines and 8,907 bus stops within the city.

3.3 Data Collection

The reference data utilised in our study was meticulously and qualitatively sourced through secondary channels, primarily the Chalmers Library database utilising Scopus, and supplemented by other open-source academic platforms such as Google and Google Scholar. This initial stage of gathering information was critical, setting the stage for the subsequent, crucial step of rigorously evaluating the sources to ascertain their reliability and relevance to our specific research topic. This evaluative process entailed a detailed analysis of several key aspects: the credibility of the authors involved, the publication dates of the materials, and the overall academic competence of the sources.

The diverse array of reference sources accessed provided a comprehensive and well-rounded foundation for the study, enabling an in-depth and multifaceted examination of the subject matter from multiple academic perspectives. Such a rigorous approach to sourcing and referencing not only significantly bolstered the scholarly credibility of our research but also profoundly enriched the depth and breadth of the

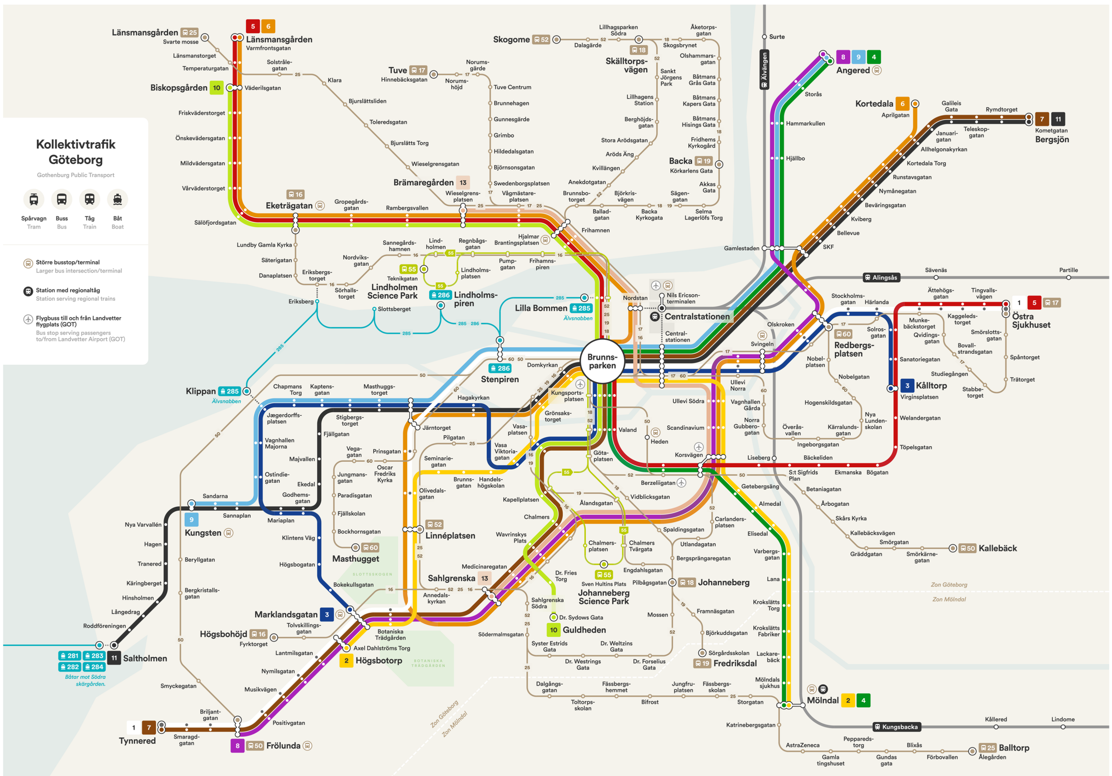


Figure 3.2: Public Transit Map of Gothenburg in 2022, source: Jens Svanfelt, 2018

discussions within the study. As (Penders, 2018) emphasised, thorough and critical sourcing is imperative in enhancing the academic rigour and integrity of research outcomes.

3.4 Data Sample

The study extensively utilised POIs, bus transit GTFS, e-scooter space, and temporal data, which were obtained from secondary sources. The datasets of e-scooter trips were exclusively based on Gothenburg, whereas the data encompassing POIs and bus transit GTFS covered the entirety of Sweden. The bus transit GTFS and e-scooter space-time datasets comprised quantitative data gathered in June, July, November, and December of 2022 and sourced from the Trafiklab website. The dataset included detailed records for Västtrafik bus trips. The VOI e-scooter trips were obtained from the Chalmers Urban Mobility Division and GIS layers of POIs in Gothenburg were obtained from Openstreetmaps.

In terms of volume, the study processed a substantial amount of data: 349,854 records of bus trips, 313,464 records concerning e-scooter trips, and 133,999 POI locations. This dataset summarised in Table 3.1 was used as a robust foundation for the analysis based on the selected months within the year 2022.

The datasets for e-scooter usage included detailed information about individual trips, each clearly identified and recorded with distance, time, and location data, as well as battery usage statistics. These datasets contained detailed records about each trip, such as the start and end times of trips, GPS coordinates at the start and end points, and initial and final battery levels, along with measures such as distance travelled, usage time, trip duration, and average speed.

The datasets for bus transport included a wide range of public transit data across several key documents that gave a complete overview of the transit network. The "agency" file compiled a full list of all the transit authorities in Sweden, providing a broad view of the operational scope. The "stops" file described the transit networks and marked the locations of commuter interactions with bus stops. "Routes" describes the public service routes available through the transportation system. The "trips" file detailed each journey's attributes, plotting routes through a series of stops over a set time frame. The "stop times" file recorded the scheduled arrival and departure times at each stop Finally, the ”*calendardates.txt*” file contained the operational schedule.

The POI datasets contained GIS layer files in shape files. They covered seven main name categories about land and building use in the city and included areas namely, Residential, Commercial, Recreational, Educational, Public, Medical, and others. A more elaborate breakdown of the categories can be found in APPENDIX A.

Table 3.1: Data Overview

Platform	**VOI**	**Västtrafik**	**Gothenburg**
Service Type	E-Scooter	Bus Transit	
Total number of trips	313,464	349,854	
Location type	Origin to destination	Bus Stops	Point of Interest
Total number of locations	626,928	8,907	133,999
Key Attributes	Space and Time	Space and Time	Space

3.5 Data Wrangling

Given the precise demands of the study, a thorough data cleaning process was crucial to guarantee the accuracy and pertinence of the data in alignment with the research objectives. Figure 3.3 shows a visual path of the processes used.

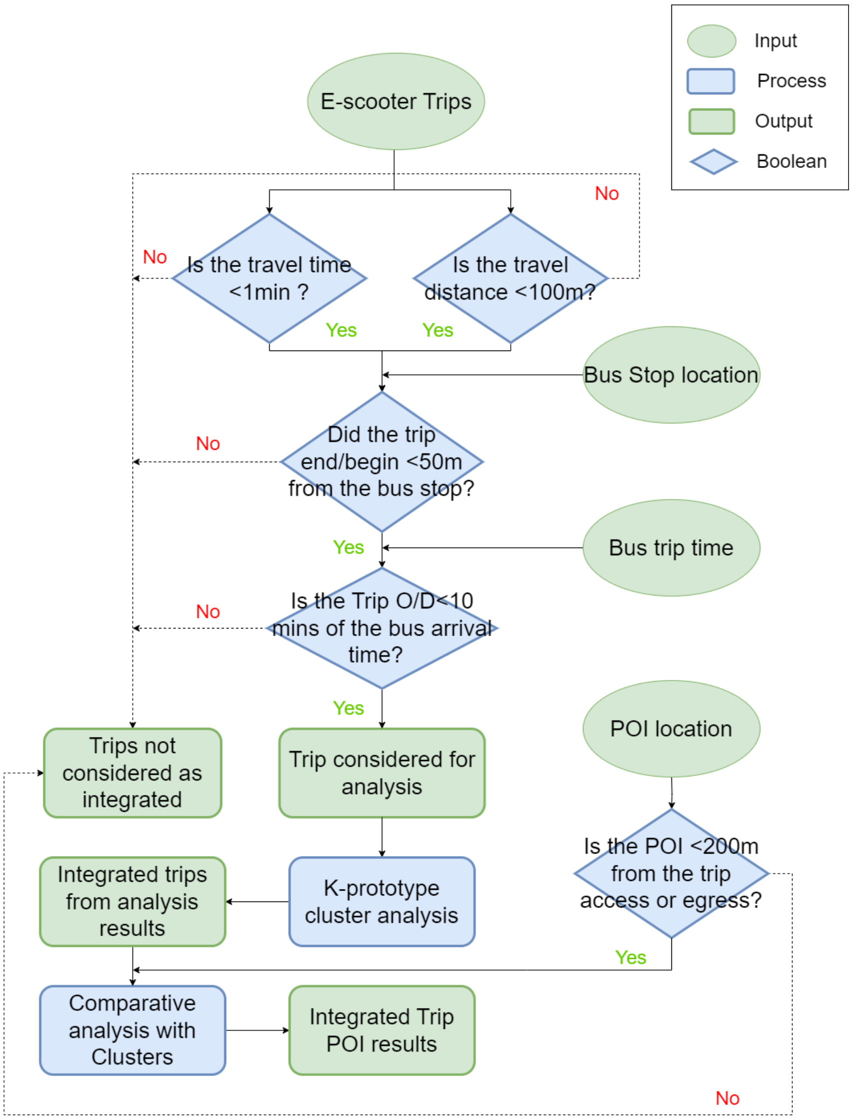


Figure 3.3: Illustration of Data Wrangling Process

3.5.1 Bus Transit and Stops

The GTFS data obtained included data from all of Sweden's. To isolate data relevant to Gothenburg from the broader national dataset, geographic filters were applied using the location data embedded within the GTFS. The GTFS dataset was filtered to only include local bus trips and bus stop locations by using the agency code specific to Gothenburg's Västtrafik (agency code 279).

To ensure accuracy and standardise units across datasets, corrections were made to erroneous entries. Errors were detected in the time data for the bus trips, with some trips recorded as lasting more than 24 hours. The abnormality was adjusted to a standard date-time format—for example, converting '30 hours' to 'plus 1 day and 6 hours'.

In this, the intention was to identify each bus stop and its connected trips. To ensure that the data was well-represented and generated an accurate date, time, and location, follow the steps depicted in Figure 3.4. First, filtering was executed using the agency ID mentioned above for Västtrafik against the route ID to obtain routes within Gothenburg. The data within this file has no spatial data but only a unique identifier code that links it to the route location. The next step was to use the route ID to filter the unique trip IDs, and the trip IDs were used to obtain the stop IDs, which had a direct link to the latitude and longitude of each bus stop. Finally, the trip ID and route IDs were used to filter the stopping times of each trip at each bus stop. Datasets after the processes resulted in bus stops; location, bus trip; date and time, e-scooter trips; origin's location with date and time, and destination's location with date and time.

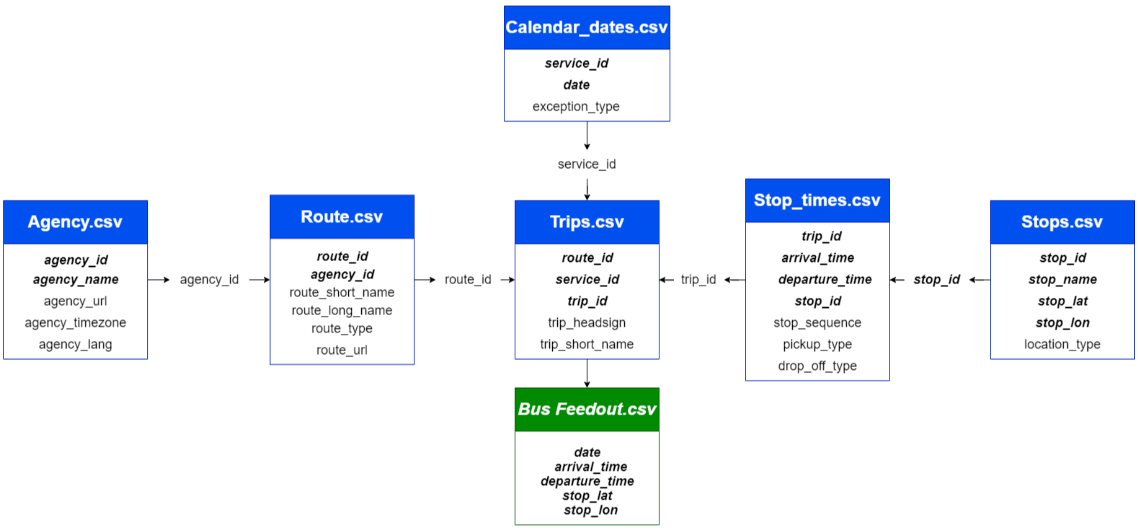


Figure 3.4: Bus GTFS filtering

3.5.2 E-scooter

Through outlier removal, we ensured that the dataset was reliable. This preprocessing step helped filter the dataset to ensure valid and actionable results (Ziedan et al., 2021). The process involves identifying and excluding parameters that meet specific criteria for outliers. In this case, the criteria are travel distances of exactly 100 m and travel times between 1 second and 60 minutes. The removal of time and distances was to prevent the inclusion of short trips that were presumed to be used for jolly rides. (Vinagre Díaz et al., 2023) conducted the same outlier removal process, considering a minimum time range of 30 to 60 seconds and a maximum of 120 to 125 minutes as the outlier ranges.

3.5.3 POI

The GIS layers of the POI data, which were received in shape files, were converted into CSV files over ArcGIS to make them easy to read and be in Python. Since the data included all of Sweden, we set boundaries similar to the process in Section 3.5.1 as a first step in the analysis.

3.5.4 Buffering

During our analysis, we constructed buffer ranges as shown in Figure 3.5 to support our investigation. Unlike (Kong et al., 2020), who performed a scenario analysis, we adopted buffer ranges based on the research considerations of (Li et al., 2024). Making use of a 50 m radius buffer around the origin or destination of e-scooter trips as the most suitable distance for access and egress, near the bus stop. The 50 m buffer ensures that scooter users can easily access and leave scooters without walking excessively, aligning with findings that short walking distances improve the usability and attractiveness of shared mobility services.

In addition to the 50 m buffer, we implemented another buffer to exclude trips that both originated and ended within a 500-m range using a function with ranges that define it at latitude ± 0.0045 degrees and longitude ± 0.0055 degrees. The values assume that 1 degree of latitude is approximately 111 km (thus, 0.0045 degrees is about 500 m) and adjust for longitude according to the cosine of the latitude (since degrees of longitude get closer together as you move away from the equator) from the e-scooter. This exclusion criterion was based on the premise that short trips within a 500 m range might not provide significant insights into the typical integration use patterns of e-scooters, possibly representing anomalies or misuse. Research on first- and last-mile distances supports the strategy by emphasising the significance of excluding excessively short trips to concentrate on more representative travel patterns (Li et al., 2024). Similarly, (Kong et al., 2020) performed the same buffering, making buffer zone considerations of radius between 100 m and 400 m, as explained in Section 2.6.

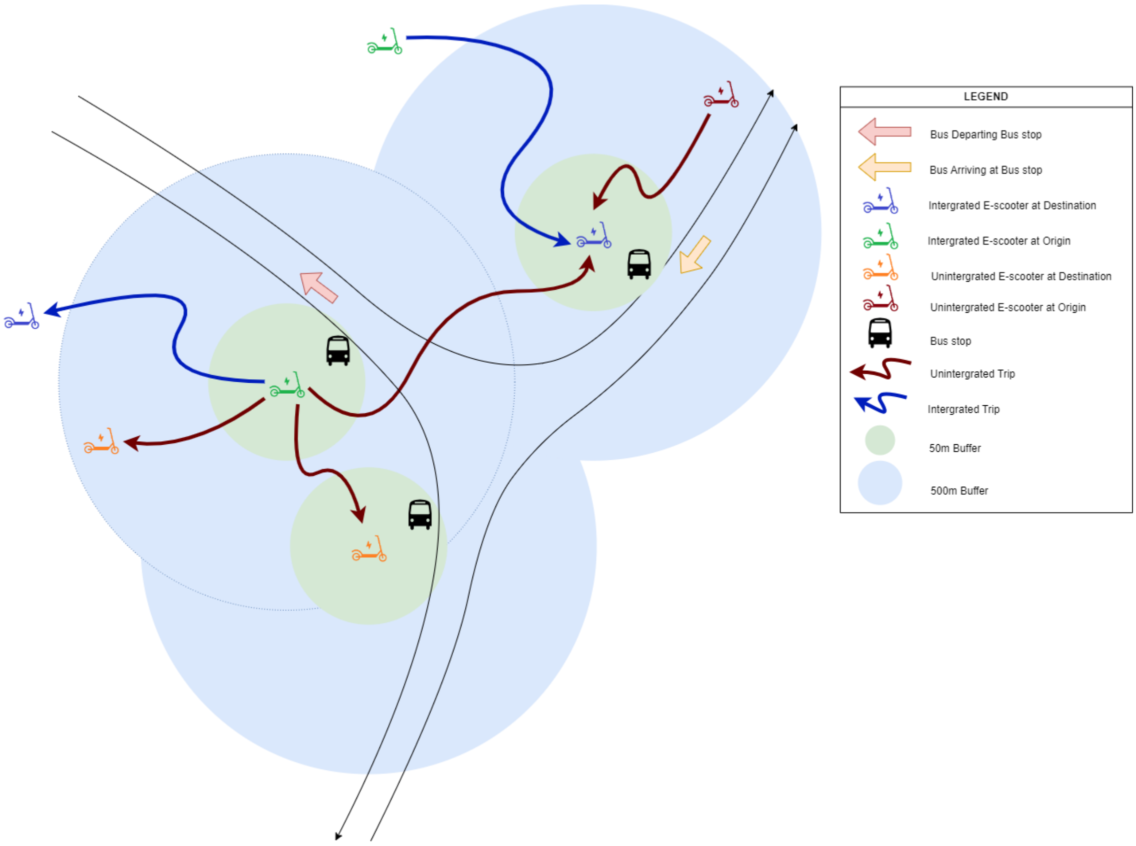


Figure 3.5: Illustration of Buffer zones and Analysis considerations

We also considered trips that had their first or last mile beyond 500 m from the origin or destination in our analysis. Including these trips gives a bigger picture of how far people use e-scooters, which was important for figuring out if they could be a good alternative for medium-range city travel (Radzimski & Dzięcielski, 2021). E-scooter trips that started or ended within 10 minutes of a bus's arrival at a bus stop were also included in our analysis.

3.6 Integration

In the process of analysing the temporal and spatial data derived from e-scooters and public transportation usage, we employed a structured parametric breakdown to enhance our understanding and management of the data. This approach was crucial for dissecting the dynamics of commuter movement patterns, focusing particularly on the hours most indicative of peak commuting times, which include regular working hours and other high-traffic periods.

We utilised a systematic parametric breakdown during the analysis to improve our comprehension of the temporal aspects. To streamline this analysis, we initially set up a time buffer that specifically included hours when commuter activity was at its peak. The times are between 6:00 AM and ending just before midnight at 23:59:59. this range was selected to encompass the complete range of daily commuter movements, including both the busy morning periods and the late evening returns. We divided the data into nine equal intervals, each lasting two hours, and arranged them numerically from 1 to 9. The remaining portion of the 24-hour day is consolidated and regarded as zero.

Our analysis was based on the standard workweek observed in Sweden, taking into account the cultural and regional variations that greatly influence commuting patterns. We classified the days into three distinct groups to more accurately represent the overall work culture: Monday to Thursday were considered as complete working days, representing a typical workweek labelled as 1. Friday was typically regarded as a half day, acknowledging the widespread custom of shorter working hours and separated as 2. The weekend, Saturday, and Sunday, considered trips that were usually unrelated to work, were labelled as 0.

The segmentation was crucial in identifying the variability in commuter behaviour, which frequently changes based on the day of the week. By grouping the days in this way, we can conduct a more detailed analysis that accurately captures the movement of commuters, taking into account both regular workdays and the unique patterns of weekends and half days. Our methodological framework is in accordance with the findings of (Bozzi & Aguilera, 2021), who highlight the significance of taking into account geographical biases in transportation research. By tailoring our analysis to the particular cultural and work practices of Sweden, we recognised that these patterns may differ considerably in other nations.

3.7 K-Prototype Analysis

To comprehensively analyse the datasets, our research aimed to evaluate various clustering methods to determine their suitability for managing diverse data types. This assessment revealed that while some algorithms offer specific benefits, they may not be appropriate for the complexities inherent in mixed data types.

When deciding on suitable methods, it is important to consider the nature of the data, desired cluster shapes, computational limits, and the specific requirements

Input	Description
o stops within 50m	Count of bus stops at the Origin of e-scooter within 50m
d stops within 50m	Count of bus stops at the Destination of e-scooter within 50m
new d to o near stop distances	Origin of e-scooter to Destination of Bus
new o to d near stop distances	Origin of Bus to Destination of e-scooter
o count	Count of bus trips at Origin within 10 mins
d count	Count of bus trips at Destination within 10 mins
Days (0,1,2)	Days of the week - monday to thursday - 1, Friday - 2 weekend - 0
Time groups (0 to 9)	Time between 6:00 to 23:59:59 divided at 2 hour intervals - 1 to 9 and other times as 0

Table 3.2: Input of mixed data X_i for Analysis

of the intended application domain, since each algorithm offers unique advantages tailored to meet different analytical challenges and complexities for different data environments. DB-SCAN is effective at detecting clusters in spatial datasets, making it a great tool for analysing geographic data. Its ability to efficiently handle noise and outliers is essential when addressing spatial irregularities (Ester et al., 1996). Alternative approach Hierarchical clustering is renowned for its capacity to produce intricate dendrogram structures, enabling a more profound understanding of data relationships. The method is highly adaptable in analysing both numerical and categorical data (Nielsen, 2016).

To conduct a thorough analysis of the datasets, we assessed these different clustering techniques to ascertain their appropriateness for handling a wide range of data types. The assessment showed that although certain algorithms provided distinct advantages, they may not be suitable for the complexity of mixed data types.

Ultimately, we opted for the K-prototypes algorithm due to its practical utility in real-world scenarios where data often consists of mixed-type objects. The K-prototypes algorithm improves the usual clustering method by adding a distance measure that combines squared Euclidean distance for numbers and a simple matching dissimilarity measure for categories. A key feature of this algorithm is the introduction of a weighting parameter, γ which helps to balance the impact of numerical and categorical distances during the clustering process. This algorithm updates cluster centroids for numerical data by calculating the mean of the feature values, while for categorical data, the mode is used. The algorithm assigns data points to the closest cluster based on the total distance measure and keeps the centres up-to-date until convergence is reached (Hernández et al., 2023).

Consider a collection of n objects represented as

$$X = \{X_1, X_2, X_3, \ldots, X_n\},$$

where each object X_i is composed of a set of attributes

$$X_i = \{X_{i1}, X_{i2}, X_{i3}, \ldots, X_{im}\}.$$

Within this framework, the attributes are further categorised into two distinct types: m_n numerical attributes and m_c categorical attributes, making the total number of attributes for each object,

$$m = m_n + m_c.$$

The primary objective of clustering in this context is to organise these n objects into k distinct and non-overlapping clusters, denoted as

$$C = \{C_1, C_2, C_3, \ldots, C_k\}.$$

The algorithm proceeds by initialising k centroids, each representing a cluster. These centroids are iteratively refined through the algorithm's execution: in each iteration, every object X_i is assigned to the cluster whose centroid is nearest to it, according to the combined distance measure across the attributes. Post-assignment, the centroids are recalculated to reflect the mean (for numerical attributes) and mode (for categorical attributes) of the objects now contained within each cluster. The process is repeated until a stopping criterion is met, typically when the centroids stabilise with minimal or no change, indicating that the clusters have become sufficiently distinct according to the dataset's inherent structure.

To combine numerical and categorical data, the K-Prototype algorithm employs a combined distance measure:

$$D(X_i, C_k) = \sum_{j \in \mathrm{Num}} (x_{ij} - c_{kj})^2 + \gamma \sum_{j \in \mathrm{Cat}} \delta(x_{ij}, c_{kj}) \tag{3.4}$$

where:

- X_i is the i-th data point.
- C_k is the k-th cluster centroid.

- Num and Cat are the sets of numerical and categorical features, respectively.
- x_{ij} and c_{kj} are the values of the j-th feature for the i-th data point and the k-th cluster centroid.
- $\delta(x_{ij}, c_{kj})$ is an indicator function that equals 1 if $x_{ij} \neq c_{kj}$ and 0 otherwise.
- γ is a weighting parameter to balance the numerical and categorical distances.

For numerical features, the cluster centroid is the mean of the feature values of all points in the cluster:

$$c_{kj} = \frac{1}{|C_k|} \sum_{X_i \in C_k} x_{ij}$$

For categorical features, the cluster centroid is the mode of the feature values of all points in the cluster:

$$c_{kj} = \text{mode}\{x_{ij} : X_i \in C_k\}$$

3.7.1 Algorithm Steps

1. **Initialization**:
    - Randomly select K initial cluster centroids, where K is the number of desired clusters.
    - Each centroid consists of both numerical and categorical components.
2. **Assignment Step**:
    - Assign each data point X_i to the nearest cluster centroid C_k based on the combined distance measure $D(X_i, C_k)$.
3. **Update Step**:
    - Update the cluster centroids C_k by calculating the mean of the numerical features and the mode of the categorical features for all points assigned to each cluster.
4. **Convergence Check**:
    - Repeat the assignment and update steps until the cluster assignments no longer change or until a specified number of iterations is reached.

3.7.2 Standardisation of Results

The outputs are similar to the parameters set for the input in Table 3.2. The scores have been made more comparable across different types of variables by standardising them.

Specifically, the data is standardised using the following formula:

$$z = \frac{x - \mu}{\sigma}$$

Where:

- x is the original data.
- μ is the mean of the data.
- σ is the standard deviation of the data.

3.8 POI Analysis

The section aimed to assess how Points of Interest (POIs) affected integrated e-scooter trips, specifically how they affected first- and last-mile trips. First, we gathered information about POIs and divided them into seven different categories: commercial, residential, recreational, educational, public, medical, and others. To enable a more detailed and nuanced examination, we subsequently expanded this framework to 14 POI groups, allowing us to analyse each type of POI at both the start and end points of e-scooter journeys. Following the categorization, we implemented a clustering method to precisely identify and count points of interest within a 200 m radius of both e-scooter trip origins and destinations.

4
Results

This chapter presents the findings of our study. The results are organised into several key areas: transfer distance and possible integration, seasonal and time-of-day variations, trip density, cluster results, summer cluster results, winter cluster results, comparison of centroids, and points of interest (POI) analysis.

The first part covers the transfer distances and the potential for integrating e-scooters and bus services. Next was on how e-scooter usage varies with seasons and times of the day, as well as the results of trip density, highlighting the most frequent routes and areas of activity. We then present the clustering results, with separate findings for summer and winter. A comparison of cluster centroids is included to illustrate spatial distribution patterns. The POI results identified significant locations that play a crucial role in the integration of these transport modes.

4.1 Transfer Distance and Possible Integration

The 2D histogram represents the counts of origin and destination points of e-scooter trips in comparison with access and egress distances to the nearest bus stations as plotted on the x- and y-axes, respectively, and uses a colour gradient to represent trip density, with brighter colours indicating a higher concentration of trips. To breakdown further, they do not represent the first- and last-mile trips but instead the walked distances by commuters to access or egress an e-scooter.

The highest concentration of trips starting and ending near bus stations are clubbed within the first 500 m and start to diminish after 1 km. The bright colors in the bottom left corner of the histogram indicate that the bus stations' first 50 m to 100 m are where the majority of trips occur. Emphatically, it is key to note that there are little to no trips after the 1 km distance.

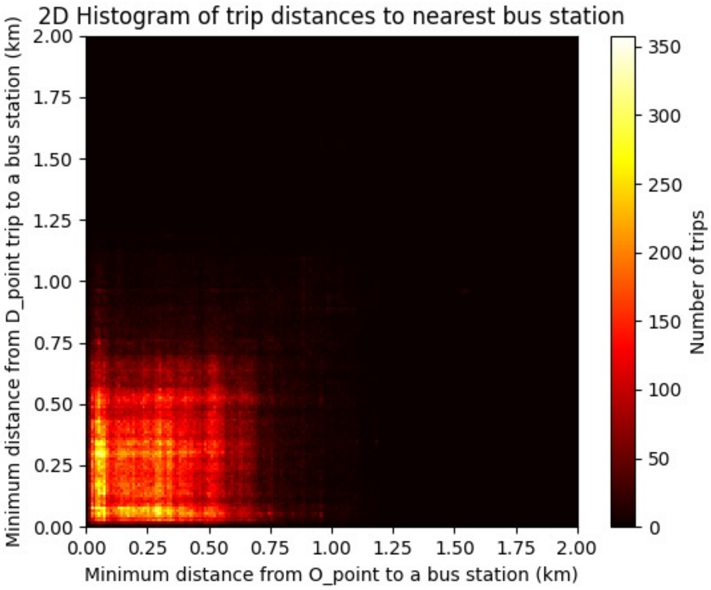


Figure 4.1: 2-Dimensional histogram of trip distances to nearest bus stop

4.2 Seasons and Temporal Analysis

The frequency of e-scooter trips, both overall in Figure 4.2 and within the specific time window of 6:00 to 23:59:59 in Figure 4.3, demonstrates seasonal and daily usage patterns when comparing usage during the summer (months of June and July) with the winter months (November and December).

In June, there are 70,782 trips in total, and in July, the peak month, there are 107,761 trips, leading to a combined total of 178,543 trips during both months. The majority of daytime trips in summer are in June, at 65,924, and in July, at 99,101, totaling 165,025 daytime trips. Nighttime trips are fewer but still notable, with 4,858 in June and 8,660 in July, summing up to 13,518 summer night trips.

In the winter months, the use of e-scooters is much lower. November shows 43,210 trips, and December, the lowest month, records 14,261 trips, resulting in a total of 57,471 trips during the winter months. Daytime trips also decreased during this season, with 41,365 in November and 13,349 in December, totaling 54,714 daytime trips in winter. Night trips reduce significantly, with 1,845 in November and 912 in December, adding up to 2,757 winter night trips.

Comparing these seasons, total trips drop by 68% from summer to winter, daytime trips drop by 67%, and nighttime trips fall by 80%.

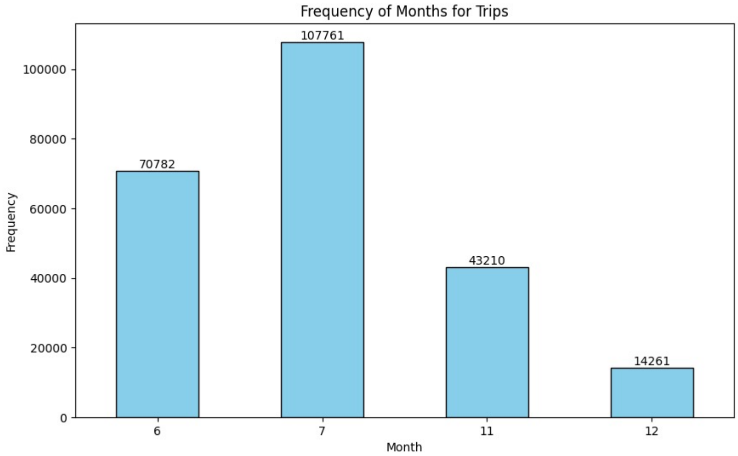


Figure 4.2: Total number of trips

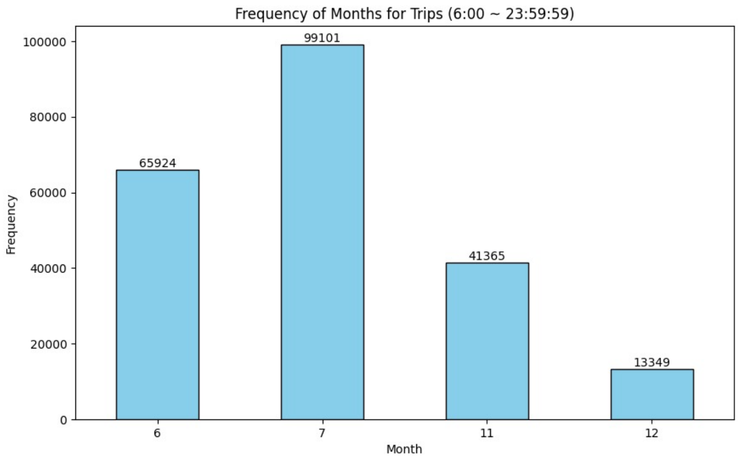
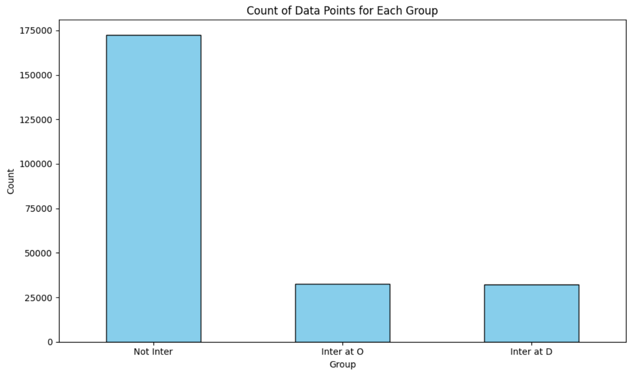


Figure 4.3: Total daytime trips

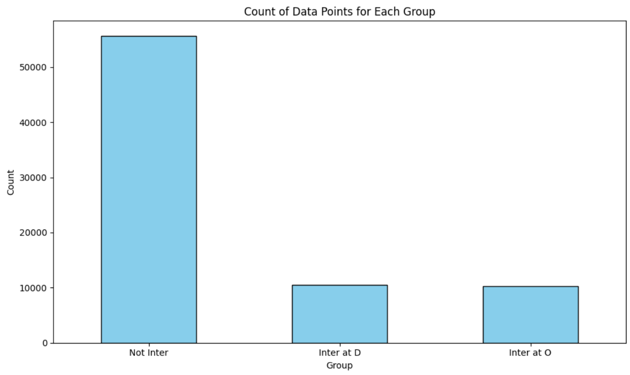
4.3 Cluster Integration Analysis in Comparison with Seasons

Figure 4.5 shows the counts of integrated and non-integrated e-scooter trips by summer and winter clusters. Figure 4.5 shows that non-integrated trips from clusters 4, 5, and 6, resulting in about 80% of the total trips, outnumber the integrated trips from clusters 0, 1, 2, and 3 during both seasons.

Among the integrated trips, those starting from public transport locations in clusters 0 and 2 and associated with the first mile trips resulted in about 10% of the trips, and those ending at public transport locations in clusters 1 and 3 associated with the



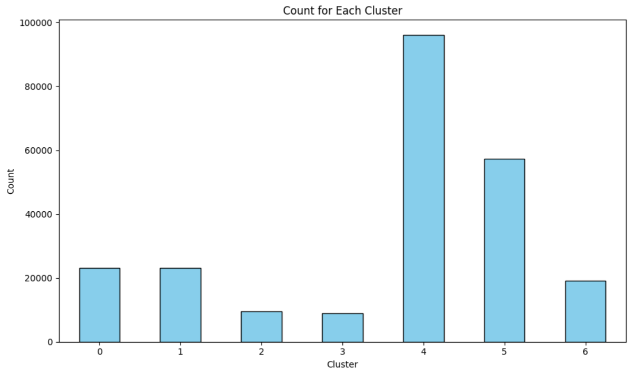
(a) For Summer



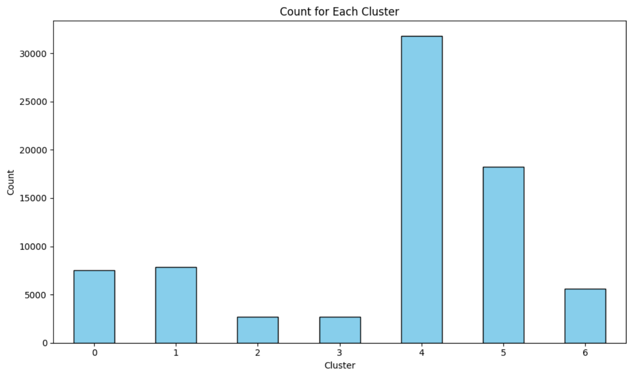
(b) For Winter

Figure 4.4: Bar chart of Integrated and Non-integrated Trips

last mile trips also resulted in about 10% of the total trips being evenly distributed. Each accounts for an equal number of trips, indicating a balanced use of e-scooters for both first- and last-mile trips.



(a) For Summer



(b) For Winter

Figure 4.5: Bar chart of Count of e-scooter trips per Cluster

4.3.1 Clusters Analysis for Summer

From Table 4.6, we observed that Clusters 0 and 2 show significant values within the first-mile. In Cluster 2, the count of bus trips associated with the first-mile trip that occurred within 10 minutes after a bus arrives is higher than in Cluster 0, with counts of 18.04 and 4.63, respectively. Both clusters have an equal positive count of bus stops with their first-mile trip. This situation doesn't go in favour of destination trips where the number of buses arriving within 10 minutes and count of bus stops are both less than zero. The impact pattern of trip arrivals was also reflected in their first- and last-mile distances, with cluster 2 resulting in an average distance of about 1.21 km and cluster 0 at about 1.03 km.

The integration peak observed in Cluster 0 and 2 occurs in the mid-week, on Thursdays, which is a workday. The common activity time is early afternoon, from 14:00 to 16:00 for both clusters.

Clusters 1 and 3, conversely show significant activity related to the destination, where Cluster 3 has a higher count of bus trips departing the bus stops at the destination point than Cluster 1, with counts of 17.86 and 4.37, respectively. Similar to Cluster 0 and 2, the average count of bus stops at the last mile for both is also 1, with their first and last-mile distances measuring at about 1.03 km and 1.25 km for both Cluster 1 and 3, respectively. The common activity time is early afternoon, from 14:00 to 16:00 for both clusters, which occurs on Thursdays.

Clusters 4, 5, and 6 show lower results across its metrics. Especially with their counts of bus stops within 50 m at both the first- and last-mile being less than zero, we rule out the possibility of integration. However, the first- and last-mile distances for clusters 4, 5, and 6 resulted in 0.63 km, 1.54 km, and 2.98 km, respectively. The day of usage for clusters 4, 5, and 6 was Thursday, and times of usage were in the early afternoon, also between 14:00 and 16:00.

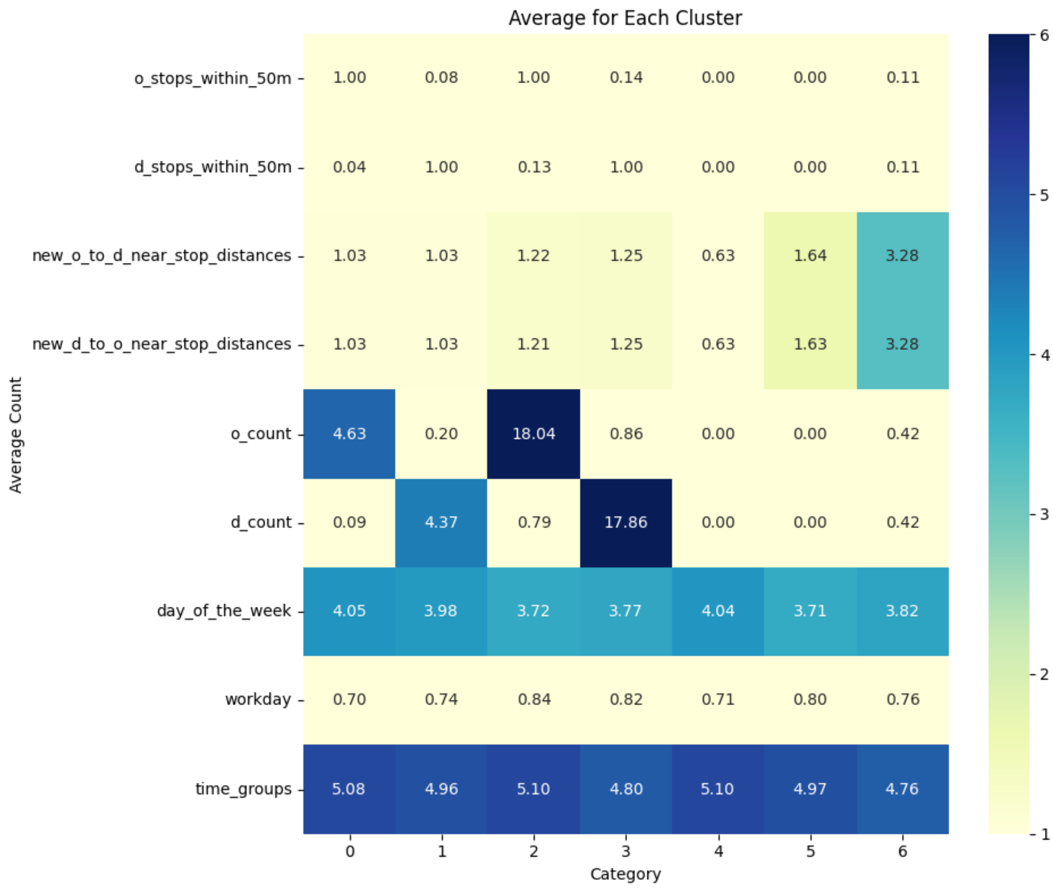


Figure 4.6: Cluster Analysis Heatmap for Summer

4.3.2 Clusters Analysis for Winter

The results in Figure 4.7 show patterns similar to those in summer. Clusters 0 and 2 have a lot of activity at the e-scooter starting points, while Clusters 1 and 3 have a lot of activity at the destinations. Clusters 4, 5, and 6 also show close to no activity to bus stop integration.

Cluster 2 has a significantly higher count of bus trips in the first-mile trip within 10 minutes compared to Cluster 0, with counts of 25.09 and 5.76, respectively. Both clusters have a high count of integrated bus stops at the first- mile, with a value of 1.00 each. However, at the last mile, both clusters show very low counts of integrated bus stops and bus trips, with values less than zero, indicating a lack of integration. In terms of the first- and last-mile distances, cluster 0 had about 0.94 km and cluster 2 had 1.12 km. Activities in Cluster 0 typically occur on Wednesday, which is a workday, whereas in Cluster 2, they occur on Tuesday. The common activity time is early afternoon, with cluster 0 being between 14:00 and 16:00 and cluster 2 at 12:00 to 14:00.

Cluster 3 has a higher count of bus trips at the last mile within 10 minutes compared to Cluster 1, with counts of 24.75 and 5.48, respectively. Both clusters have a high count of bus stops at the destination, each with a value of 1.00. However, both clusters have low counts of bus stops and first-mile trips, with values less than zero. Similar to clusters 0 and 2, the first- and last-mile distances for clusters 1 and 3 resulted in 0.95 km and 1.20 km, respectively. Activities in these clusters typically occur mid-week and on workdays, with Cluster 1 active around Thursday and Cluster 3 around Wednesday. The common time for activities is the afternoon for both clusters, with Cluster 1 typically around 14:00 to 16:00 and Cluster 3 around 12:00 to 14:00.

Clusters 4, 5, and 6 exhibit lower activity levels across most metrics. The counts of bus stops within 50 m at both the first- and last-mile are less than zero, indicating a lack of integration. However, the first- and last-mile distances for clusters 4, 5, and 6 were the same as in the summer. The day of usage for clusters 4, 5, and 6 was Thursday, and the time was in the early afternoon, between 14:00 and 16:00 for clusters 4 and 5 and 12:00 to 14:00 for cluster 6.

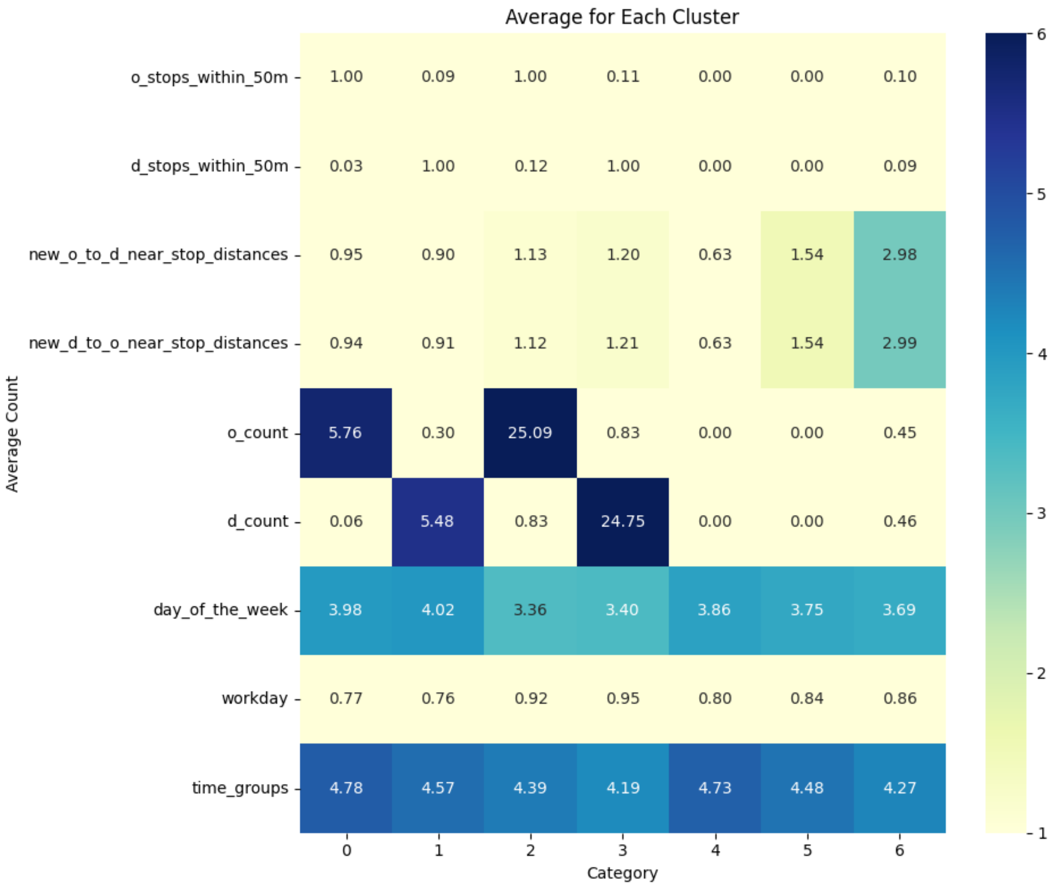


Figure 4.7: Cluster Analysis Heatmap for Winter

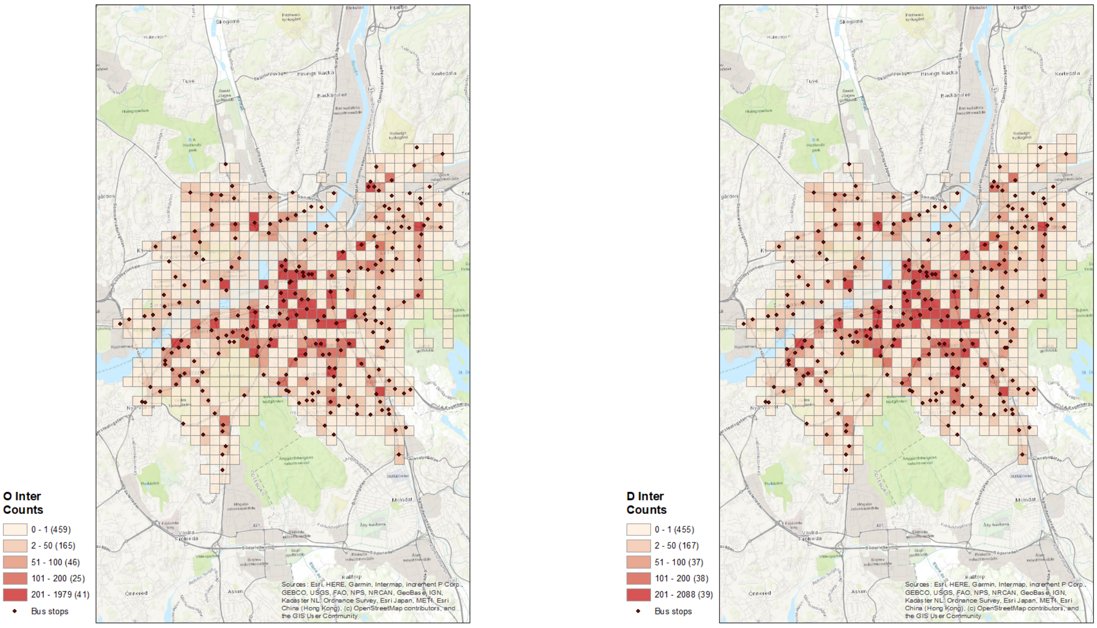
4.4 Seasonal Geo-spatial Integration Analysis

The geo-spatial maps show the spatial distribution of e-scooter trips in Gothenburg over the summer and winter seasons, with colour intensity representing trip counts within each grid cell. The entire grid does not represent all of Gothenburg, but rather only the Geo-fence area of Gothenburg as of 2022. The maps illustrate the raw counts and percentages of integrated e-scooter trips and categorise the data into five distinct ranges.

With that, we elaborate on the total e-scooter trips for summer, which consists of the number of trips in each grid cell, to help understand the results. Most cells, 443 out of 736 or 60.2% of cells, display very low e-scooter trip counts in the range of 0-1. A noticeably smaller number of cells, 69 or 9.4% of cells in total, showed very high counts in the range of 201–4067. This would mean that real intense e-scooter uses are in very few places and very minute in several others. Similarly, for trips in the mid-range categories, the distribution is very different. 2 to 50 trips in 129 cells, from 51 to 100 trips in 51 cells, and in the last category, from 101 to 200 trips in 44 cells, very much gives the idea of the variation in e-scooter trip count across Gothenburg.

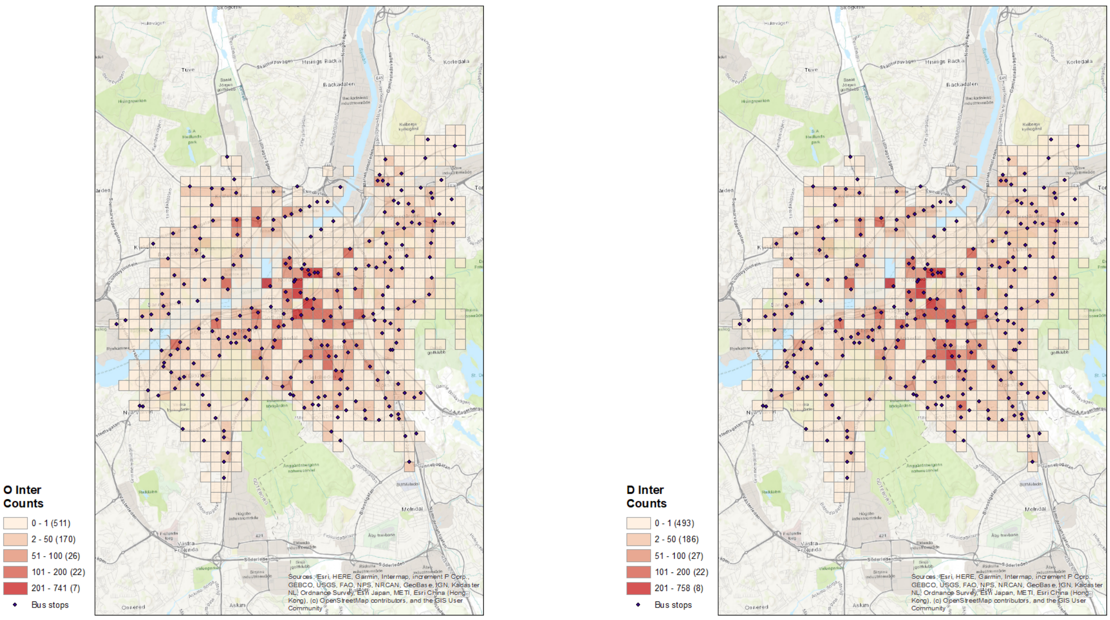
Analysing the integration rate, a majority of the cells, 596 out of 736, or 81% of cells, have a low relative concentration of e-scooter trips, within 0% to 20%. The very low number of cells, 4 or 0.5% of cells in total, experience anything from 81% up to as high as 100% relative concentration. This would mean that the low utilisation is widespread in the city and that, in total, many locations experience very little use of e-scooter integration in Gothenburg.

Figures 4.12 and 4.13 show that there were a lot of trips made in the city centre. However, when the frequency was compared to the chance of an integrated e-scooter trip happening, it dropped by a huge amount. For more information, look at Figure 4.8 and 4.9. They both show a balanced integration in both seasons at the first- and last-mile, which is similar to what we saw in Figure 4.4. Visualising both trips as combined total trips, we did notice that the highest count of trips per cell occurred relatively near the centre of the city at stops such as Central Station Drottningtorget, Stenpiren, Nordstan, Brunnsparken, kaptensgatan, Järntorget, Linneplatsen, and Chalmers. The moderate-count trips occurred at stops such as Blåsutgatan, Vagnhallen Majorna, Klippan, and Djurgårdskolan.



(a) First-mile trips **(b)** Last-mile trips

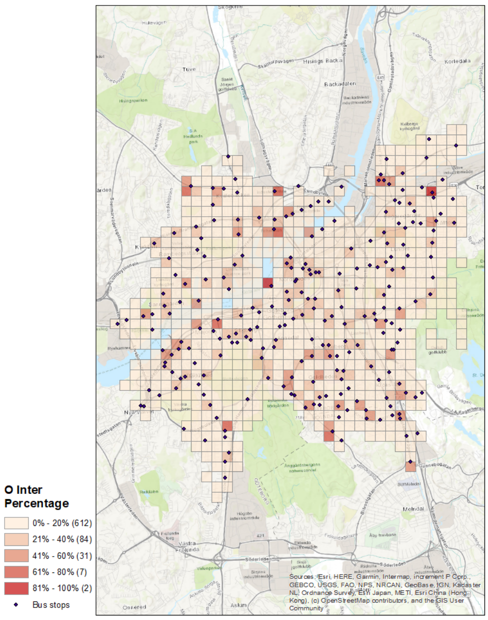
Figure 4.8: Geo-spatial map of Summer's Count of Integrated Trips



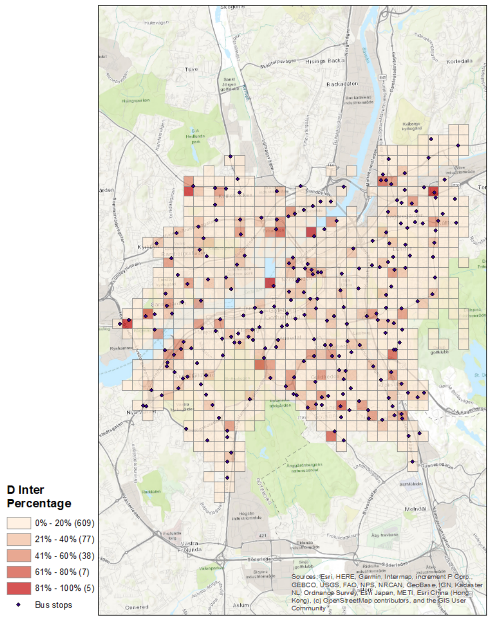
(a) First-mile trips **(b)** Last-mile trips

Figure 4.9: Geo-spatial map of Winter's Count of Integrated Trips

The Figure (Fig. 4.10) shows the integration rate in relation to the possible highest interactions within each grid cell at the first and last mile. From that, we see that the trips with the highest percentages were few and widely dispersed across the city, with no specific focal point but were mostly found on the edge of the geo-fence or city's outskirts, except for one location in the epicentre of the city. The highest percentages of integrated trips were found at Stenpiren, Kungssten, SKF R-porten, and Synhållsgatan. The higher ranges were at Bjurslätts Torg, Dalgångsgatan, Krokslätts Fabriker, Kvibergsskolan, and Kaptensgatan. Observing that except for Stenpiren in the central part, the rest were in the peripheral part of the geo-fence. For the total chance of the trip happening, we saw from Figure 4.13 that they happened in the same places between the first- and last-mile stops. Although the values in summer were much higher than that of winter, they exhibited a pattern of occurring at similar locations, which is evident from comparing the seasons in Figure 4.13. Likewise, there were similar first- and last-mile integration patterns between summer and winter, as shown in Figure 4.10 and 4.11.

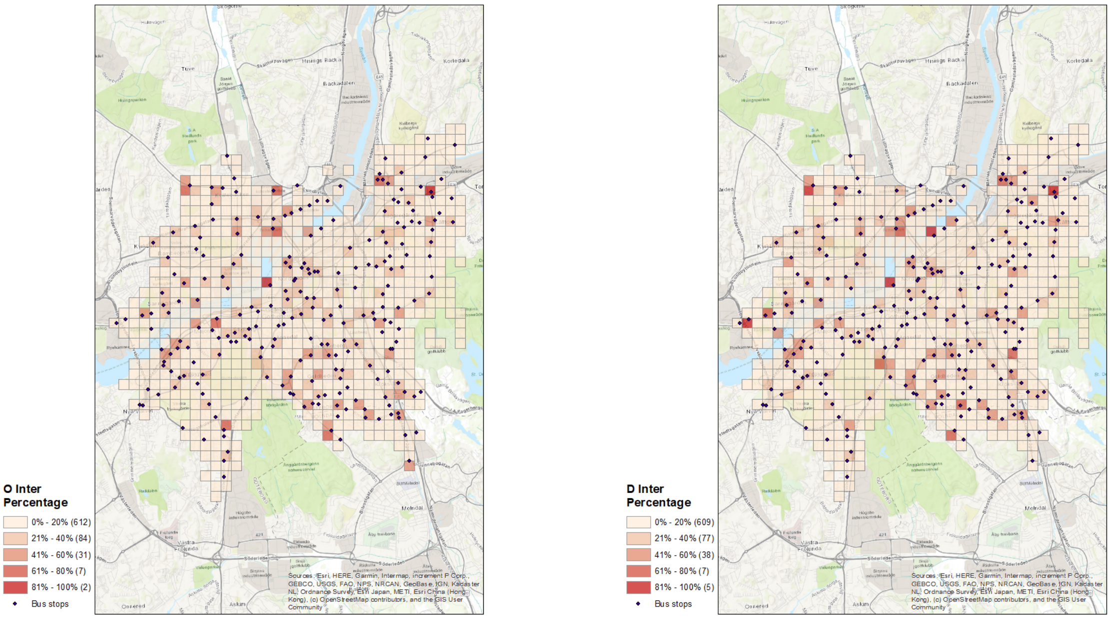


(a) First-mile trips



(b) Last-mile trips

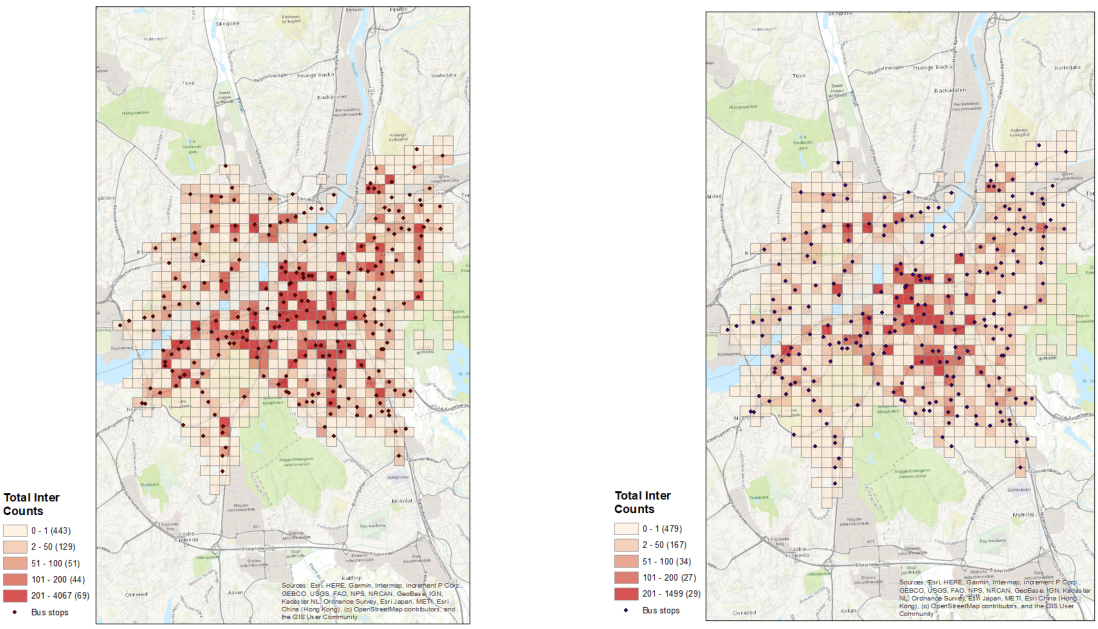
Figure 4.10: Geo-spatial map of Summer's Trip Integration Rate



(a) First-mile trips

(b) Last-mile trips

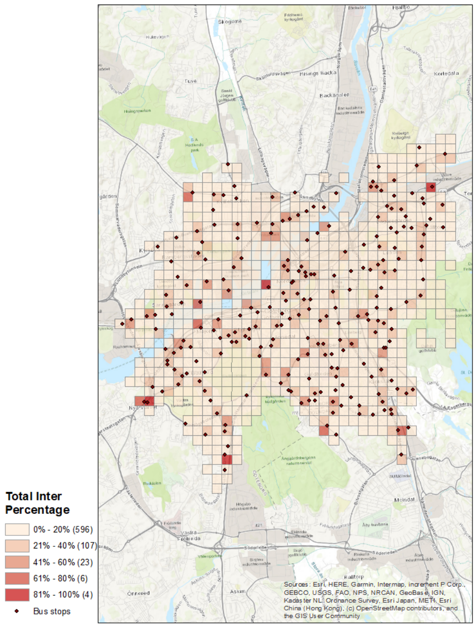
Figure 4.11: Geo-spatial map of Winter's Trip Integration Rate



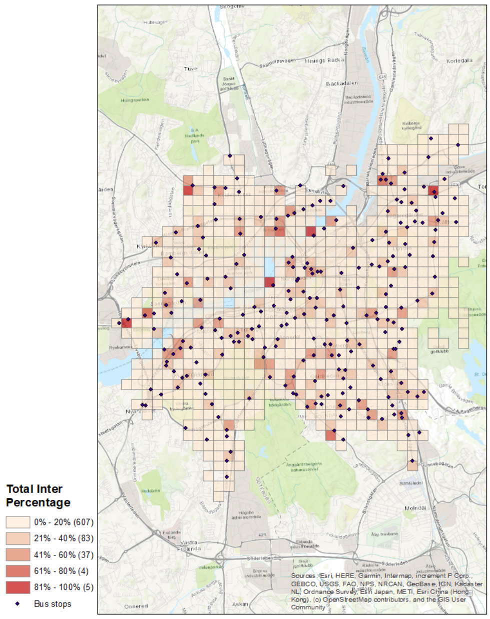
(a) Summer trips

(b) Winter trips

Figure 4.12: Geo-spatial map of Total Count of Integrated Trips



(a) Summer trips



(b) Winter trips

Figure 4.13: Geo-Spatial map of Total Trip Integration Rate

4.5 POI Results

The most important things we learned from looking at e-scooter trips in five groups are shown in Figure 4.15. These include the number of trips that started and ended at different points of interest (POIs) and how they connected to the bus system. Observations were that the highs and lows observed in the summer were the same as in the winter but in different quantities. The observations are quantified as presented in Figure 4.14 for summer and winter in Figure 4.15.

First, we look into which clusters to focus on in the POI results report. We note from the previous Figures 4.6 and 4.7 that less than zero buses are arriving at the e-scooter origin in clusters 1 and 3, and the destination reflects clusters 0 and 2. For this, we ignore these reflective conditions in the POI since there are no integration conditions. We also note the similar dominance patterns as in Figure 4.6 and Figure 4.7, where for the origin trips, cluster 2 was dominant over cluster 0 and at the destination, cluster 3 dominated over cluster 1.

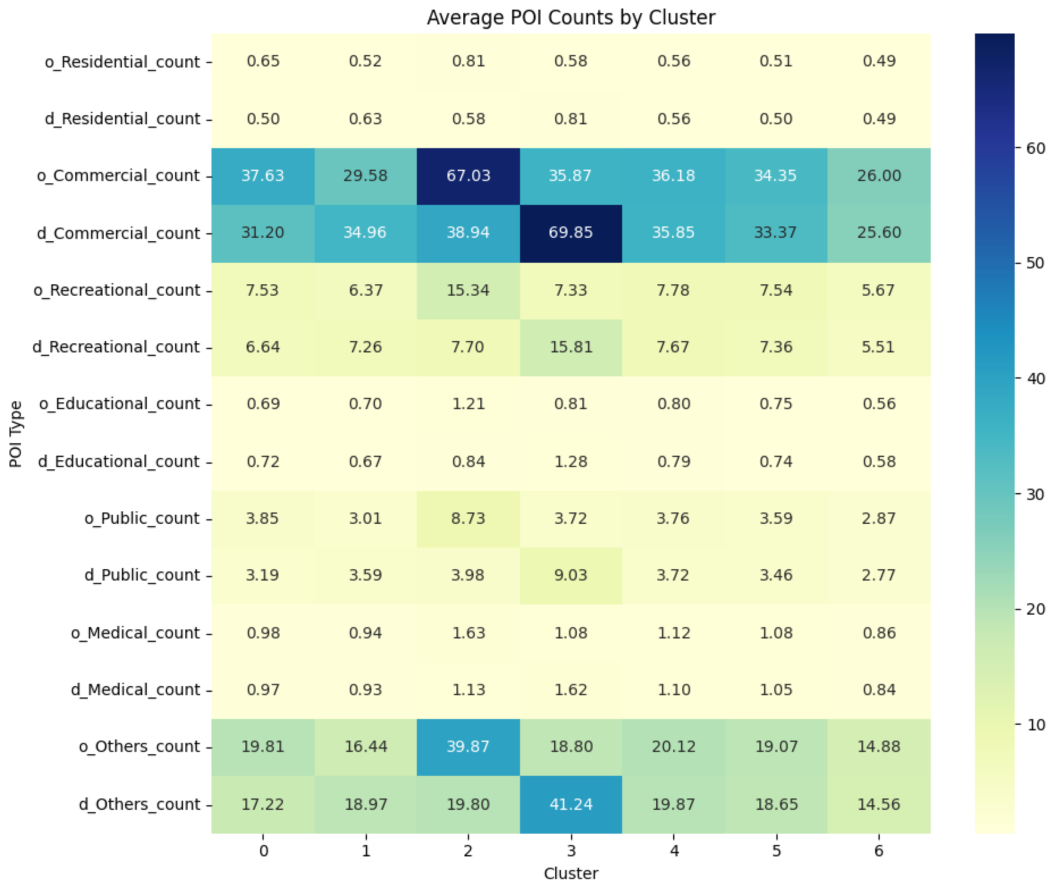


Figure 4.14: Heatmap of POI for Summer

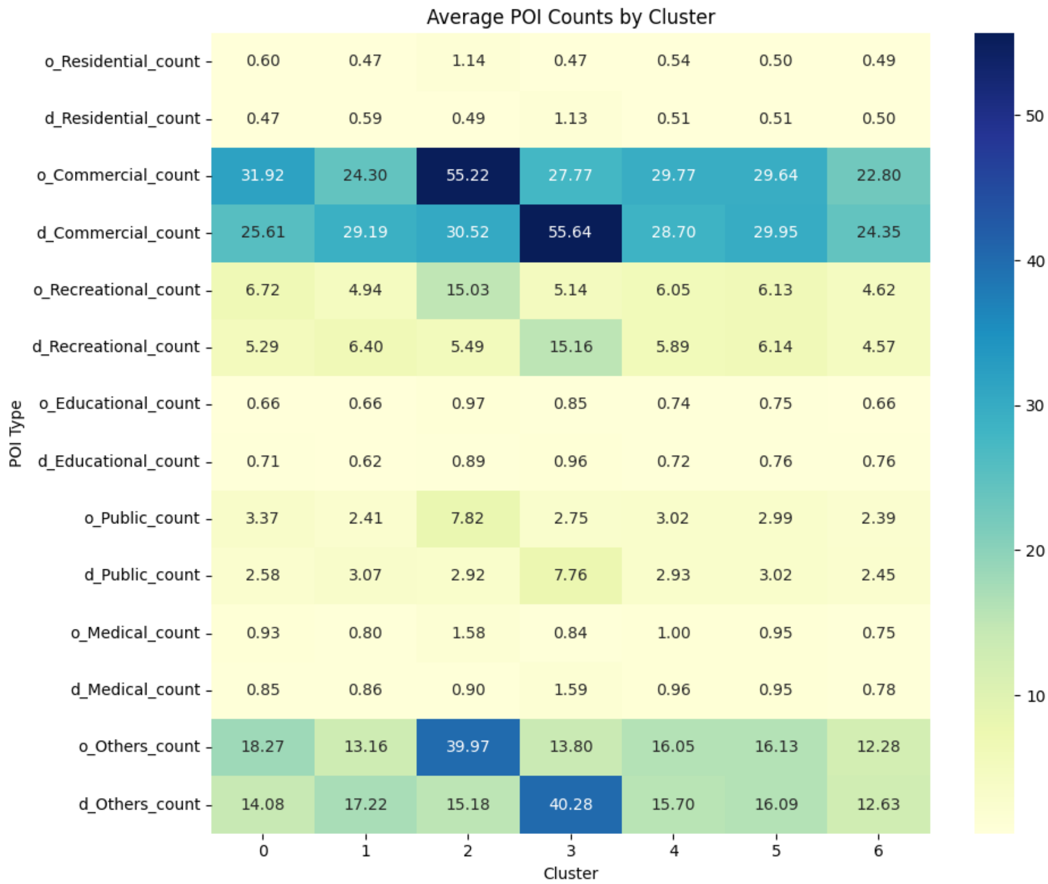


Figure 4.15: Heatmap of POI for Winter

Observe that the most dominant POI groups at both origin and destination are commercial, others, recreational, and public, in order of ranking, with commercial being the most dominant and public being the least, respectively. When comparing cluster 0 and cluster 2, we notice multiple regions with significant similarity in being dominant at the origin point. Clusters 1 and 3 also exhibit dominance at their destination points. As mentioned earlier, the trends match those of Figure 4.6 and Figure 4.7, which exhibited similar dominance at their o and d counts.

5

Discussion

5.1 Access/Egress and Distance analysis

The 2D histogram in Figure 4.1 suggests that trip frequency declines noticeably as the distance from or to bus stations increases beyond the initial dense region, suggesting that the majority of riders tend to have access or egress distances, though likely to be very short distances. It is interesting to observe the majority of the trips occur at a distance of less than 500 m. In an interesting twist, the standard distance between bus stops is about 500 m (El-Geneidy et al., 2014; Jin et al., 2019) as from Section 2.6, which is slightly less than our observed 500 m radius.

The range between 50 m and 100 m depicts a high population of trips as it falls within the area of highest trip density in heightened yellow (refer to Figure 4.1). The high frequency of counts within this range suggests that it is a favourable distance for walking for a significant number of users.
The sparse regions occur when the access or egress distance exceeds 1 km. Considering that the approximate average distance and time of e-scooter trips in Gothenburg are 1.8 km and 7 minutes, respectively (Peci et al., 2022). It suggests that distances beyond 1 km are not very indicative of an integrated trip, as they can be done by foot and will take very much less time to cover with an e-scooter. It is also worth noting that the typical distance a person is willing to walk to a destination is on average 1.25 km (Manaugh & El-Geneidy, 2013). Refer to Section 2.4. This conforms with the idea that e-scooters are used for distances that are slightly longer than what people would prefer to walk but still relatively short (Kapuku et al., 2021; Wang & Shen, 2022). Please refer to Section 2.1.

With a higher probability of an e-scooter being found within 50 m of a stop, there is a 20% chance of integration occurring. As observed at clusters 4, 5, and 6, where there were zero counts of buses, the chances of integration were zero. Instead, we observed an 80% rate of non-integrated trips occurring. This shows the impact of e-scooter availability proximate to a bus stop having a level of influence on its possibility of integration.

The first- and last-mile distances were observed to be used for short trips, with an average of 1.13 km for summer and 1.05 km for winter obtained from clusters 0, 1, 2, and 3. Although the integrated trips are generally observed to be used for short trips, it is interesting to note the slight decline in travel distance for winter. For the non-integrated trips, we observed a scattered distance from 0.63 km to 3.28 km, which is indicative of varied usage by users who tend to use them for varied purposes. However, in clusters 5 and 6 we observed a usage for much longer trips an indication that commuters within these clusters were substituting their entire trips and using e-scooters independently. Cluster 4 also contained very short trips which could be easily done by foot within a short time. From this, we can infer that trips meant to substitute public transport are relatively average to 1 km and not excessively short or long.

5.2 Seasons and Temporal Analysis

The winter daytime trips amounted to a total of 54,714, which is roughly one-third of the total number of trips made during the summer. This decrease highlights the influence of weather conditions on the utilisation of e-scooters. The seasonal fluctuation demonstrates a pronounced inclination towards e-scooter usage in the warmer months when unfavourable weather conditions like snow are diminished. Section 2.4 highlights the influence of severe weather conditions on the decrease in micromobility usage, as emphasised by (Abouelela et al., 2023; Bi et al., 2021) in Section 2.6. (Kong et al., 2020; Zuniga-Garcia et al., 2022) utilised clear weather days in their study, referring to them as representative commuting days. Although there are clear differences between the frequency of trips the patterns were not affected. Interestingly, when making a comparison between the percentage decline of the non-integrated and integrated trips, it indicates that non-integrated trips experience a larger percentage decline of about 70%) compared to integrated trips of about 62% between seasons. Although the difference may be little it indicates the willingness to integrate more during the winter.

For time-related aspects there we observed an evident decline in evening usage, which matches the results from our K-prototype analysis, where we found most of our trips to have the highest probability of occurring during the daytime and mostly in the early afternoon and on work days. Our findings contradict (Foissaud et al., 2022; Jiao & Bai, 2020; Noland, 2019)'s, refer to 2.4, who found the weekend instead as the periods when the demand for e-scooter services was at its highest and related that to leisure and touristic usage, it is important that their research was conducted in the USA, where their weekend and workday trends and culture do not match with Europe. It draws out the importance of considering geographical location when conducting behavioural analysis (Bozzi & Aguilera, 2021). The results however align perfectly with (Peci et al., 2022)'s study on Gothenburg refers to Section 2.7, which found usage to be higher in workdays and the afternoons as days and times for more frequent usage. This phenomenon we relate to e-scooters being restricted during night hours on weekends in Gothenburg (VOI Technology AB, n.d.), making them an undesired consideration for use on weekend or its conjoining evening.

5.3 Geo-Spatial with Cluster Analysis

From our results, we established that the relationships with the trip usage pattern between seasons are similar except for their counts (refer to Section 5.2). Similarly, when comparing usage patterns between seasons with integrated trips, we found both seasons to be the same. This is indicative that the perception of usage is the same and not affected by changes in the weather but the possibility of usage due to safety concerns of weather effects causes the actual usage to reduce. However, in the summer, the general level of activity and city density increases with summer events and festivals, adding to the already existing POIs and further boosting e-scooter usage.

With a higher probability of a bus arriving, there is a higher opportunity for integration to occur. This observation is made when comparing clusters 0 and 2 since they are both first-mile trips. Cluster 0 shows a low level of trip integration, while Cluster 2 shows a higher level.

Narrowing down to the geo-spatial maps, we realise that the integrated trips occurred sparsely in the centre of the city. The observed bus stops with high integrated trip counts included Central Station, Drottningtorget, Stenpiren, Nordstan, Brunnsparken, Kaptensgatan, Järntorget, Linneplatsen, and Chalmers. These and most stops were observed to be stops with either high multi-modal transport efficiency and/or densely populated locations. Specifically, they are bus stops associated with excellent transport connectivity with rail or trams and sometimes boat services, making these areas accessible for both regular commuters and tourists with the presence of commercial and tourist attractions such as shopping centres, restaurants, cultural sites, and business districts, all of which attract significant traffic. This shows that commuters prefer to ride to stops that have frequent bus arrivals or departures to easily connect to the most readily available bus, explaining why there are high counts at these stops. Section 2.3.2 made similar observations in the USA. Using the research from (Kong et al., 2020; Radzimski & Dzięcielski, 2021) and as references, we can see that more frequent public transit is often linked to more integration options with micro-mobility services. Evidently, from the cluster results, where there were high frequencies of bus arrivals or departures from a stop, there was a higher probability of integration. From a geo-spatial point of view.

Key results can be drawn while comparing the integrated trip total and integration rate. Certain areas have a high utilisation of e-scooters, with up to 4067 trips in some cells, while their integration rate is relatively low. We also observed that integration rates were scarce and scattered throughout the city. They did not converge at any specific focal point but were primarily located along the edge of the geo-fence and at one point in the centre of the city.

When referring to the integration rate, one stop, Stenpiren was found quite hot in the city and the rest were on the edges of the geo-fence in semi-suburban areas such as Kungssten, SKF R-porten, and Synhällsgatan. Indicative of a trend of usage in suburban locations with low levels of transport services, commuters tend to use e-scooters to complete a first- or last-mile trip. This finding supports that of (Martin & Shaheen, 2014) noting that in less dense areas or under-served areas, micro-mobility modes act more as a complement to public transport by bridging the first- and last-mile gaps, aiding commuters in reaching transit stations that are otherwise too distant to walk to, as mentioned earlier; also refer to 2.4.

5.4 POI with Cluster Analysis

From our POIs by elimination, we focused on clusters 0, 1, 2, and 3 since they were integrated trips. The results show the most dominant first- and last-mile trips per cluster from Figure 4.6 and Figure 4.7 also resulted with a dominant frequency count of POI, refer to Figure 4.14 and Figure 4.15. Enforcing the concept of public transit efficiency encourages trip integration, validating the claim by (Kong et al., 2020; Radzimski & Dzięcielski, 2021). From the geo-spatial maps (refer to Figure 4.12), we found high counts of integrated quite scattered in the city centre, which is populated with spots classified as commercial, other, and recreational areas (see Appendix A for breakdown) such as Nordstan, Brunnsparken, and Stenpiren. As mentioned in the results in Section 4.5, our most dominant POI ratings were commercial, others, and recreational, respectively, which are mostly located in the CBDs. This tallies with the findings by (Tokey et al., 2022), where they found a high count of trips originating and terminating in the CBDs.

Clusters 4, ,5 and 6 did not result in integrated trips, providing a reference point for comprehending the implications of non-integrated trips. Still comparing the POI counts with these clusters to the integrated, which seem to be relatively higher at points with bus stops, it infers that the integrated trips have a stronger desire to use the e-scooters with purpose.

6
Conclusion

The rise in popularity of e-scooters has raised concerns about safety, environmental impact, and costs. However, users generally view e-scooters positively, as they continuously recognise their potential as a quick and flexible sustainable transport option and advocate for their integration into urban mobility strategies. While the benefits of combining shared micro-mobility services with public transit are clear, more research is needed to fully understand the impact of integrating it. This study aimed to develop data-driven algorithms using real-world data to analyse how shared micro-mobility and public transit interact in Gothenburg while answering the key research questions.

1. "How does the mixed use of shared micro-mobility with Gothenburg's public transport system impact connectivity and user choices?"
2. "How do seasonal and temporal variations affect the coordination between bus arrivals and e-scooter departures in areas with different integration levels?"
3. "How does the coordination of bus and e-scooter services affect public transport use in areas with different levels of activity?"

6.1 Research Question 1

Considering the difficulty and inconclusive nature of deciding on suitable integration distances, it is safe to only deduce from our findings that the observed people may be willing to walk up to an access or egress of 1 km to integrate their e-scooter journeys, especially knowing that the comfortable walking distance for a person is about 1.25 km. However, we also know that the average distance between stops is about 400 m (El-Geneidy et al., 2014; Jin et al., 2019), which makes it difficult to conclude if 1 km or any distance is closer to reality. With an average travel distance of 1.13 km for the summer and 1.05 km for the winter, which we are aware is easily traversable on foot, we deduce that commuters integrate to get to their destination—a POI or a bus stop—faster.

It is worth noting, though, that at about 500 m there is a higher frequency of trip accessed or egressed for integration, making any range between 0 and 500 m viable enough to be considered as strong positive distances for integration occurrence. However, from our cluster findings, we note that if an e-scooter is within 50 m of a bus stop, the higher the probability of integration. Meaning that the availability and closeness of an e-scooter service to a bus stop will influence whether a commuter will choose to use it for integration or not. Improving the availability can encourage a shift of more riders from non-integrated and independent car use to combine their trips with public transport.

Gothenburg has 20% of complementary trips and 80% non-integrated trips since we resulted with an equally distributed usage pattern of 10% of first-mile and 10% of last-mile integration and a very high population of almost 80% of trips not integrating. From the balanced integration, we infer that riders with an intent of integration have an equal perception, whether for both first- or last-mile trips, which we found to be related to the efficiency of the bus transport and the density of the bus stop locations. This makes it not surprising to find that Stenpiren has both high counts of integration and integration rates since it is populated with POIs, multi-modal transport services, and the availability of e-scooters. We can also conclude this since most of our stops with high integration counts were at stops with a high density and multimodal transport efficiency at stops like Nordstan and Brunnsparken. It is possible that most of the riders intended to use rail services instead. This was observed by (Yan, Zhao, Han, Hentenryck, & Dillahunt, 2019) who noted integration attends to be skewed towards rail over buses.

Also, suburban areas with low transport service levels show a higher probability trips of using e-scooters to complete first- or last-mile trips considering the dominance of trips occurring at stops like Kungssten, SKF R-porten, and Synhällsgatan.

With 80% of non-integrated trips, it shows that most e-scooter users prefer to use them as a standalone mode of transportation, and mostly intend to use them for longer trips. We know that the unavailability is not the cause since these trips were within 50 m of a bus stop. However, it leaves room to rule out partial rule out bus stop availability and instead focus on other aspects such as efficiency.

The usage day of e-scooters within Gothenburg is mostly on Thursdays and some Wednesdays and time is mostly between 14:00 and 16:00 and sometimes 12:00 to 14:00. These findings clearly show less usage during the general peak times which leaves room to investigate more into and find ways to encourage usage during these hours.

6.2 Research Question 2

Seasonal variation has an impact on the number of trips with summer being the most dominant month over winter with about 68% total decline in e-scooter usage, due to safety and health concerns of riding an e-scooter in the winter and also because of an increased level of activity within the city in the summer season. However, from our findings we observe that the weather does not impact the intent or perception of e-scooter usage as the patterns remain the same between the first- and last-mile trips in both seasons but instead impacts the number of people using the e-scooter service. Interestingly, there is a larger decline in non-integrated in the winter as compared to the integrated trips.

Seemingly more riders desire to combine their trips with e-scooter trips in the winter, which is linked to reasons of being unable to ride continuously in the harsh weather. It will be beneficial to focus on improving the e-scooter availability at bus stops in the winter.

6.3 Research Question 3

The study identified that commuters who intend to integrate though driven by public efficiency still do so with a purpose. As discussed in Section 5.4, the comparison between integrated and non-integrated trips depicts this. Commuters have a strong preference to start or end their trips within 200 m of commercial, other, and recreational areas. This is a good find as businesses can coordinate with the e-scooter services providers to share targeted advertisements with commuters through the ride-hailing apps.

6.4 Future Research Recommendations

As it seems there are notable gaps with the integration of e-scooter with public transport in Gothenburg, but undoubtedly promises more benefits over disadvantages if optimised. Our findings are interesting and can direct future research in the right direction. The research recommendations are as follows:

- To conduct thorough research on each stop with a high count and low percentage or stop with a high value in both counts and percentages to understand the reasons for this trend.
- To conduct a study on the multi-modal stops, to understand the impact of other transport modes on integration and possibly understand which of them is the highest contributor. A case study location we recommend is Stenpiren as it houses not only rail and buses but also boats.
- To conduct further research into understanding the true impact of a higher decline in non-integrated trips in the winter and make recommendations to improve services in the season.

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A

Appendix A

A.1 Land Use POIs

Main categories	**Counts**	**merged Major fclass**
’Residential’	31	shelter’, ’chalet’
Landuse areas primarily used for residential purposes, such as single-family homes, apartments, and mobile homes.		
Commercial’	7120	hotel’, ’restaurant’, ’bicycle_shop’, ’fast_food’, ’cafe’, ’bar’, ’supermarket’, ’convenience’, ’department_store’, ’mall’, ’pub’, ’motel’, ’outdoor_shop’, ’bookshop’, ’clothes’, ’optician’, ’car_rental’, ’nightclub’, bakery’, ’laundry’, ’hairdresser’, ’beverages’, ’florist’, ’travel_agent’, ’biergarten’, ’furniture_shop’, ’stationery’, ’recycling_clothes’, ’bicycle_rental’, ’food_court’, ’beauty_shop’, ’doityourself’, ’video_shop’, sports_shop’, ’mobile_phone_shop’, ’shoe_shop’, ’jeweller’, ’toy_shop’, ’car_dealership’, ’gift_shop’, ’greengrocer’, ’butcher’, ’computer_shop’, ’vending_parking’, ’vending_machine’, ’vending_any’, ’car_wash’
Landuse areas that provide services and goods to consumers, such as stores, offices, and shopping centers.		
Recreational’	1493	garden_centre’, ’park’, ’theatre’, ’tourist_info’, ’cinema’, ’playground’, ’sports_centre’, ’attraction’, ’picnic_site’, ’zoo’, ’fountain’, ’viewpoint’, ’artwork’, kiosk’, ’archaeological’, ’ruins’, ’arts_centre’, ’drinking_water’, ’car_sharing’, ’theme_park’
Landuse areas that are used for leisure and recreation, such as parks, playgrounds, and sports fields.		

Educational'	237	'university', 'school', 'college', 'hostel', 'kindergarten'
Landuse areas that are used for educational purposes, such as schools and universities.		
Public'	808	community_centre', 'bank', 'atm', 'post_office', 'museum', 'monument', 'memorial', 'toilet', 'library', 'embassy', 'police', 'post_box', 'fire_station', 'courthouse'
Landuse areas that are owned by the government and open to public, like museums, courts, banks, library.		
Medical	258	hospital', 'clinic', 'dentist', 'nursing_home', 'pharmacy', 'doctors', 'chemist', 'veterinary'
Landuse areas that are used for healthcare purposes, such as hospitals and clinics.		
Others	4369	'recycling_glass', 'recycling', 'bench', 'windmill', 'lighthouse', 'comms_tower', 'camera_surveillance', 'waste_basket', tower', 'pitch', 'water_well', 'recycling_paper', 'general', 'newsagent', 'water_works', 'recycling_metal', 'water_tower'
Everything else that has nothing to do with e-scooter usage like recycle, water towers, towers, etc.		

Table A.1: POI parameters for land use in Sweden

A.2 Building Use POIs (Additional)

Main categories	**Counts**	**merged Major fclass**
'Residential'	16550	'bungalow', 'allotment_house', 'mixed', 'semidetached_house', 'detached', 'dormitory', 'hut', 'semi', 'house', 'residential', 'apartments', 'cabin', 'shelter'
Commercial'	1271	retail', 'supermarket', 'hotel', 'hangar', 'factory', 'store', 'industrial', 'office', 'nursery', 'commercial', 'restaurant', 'warehouse', 'cafe'

Recreational'	255	sports_hall', 'park', 'theatre', 'church', 'religious', 'kiosk', 'cathedral', 'social_facility', 'subway_station', 'cultural', 'palace', 'gazebo', 'sport', 'sports_centre', theatre', 'stadium', 'ruins', 'synagogue', 'chapel', 'pavilion', 'mosque', 'cinema', 'museum', 'conference_centre', 'concert_hall'
Educational'	615	'university', 'school', 'college', 'hostel', 'kindergarten', 'riding_school'
Public'	90	'train_station', 'civic', 'library', 'community_centre', 'bank', 'atm', 'post_office', 'government', 'public', 'railway_station', 'depot', 'observatory', 'embassy'
Medical	66	hospital', 'clinic'
Others	14204	'greenhouse', None, 'parking', 'gasometer', 'storage_tank', 'military', 'garage', 'tower', 'roof', 'transportation', terrace', 'riding_hall', 'toilets', 'fire_station', 'power_station', 'ship', 'service', 'garages', 'grandstand', 'windmill', 'container'
	33051	farm_auxiliary', 'shed', 'water_tower', 'farm', 'guardhouse', 'barn', 'stable', 'carport', 'power', 'boat', 'bunker', 'parking_garage', construction', 'bridge', 'garage_shed', 'chimney', 'houseboat', 'elevator', 'boathouse', 'chicken_coop', 'covered_footbridge'

Table A.2: POI parameters for Building use in Sweden

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