E-scooter driving behaviour analysis using BEAM data: a case study from Brisbane, Australia

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***Abstract*—As cities around the world adapt to evolving urban environments, sustainable mobility solutions such as electric scooters (e-scooters) have captured the attention of the public and policy makers. Despite their advantages, e-scooters pose several challenges related to safety and driving behaviour. This study uses data from BEAM Mobility, a Singaporean ride-share company, to explore the spatial and temporal dynamics of e-scooter usage in Brisbane, Australia. We highlight e-scooter usage trends and factors influencing urban density, offering insights and strategies helpful for optimising micro-mobility in urban areas. Data analysis reveals that since the mid-July 2021 launch, e-scooter usage has steadily grown, peaking on weekends between 4-5 pm. The average travel duration ranged from 7 to 20 minutes, with travel distances averaging 0.88 km. Overall, weekend and holiday usage accounted for 31% of total trips. Residential areas saw the most trips, while commercial areas exhibited the highest number of trips. Regular users made up 56% of riders, indicating a higher interest in micromobility modes among citizens.**

***Index Terms*—micro-mobility, e-scooters, analytics.**

I. Introduction

As urban environments continue to grow and evolve, new technological innovations follow to adapt to changing infrastructure. Among these innovations is the rapid rise of electronic scooters, or e-scooters, which have gained rising interest from the general public, researchers, and policymakers. Australia is one country that has started to adopt the use of e-scooters as an eco-friendly and handy alternative to conventional transportation methods. The use of ride-share companies has allowed easy access for the Australian public, with the first share-hire e-scooter being introduced in Brisbane in November 2018, launched by Lime Scooter [1]. Despite their popularity and many benefits, adopting and utilising e-scooters also brings new complexities in understanding and optimising their use and distribution within Australian urban landscapes. Brisbane, like many other cities around the world, has seen a dramatic increase in e-scooter usage and thus has been quick to legislate them faster than other states in Australia. However, there has been an increase in both personal and ride-sharing e-scooter usage in Australian cities. As recent studies suggest [2], the spatial and temporal dynamics of e-scooter use are influenced by various factors, making it a complex task to predict and manage e-scooter demand effectively. However, understanding these dynamics is crucial for urban planners, policymakers, and ride-share providers to ensure the safe and efficient use of micro-mobility systems. Statista (2023) has projected revenue in the e-scooter sharing segment to have a projected annual growth rate of 16.8% and have a projected market volume of US$81.78m by 2027 in Australia, showing the necessity to understand the dynamics in Australian urban environments.

This paper uses data from BEAM to draw insights into the spatial and temporal dynamics of e-scooter usage in Brisbane. The results will build upon studies that have already drawn insights into their respective cities across various countries, adding complementary characteristics tailored toward existing urban infrastructure. Our approach will present spatial, temporal, and density trends in e-scooter usage to better understand how ride-share e-scooters are utilised. The findings fo this study will benefit local stakeholders and offer valuable insights into future urban environment planning. More specifically, in this study, we aim to address the following three key research questions:

1) How does e-scooter usage fluctuate throughout the week, across different times of the day, and in different years in urban Australian cities?
2) What are the critical characteristics of e-scooter trips (e.g., trip duration/distance, time of day), and how do these characteristics correlate?
3) How do departures, arrivals, and journey densities differ across various mesh blocks, and what patterns can be observed?

The paper is structured as follows: Section II provides an overview of relevant literature. Section III details the case study. Section IV outlines the methodology and analysis techniques utilised in this paper. Section V presents the results of our analysis. Finally, Section VI concludes the paper with a discussion and future research directions.

II. Related works

The expansion of e-scooter sharing systems has led researchers to agree on their potential to reduce congestion, emissions, and reliance on personal vehicles in metropolitan areas [3]. Recent studies [4] have shown that e-scooters can provide short automobile trips, promoting a shift towards more eco-friendly transportation methods. For instance, Gebhardt et al. [3] discovered that e-scooters could replace up to 34% of car journeys in Germany, showing their potential to contribute to green energy transportation systems. Moreover, e-scooters have been found to supplement existing public transport systems, offering a last-mile solution for commuters [5]. In [6], authors showed that e-scooters can bridge the gap between public transit stops and final destinations, enhancing accessibility and encouraging multi-modal transportation.

Despite the general agreement on e-scooters' advantages, differing research outcomes have been noted, particularly regarding their spatial distribution and usage habits. In [7], [8], they found a close relationship between e-scooter usage patterns and urban land use, with increased usage in commercial zones and near public transit stops. Contrasting this, in [9], they indicated that the built environment and socio-economic factors, such as population density, income levels, and bike lane availability, were key determinants of e-scooter trip patterns. Similarly, in [10], they noted distinct spatio-temporal differences between e-scooter and bike-share utilization in Washington, D.C., suggesting that factors impacting e-scooter density may differ among urban contexts. For example, e-scooter usage was more prevalent during weekends and evenings, while bike-sharing was more common during weekdays and regular commuting hours. Existing research has provided valuable insights into e-scooter mobility, but research gaps still exist. One major gap is understanding how urban e-scooter density can be precisely determined and identifying the factors that affect e-scooter density in different urban settings. To address this, we build on findings from studies like [4], [7], [9], [10], combined with our analysis of the data collected from the Singaporean e-scooter company BEAM (described in Section III), to pinpoint common themes and contrasting results.

Thus, this study aims to develop a deeper understanding of the complex factors influencing e-scooter distribution and utilisation patterns across various urban landscapes. It will explore the relationships between e-scooter density and factors such as land use, the built environment, and socio-economic features. The findings of this study will help identify the elements that affect e-scooter density, allowing researchers and decision-makers to develop targeted strategies to enhance e-scooter networks, promote eco-friendly urban transportation, and mitigate the negative impacts of poor planning and management. Furthermore, this study will lay the groundwork for ongoing exploration of e-scooter mobility within Australia, addressing current knowledge gaps and enhancing the overall understanding of e-scooter dynamics in urban environments.

III. Case Study

This section details some background about BEAM, the data provided and its breakdown of the data whilst highlighting the selection of data used.

A. BEAM Mobility Overview

BEAM Mobility, established in 2018, is a micro-mobility company headquartered in Singapore with a mission to turn little drives into better rides and make cities flow better for everyone. As a leading player in the Asia-Pacific micro-mobility industry, BEAM has made strides towards creating environmentally-friendly transportation alternatives catering to short urban trips. Their primary offering, electric scooters (e-scooters), is a viable option for last-mile commuting in an area often underserved by traditional public transit systems.

In this study, the data provided by BEAM, from April 2021 to February 2023 forms the backbone of our exploration into e-scooter utilisation in urban Australia. The collected data spotlights the spatial and temporal trends of this emerging mode of transport. The following subsection explains the characteristics of the gathered data.

B. Data Overview

For the city of Brisbane, the BEAM e-scooter trip data presents a detailed account of micro-mobility interactions within the urban spaces of the Brisbane CBD, Logan City, and their associated regions from April 2021 to February 2023. This data set is comprised of the following attributes:

- **city_id:** Represents an internal integer identifier by BEAM, primarily signifying Brisbane.
- **created_at:** Provides the start of each e-scooter trip, dated and timestamped in the UTC format.
- **updated_at:** Provides the end of each e-scooter trip, dated and timestamped in the UTC format.
- **id:** Represents the unique identifier of the e-scooter utilised for the trip.
- **user_id:** Represents the unique identifier of the individual user for each trip. Used to distinguish regular riders from casual riders.
- **start:** Provides a geographical coordinate presented as 'POINT(x y)', where 'x' and 'y' signify the longitude and latitude, respectively. This data was assumed to mark the start of each trip.
- **end:** Provides the geographical coordinates presented similarly as 'POINT(x y)' assumed to be the location for the end of a trip.

IV. Methodology

This section outlines the methods undertaken to collect, process, and analyse the data provided by BEAM. The methodology is divided into several components: Data Processing, Descriptive Analysis, Temporal Analysis, Spatial Analysis and Correlation Analysis.

A. Data Processing

The initial step in this study was to prepare and cleanse the raw data for subsequent analyses. This process involved dealing with missing or erroneous data (by either suppression of missing fields or modification according to average duration times), standardising data formats, and parsing geographic coordinates for spatial analysis.

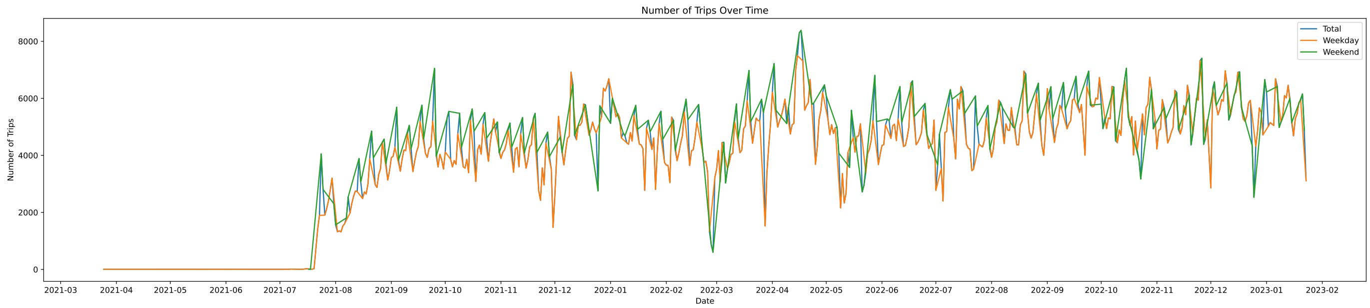


Fig. 1: Total daily trips recorded in Brisbane, including weekdays versus weekends, since the study has started.

B. Descriptive Analysis

The primary investigation of the data commenced with a descriptive analysis. This initial analysis aimed to identify central tendencies, dispersions, and the overall distribution of the dataset. The characteristics of e-scooter trips, including total counts, duration, averages and spatial distribution, were assessed to provide an introductory understanding and insight into the data.

C. Temporal Analysis

The study further investigated the temporal aspects of e-scooter usage. This involved examining usage patterns across hourly, daily, and annual time scales. The temporal analysis enabled the identification of peak usage times, trends, and fluctuations in e-scooter usage over different periods.

D. Spatial Analysis

The spatial analysis of the data was analysed in detail to gain insights into the geographical aspects of e-scooter usage. The Haversine or Straight Line method was used for Brisbane to get distances between the start and end point. This analysis examined e-scooter trip distribution across Brisbane. Density was also calculated in this analysis section, and the measure used was trips per km^2. There were two main methods used for spatial analysis and their results will be later presented in section V-C:

1) Choropleth Analysis Further into the spatial analysis, the data was examined at the mesh block level - the smallest geographical unit used by the Australian Bureau of Statistics. Choropleth maps were created to visualise the variations in e-scooter density and usage patterns across different mesh blocks. Density analysis took place at a mesh block level to better understand trends in e-scooter usage. Trip counts were logarithmically transformed in order to normalise the data distribution and make it easier to visualise areas that have vastly different trip densities. A binning strategy was also employed to categorise mesh blocks into different density brackets based on quantiles for ease of identification.

2) O-D Matrix Analysis The Origin-Destination (O-D) Matrix Analysis is constructed using trip initiation points and their respective destinations. By correlating and aggregating these points we can construct a comprehensive matrix which reveals the flow dynamics of urban areas. To see spatial differences between mornings and afternoons; two temporal windows were created where mornings were from time periods 6 AM to 2 PM and afternoons from 4 PM to 12 AM. A binning strategy for latitude and longitude coordinates was employed, where a granularity of 0.005 degrees was used to ensure the spatial resolution was at a manageable level.

In addition to the separate morning and afternoon matrices, we computed an imbalance matrix by subtracting the afternoon O-D matrix from the morning O-D matrix. This resultant matrix highlights the asymmetries in e-scooter trips between the two time periods, offering insights into directional flow tendencies and potential re-distribution requirements. This will be laters discussed in Fig. 9.

V. Results

A. Preliminary Data Insights

From July 2021 onward (see Fig. 1), we can see that e-scooter trips started to gain public traction (3 months later than the data recording time), but no seasonal pattern can be extrapolated. Very minimal insight can be gained except for the popularity of e-scooters being very spontaneous.

B. Temporal Data Insights

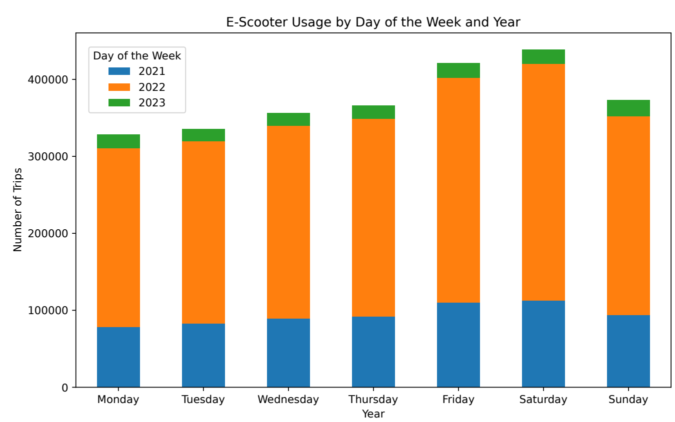
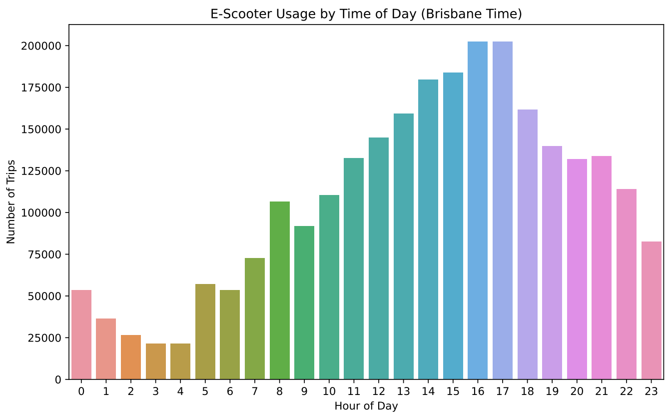
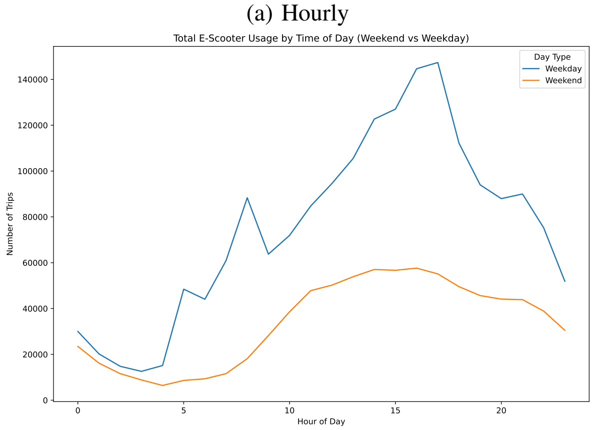


Fig. 2: Brisbane E-Scooter Usage by Day of Week and Year.

As depicted in Fig. 2, Brisbane exhibits strong e-scooter activity, with trip counts soaring above 300,000 for each day of the week. The end of the week shows a marked preference, with Fridays and Saturdays reaching peak usage, surpassing



(a) Hourly



(b) Hourly (Weekday vs Weekend)

Fig. 3: Brisbane E-Scooter usage by time of day.

the 400,000-trip mark, indicating a strong inclination towards e-scooters for weekend outings and social engagements.

Furthermore, Fig. 3 a) shows a peak usage of e-scooters in Brisbane between 1-5 pm, which is more akin to leisurely use as opposed to a mode of transportation for locals. Moreover, it can be seen that the spike in total trips starting by that hour, with trips starting past 5 pm gradually decreasing; the same deduction can also be made from Fig. 3b. There is a small spike at 8 am which may showcase users using it as a means of transportation in the morning.

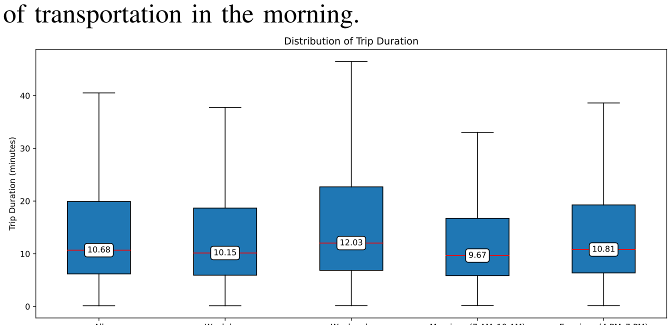


Fig. 4: Average Trip Duration (Brisbane)

In Fig. 4, we display a box plot of Brisbane's average e-scooter trip durations under different conditions. Overall, trips last about 10.68 minutes, with weekday trips slightly shorter at 10.15 minutes and weekend trips longer at 12.03 minutes, hinting at more leisurely weekend use. Morning trips (7-10 am) are the briefest, averaging 9.67 minutes, likely reflecting the morning rush, while evening trips (4-7 pm) stretch a bit longer to 10.81 minutes.

C. Spatial Data Insights

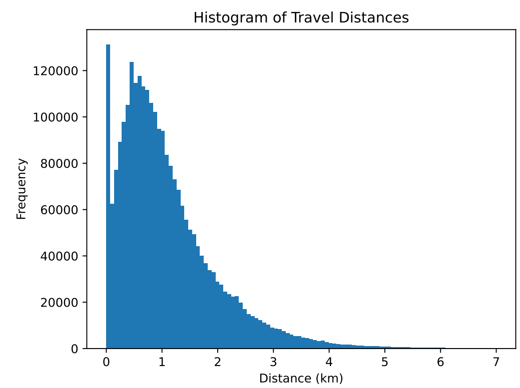


Fig. 5: Brisbane Travel Distance Histogram (Haversine Method)

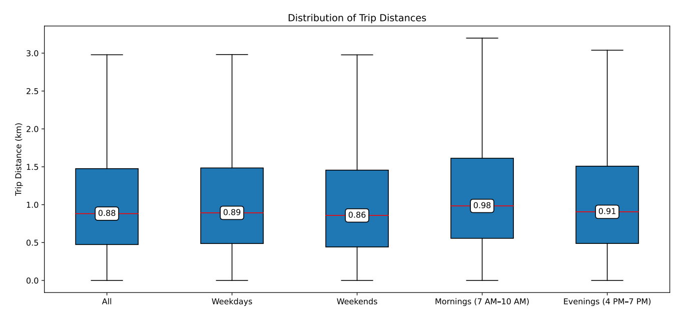
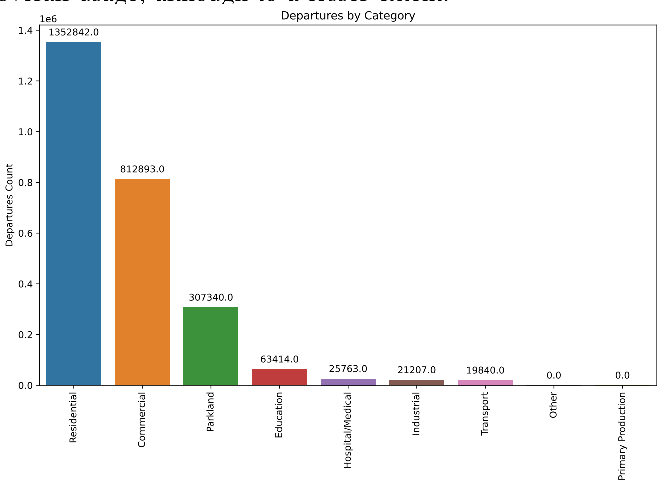


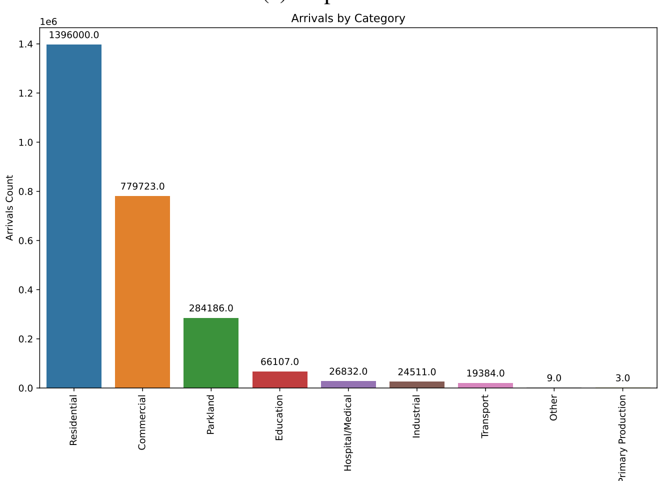
Fig. 6: Brisbane Average Trip Distance (Haversine Method)

The two plots (histogram and boxplot) in Fig. 5 and Fig. 6, which both utilise the Haversine formula, reveal insights into Brisbane's e-scooter trip distances. The histogram shows a sharp peak at 0 km, which may likely be due to trips that were initiated by users but did not proceed - a common scenario when users encounter difficulties kick-starting their journey due to some potential reasons: either payment errors or mobile app errors or simply impossibility to use the e-scooter due to non-familiarity with the device. The rest of the histogram settles at a common distance under 1 km, with frequency dwindling past this range and diminishing near 6 km. The boxplot indicates average distances are relatively consistent, with all trips at 0.88 km, slightly longer on weekdays (0.89 km) and shorter on weekends (0.86 km). Morning trips average 0.98 km, suggesting a longer commute, while evenings are at 0.91 km. However, these averages, derived from direct-line distances (Haversine Method), may under-represent actual travel due to route variations and different routing choices throughout the day.

1) Choropleth Insights In Fig. 7, we provide more insights into the Brisbane e-scooter journeys based on mesh blocks and their categories - both (a) departures and (b) arrivals. More specifically, we classify urban mesh blocks into several categories, with a focus on the top five: residential, commercial, parkland, education, and hospital/medical. The results reveal the highest e-scooter mobility happens in residential areas, with 1,352,842 departures and 1,396,000 arrivals. This prominence of residential areas suggests that e-scooters are frequently used for local commuting or leisure trips within neighbourhoods. Commercial areas come next with 812,893 departures and 779,723 arrivals, indicating substantial e-scooter activity related to work or shopping trips. Parkland, education, and hospital/medical areas also contribute to the overall usage, although to a lesser extent.



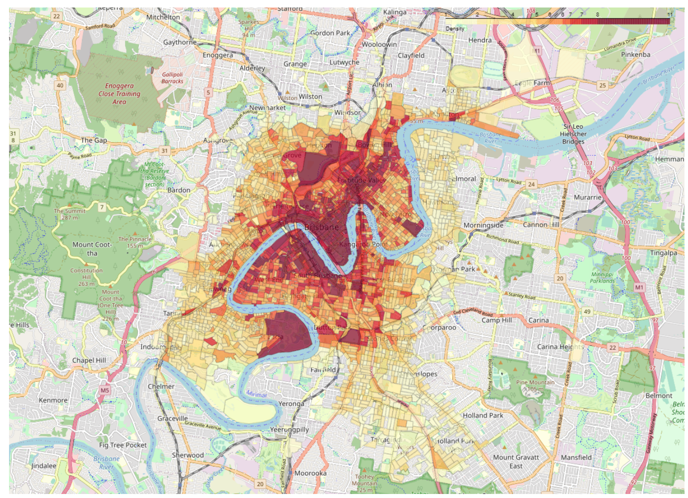
(a) Departures



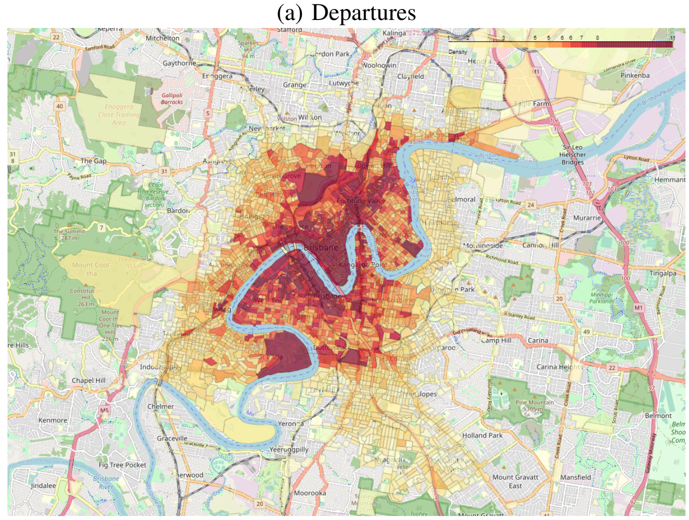
(b) Arrivals

Fig. 7: Brisbane Block Category Count.

Further, we look into visualisations of urban mesh blocks (areas) in the city of Brisbane, by using a logarithmic scale to produce better gradient and differentiation between mesh blocks. Fig. 8a and 8b illustrate mesh block choropleth maps for Brisbane's CBD separated by a) the departures (pick-up zone) versus b) the location of arrivals (drop-off zone). The colour gradation in these maps indicates the density of e-scooter usage, with darker red shades representing higher densities and yellow shades - lower densities. The visualizations reveal a consistent pattern across all areas, with departure locations notably concentrated in specific areas, illustrating high e-scooter usage. This can be observed most prominently within the Brisbane CBD, demonstrating that urban centres tend to be focal points for e-scooter departure. Conversely, the arrival locations presented in (b) parts of each figure are more dispersed in the outskirts of the city, extending to the surrounding suburbs. This observation suggests a broader spread of e-scooter usage as riders complete their journeys, implying that e-scooters are used to connect the city centre with peripheral areas. These visuals underscore the utility of e-scooters for facilitating mobility across a broader urban area, hinting at their potential to complement existing public transport networks by providing a means of transportation for the "last mile" of travel.



(a) Departures



(b) Arrivals

Fig. 8: Brisbane CBD Choropleths.

2) O-D Matrix Insights The Origin-Destination (O-D) matrices for the Brisbane area offer a visual representation of the overall travel behaviour, mapping out the flow of trips from various origins to their respective destinations. These matrices serve as a graphical interpretation of the city's e-scooter transportation dynamics, illustrating the interaction between the urban environment and the movements of its inhabitants.

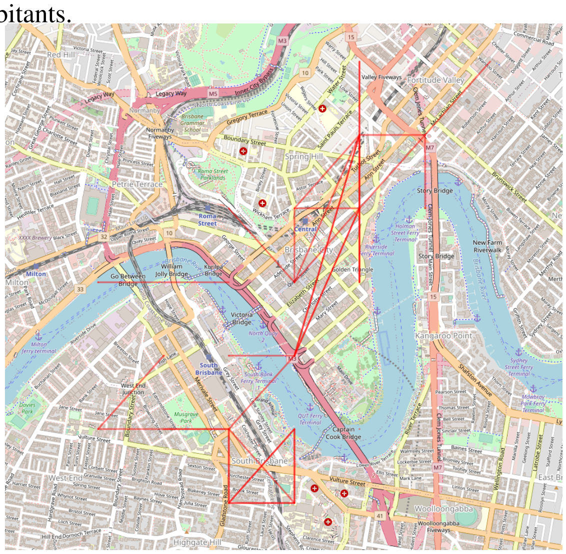


Fig. 9: Brisbane Imbalance O-D Matrix - Top 50

In Fig. 9, we present a visualisation of the top 50 trips of the imbalance O-D matrix for Brisbane (a line represents an imbalanced trip from an origin to a destination - for reading simplicity and due to lack of space we filtered the OD trips only to the top 50 but in reality there is a mesh of trips spreading in the city). As it can be observed, the highest imbalance and activity are localised around the heart of the Brisbane CBD and Brisbane River. This indicates high levels of usage and can be useful in updating infrastructure around the CBD.

D. Key Findings

This study analysed the patterns of e-scooter usage in an Australian city with the purpose of understanding the factors that influence urban mobility. Our analysis indicates that e-scooters are predominantly used for short distances, with the majority of trips falling within a range conducive to leisure activities. This finding is consistent with the observed spikes in usage during weekends and late afternoon hours, suggesting a recreational component to e-scooter utilization. However, the presence of trip distance spikes during typical commuting hours points to a dual-function of e-scooters, serving not only as a means of leisure but also as a viable option for commuters.

Interestingly, while the density of trips is higher in the aforementioned central zones, the data reveals that the departure and arrival location of most trips occur within residential areas in the city of Brisbane. This suggests that while e-scooters serve inner-city mobility needs, they are also an important transport mode for residents within suburban areas, possibly for connections to public transport networks or local amenities.

Despite the clear patterns observed, this study is not without limitations. The data does not account for multi-modal trips and lacks the qualitative insights that could explain the preferences for e-scooter usage over other forms of transport. Additionally, the influence of external factors such as weather, infrastructure, and economic conditions on e-scooter usage will need to be further analysed. Furthermore, despite its static nature for most of the day, the correlation between the time of day and trip distance shows distinctive spikes that may align with particular daily routines or activity patterns. The presence of these spikes highlights the significance of temporal factors in shaping e-scooter utilisation patterns. Combining these insights forms a comprehensive understanding of e-scooter usage, providing a solid foundation for future explorations.

VI. Conclusion and Future Work

E-scooters have emerged as a significant component of urban mobility in Brisbane, with usage patterns indicating a strong preference for short, flexible trips. The integration of e-scooters in the daily commute and their role in leisure activities underscore their versatility and potential to supplement public transportation. To capitalize on this potential, urban planners and policymakers should consider enhancing e-scooter infrastructure, ensuring safe, accessible, and connected networks for users. Investments in bike lanes, parking zones, and integrated ticketing systems could further embed e-scooters into the urban transport fabric, promoting sustainable mobility solutions. By building upon the groundwork laid in the results from this study, future research should deepen our knowledge of spatial-temporal dynamics, refine correlation analyses, and expand our understanding of user behaviour. More significant insights can be drawn by recognising these potential areas of future exploration.

Acknowledgment

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