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Analysing ride behaviours of shared e-scooter users – a case study of Liverpool

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Abstract

The shared e-scooter is a relatively new form of Micromobility service in urban transit. A better understanding of the use of the scheme will help operators and stakeholders promote this travel mode, contributing to a more sustainable, resilient, environmentally friendly and inclusive transportation system. The availability of high resolution sensor-based location data, when co-analysed with socio-demographic survey data allows insights on where, how, and by whom the service is used. This study focuses on analysing the usage pattern of a recently introduced shared e-scooter scheme in Liverpool, UK, combining survey data of users' sociodemographic attributes and their full trip records at a fine spatiotemporal granularity. Recency-Frequency (RF) segmentation is used to categorise user behaviour based on their frequency and recency of usage, and a Functional Signatures (FS) dataset is used to enrich contextual information on the origin and destination of e-scooter trips. Overall, this study provides insights into the behaviour of users of shared e-scooters and how the behaviours might vary in different user groups regarding sociodemographic characteristics. The developed analysis framework is also readily transferable to other cities.

Keywords: *Micromobility; sustainable transportation; e-scooter; location data; customer segmentation.*

1. Introduction

Shared e-scooters are a relatively new form of transport mode in the Micromobility family, they refer to electric scooters that are available for rent through a sharing scheme. Access to the scooters depends on whether the scheme is based on a docked or dockless system. For a dockless system, users can first find and unlock the e-scooter with a smartphone app, ride to the destination, and then leave the vehicle at the destination (sometimes with restrictions or geofencing) for the next user. The benefits of a dockless system (Yang et al., 2019) is that scooter availability is not limited to the fixed points of docking stations, therefore shared e-scooters are flexible to use. They are suitable for relatively short travel and solving the "first/last" mile problem – the distance between public transport station and destination (Yang et al., 2019; Hosseinzadeh et al., 2021).

The shared e-scooter scheme offers a convenient and relatively low-cost travel option, and it can bring various benefits to cities and their inhabitants, including reducing congestion, improving air quality and increasing accessibility to various services (Abduljabbar et al., 2021). Shared e-scooters have recently been introduced in several cities and towns in the UK, under government-approved trials (Speak et al., 2023).

Much research has used a qualitative approach or questionnaire survey (König et al., 2022; Speak et al., 2023) to understand the underlying driven factors or related sociodemographic characteristics to different opinions and usage (self-reported) of e-scooters. Studies that consider actual riding behaviours (as revealed through the high-resolution scooter location data), linked to sociodemographic characteristics are rare. This is despite the potential advantages of the insights generated, such as the choices made by user sub-segments, but is at least partly due to limited access to both data in the literature.

This study analysed the usage patterns of shared e-scooter users in Liverpool, a city in the northwest of England, UK. Users' sociodemographic information from a survey and their full trip records at a fine spatiotemporal granularity are obtained (with their permission) and investigated. This research demonstrates the value of integrating the two data types – a large scale digital database and more traditional user survey, and analyses riding behaviours. It provides evidence on how the behaviours might vary in different user groups (e.g. differences in car ownership).

2. Data and Method

This study focuses on a survey dataset of shared e-scooter users and corresponding journey profiles from a shared e-scooter operator (Voi) in the UK. This research focuses on a subset of records relating to the city of Liverpool, as a case study, though in a future paper we will present findings from a larger number of cities and users.

The survey data includes participants' varying sociodemographic attributes, covering age band, gender, ethnicity, self-reported basic health status, car ownership, household income, employment, occupation, educational attainment, and responses to several questions related to subjective wellbeing. As a part of the survey, participants are asked if they agree to share their trip records for research purposes. With the users' consent, this study obtained 89 participants' (in Liverpool) complete history of shared e-scooter usage (from their first-time use to October 27, 2021). The trip data include the following variables: User ID, trip origin coordinates, trip destination coordinates, trip start time, trip end time, travel distance (route distance) and ride speed.

Recency-Frequency (RF) segmentation is utilised to disaggregate users' behaviours from their complete trip profiles. RF analysis is a technique that has many implications in marketing (McCarty & Hastak, 2007; Beecham & Wood, 2014), and it can be used for segmenting customers based on two factors:

- Recency: how recently a customer has made a purchase or used a product
- Frequency: how often a customer make a purchase or use a product.

Both factors are considered to be good predictors of future engagement (usage or purchase) (McCarty & Hastak, 2007; Beecham & Wood, 2014). To perform RF analysis, customers are ranked for the two factors on a *n*-level scale (e.g. n= 3, 4, 5 …). The scores are further concatenated to give at most n*n segments (Beecham & Wood, 2014).

RF segmentation has rarely (if any, to authors' knowledge) been used for analysing e-scooter data. In the e-scooter dataset, "Recency" scores were determined by the most recent e-scooter trip, and assigning discrete scores with three equal recency bins, from most (score 3) to least (score 1) recent (Beecham & Wood, 2014). "Frequency" scores are calculated in two steps: (1) Calculate the first and last trip in each user's trip profiles, getting the length of the "active" period. (2) the "Frequency" score can be obtained by dividing the total number of trips by the length of the "active" period. People with the highest scores in both Recency and Frequency (3-3) are the most "heavy" and "loyal" users - they ride shared e-scooter frequently, with very recent trips. Those classified as the lowest RF group (1-1) may use e-scooter after registering, but have made relatively few trips afterwards (Beecham & Wood, 2014).

The Functional Signatures (FS) dataset in Liverpool (Samardzhiev et al., 2022) was also applied to enrich contextual information on the origin and destination of e-scooter trips. "*The FS are contiguous areas of a similar urban function with fine spatial granularity. Rich datasets, including census, remote sensing, and point of interest data, were used as inputs for grouping based on a clustering approach* (Samardzhiev et al., 2022)". FS provides several dimensions (or qualifiers) to describe the function of each small area in the UK. In this study, due to a relatively limited sample size and geofenced service area, certain types of FS are combined. While retaining its qualifiers in terms of service and use (e.g. residential, employment), the density dimension is reduced; for example, “Residential – Low density” is recoded as “Residential”. The recoding strategies are shown in Table 1. More details of each type of FS are available in the work of Samardzhiev et al. (2022). FS-related origin-destination (O-D) pairs are discussed in section 3.2. Not all FS types (Samardzhiev et al., 2022) exist in the study area; for example, there is no “Countryside” FS in the shared e-scooter service area in Liverpool.

Each e-scooter trip’s origin and destination are intersected with FS boundaries; hence, both origin and destination have corresponding recoded FS type information. With the enriched contextual information, it is possible to deepen the understanding of the trip’s purpose. For example, a trip from industrial FS to residential FS may have the purpose of going home.

Table 1. Recoded Functional Signatures types in the case study area.

Family	FS type	Recoded FS type
Industrial	Industrial – Construction site	Industrial
	Industrial - Commercial	Industrial
	Industrial - Manufacturing	Industrial
Residential	Residential – Low density – Well-served	Residential – Well-served
	Residential – Well-served	Residential – Well-served
	Residential - Mixed-use	Residential - Mixed-use
	Residential – Low density	Residential
	Residential	Residential
	Residential Greenspace	Residential Greenspace
Service	Service - Mixed – Low density	Service - Mixed
	Services - Leisure and Cultural	Services - Leisure and Cultural
	Services - Transport and distribution hubs	Services - Transport and distribution hubs
Urban	Urban -Mixed-use – High density	Urban – Mixed use
	Urban - High employment, culture, connectivity	Urban - High employment, culture, connectivity
	Urban - High employment, amenities	Urban - High employment, amenities

3. Findings

3.1. Spatial and temporal pattern

Spatial and temporal patterns of e-scooter trips are explored in this study. The density histogram of trip distance is illustrated in Figure 1, and the most popular travel distance is between 1-1.5 km, showcasing the utility of e-scooters for making relatively short-distance journeys. Shared e-scooters can also be used for longer distance journeys, such as those exceeding 5 km. Figure 2 shows the average trip count (rescaled to [0,1], calculated by the trip starting time) across the 24 hours during the day. 1 indicates the highest hourly trip volume, and 0 indicates no trips were in this hourly interval. During a weekday, there is an evident peak in the afternoon (from 16:00-18:00), also small local peaks around 6:00 and 8:00 in the morning. At the weekend, the curve is more flattened across the day, reaching a relatively high platform from 11:00 to 17:00.

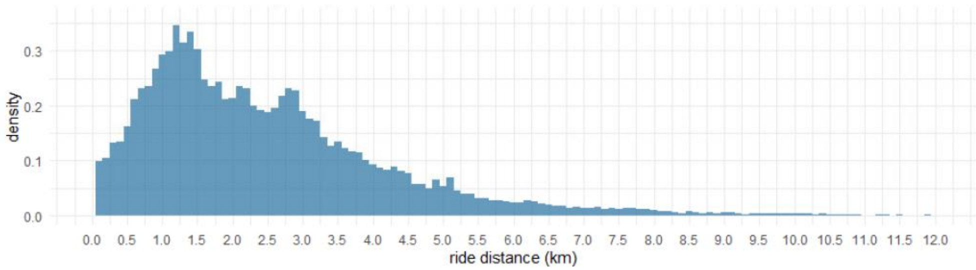

Figure 1. Density plot of ride distance (km).

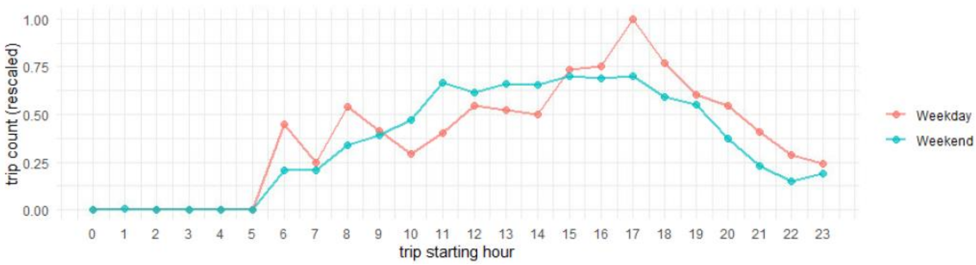

Figure 2. E-scooter trip count by hour (rescaled).

3.2. Result of Recency-Frequency Analysis

RF analysis helps segment e-scooter users into different groups depending on their scores in Recency and Frequency. This study further combined sociodemographic variables with RF scores, and the results are shown in figure 3, using car ownership as an example.

Users in the lowest FS group (1-1, Figure 3, bottom-left) have a relatively low share of “Do not have” a car. With increasing FS scores (2-2, Figure 3, middle-middle), the proportion of non-car owners increased and reached an even share in the highest FS score (3-3, Figure 3, top right) group. The result implies that e-scooter benefits personal mobility to people who do not have a car, and the service may be considered more helpful and appealing for this group – leading to "loyalty" and favour of using the service. This also aligns with the findings in the literature that shared e-scooter and the wider Micromobility services may be particularly appealing to people who live and travel in urban areas with limited parking options, or owning a car may increase the burden (Bieliński, & Ważna 2020).

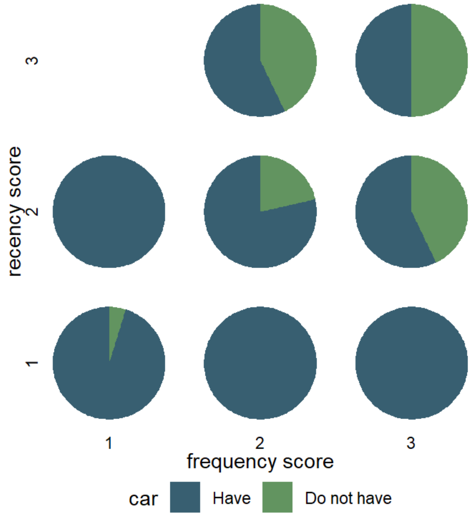

Figure 3. Recency-Frenquency score and users' distribution in car ownership.

3.3. Trip Origin and destination pair

The FS types of e-scooter trip origin and destination are identified, and Figure 4 shows the Sankey plot of O-D pairs of all trips. In total, all "Residential" FS family members have accounted for 49.92% of trip origins and 50.47% of trip destinations (Figure 4). The "Urban – High employment, culture, connectivity" also generated and attracted many travel flows, accounting for 27.50% and 29.16%, respectively (Figure 4). E-scooters are also used for "first/last-mile" trips, linking "Service – Transport and Distribution Hubs" and other FS areas, especially "Urban- High employment, culture, connectivity".

It is also possible to disaggregate the O-D FS types by differentiating sociodemographic attributes such as car ownership. The share of "Residential - Mixed use" as the trip origin is much lower for car owners than the group of not have a car (22.00% compared to 33.83%), and the major difference is contributed by "from Residential – Mixed use to Urban- High employment, culture, connectivity". This suggests that e-scooter provide a favourable alternative mode for non-car owners to travel from "Residential-Mixed" areas to "Urban-High employment, culture, connectivity" FS areas.

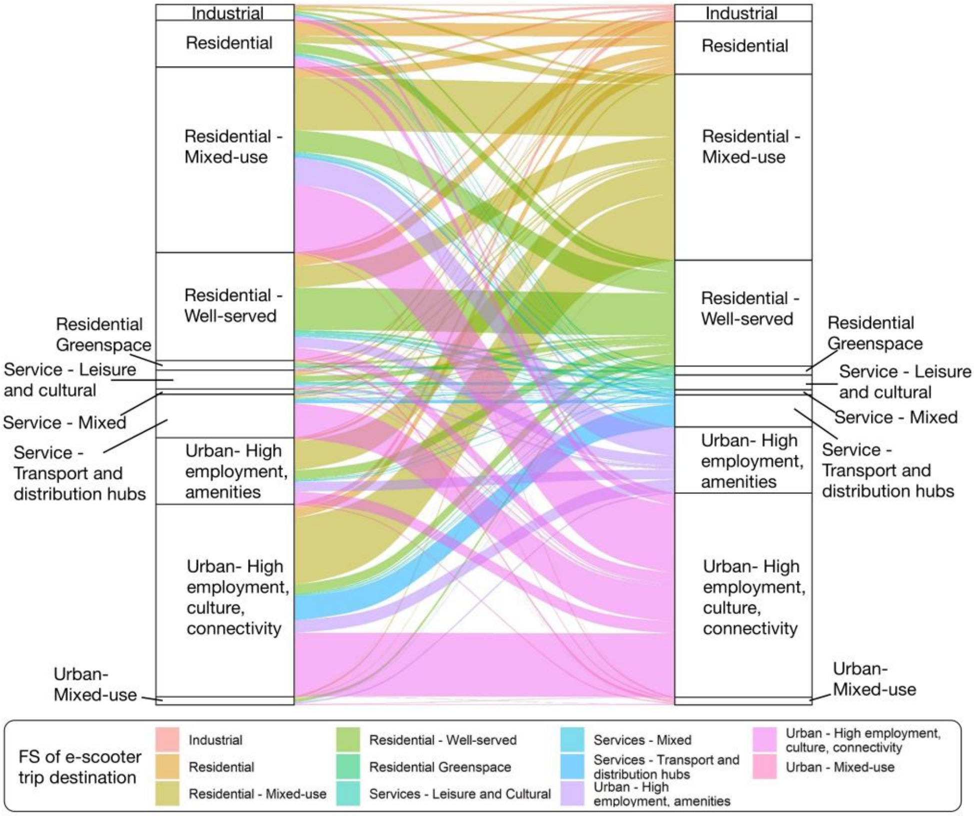

Figure 4. Sankey plot of e-scooter trip origin (left) and destination(right) FS types.

4. Conclusion

This study investigated e-scooter riding behaviours in Liverpool. Different spatiotemporal characteristics and usage patterns are identified and linked to personal sociodemographic characteristics. The findings suggest that e-scooters offer a convenient and flexible short-trip option, and the service is appealing to people who do not have cars. Furthermore, by linking user group segmentation with sociodemographic attributes such as age, gender, ethnicity, educational attainment, and employment, a more comprehensive insight into distinct user groups can be achieved.

This study benefits from rich information covering sociodemographic characteristics and users' full trip records. The trip records are sensor-based and at a fine spatiotemporal granularity, therefore is able to reflect user behaviours in detail, providing evidence on who, where, when, how and why the service is used. Such data at a larger scale also have the potential to reveal the dynamics and rhythm of urban flows in the last-mile. It is worth noting that this work includes a limited number of samples (participants) in the case study area, and the potential bias issue should not be ignored. The e-scooter travel flow and associated O-D FS types may be impacted by service provision; the availability of scooter and the geofencing of service area could all impact where trips start and end.

The analysis framework utilized in this study can provide a nuanced understanding of user characteristics, encompassing ride behaviors and sociodemographic attributes. This can help identify potential barriers and enable scheme operators and transport management authorities to strategically promote the usage of e-scooters and sustainable travel mode.

Future work might deepen the insights by utilising data at a larger scale (combining observations in other cities), possibly incorporating richer full trajectory data to understand the route choice of different users.

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