Heterogeneity of Shared Micromobility Utilization Throughout a Day: A Case Study for the City of Košice

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Abstract

This study examines spatiotemporal utilisation patterns of shared e-scooter users in Košice, Slovakia, analysing 403,683 trips recorded between 2021–2023 by Antik, a major micromobility operator. Using K-means clustering and density analysis, we identified three distinct spatial clusters corresponding to urban topology, with trips predominantly serving intra-district and district-to-centre functions (average distances 1,071–1,275 m). Temporal analysis revealed pronounced diurnal variation: early morning trips (3.93%) were longest (1,315 m), indicating supplementary first/last-mile functions during low public transit availability, while afternoon peaks (38.74%) concentrated in central districts. Critically, vehicle redistribution during night hours created dispersed morning availability, but progressive afternoon-evening concentration in central hubs and transit transfer points reduced peripheral access. These findings demonstrate that urban topology fundamentally shapes trip patterns, while operational rebalancing creates temporal inequity. The study provides empirical foundations for evidence-based fleet management strategies, public transit integration, and policy frameworks preventing regulatory crises observed in Paris and Prague.

Keywords: *micromobility, shared transportation systems, utilisation patterns, urban mobility*

Introduction

Shared electric scooters have transformed urban mobility across Europe since their introduction in major cities around 2018, offering a flexible, cost-effective solution for short-distance trips within densely populated areas (EIT Urban Mobility, 2021). From Paris to Copenhagen to eastern cities, these mostly dockless micromobility vehicles have become an addition to existing shared mobility systems implemented in modern urban transport, yet they simultaneously represent one of the most contested transport innovations of the past decade (EIT Urban Mobility, 2021). Košice, Slovakia's second-largest city, has not been exempt from this global trend—the entry of Antik's e-scooter system into the city has introduced both opportunities and challenges that demand careful, evidence-based understanding of sustainable urban mobility planning.

1 E-scooters as a shared service

E-scooters to addition to bicycles - their unpowered cousins- promise significant advantages for urban mobility. They provide rapid, accessible transport for short-distance trips—typically under 2 kilometres—filling a critical mobility gap often named as the "first-mile" and "last-mile" problem, especially when integrated with public transport networks (European Commission, 2021; Mulasi, 2024).

In cities like Košice, where residents face substantial traffic congestion, e-scooters offer an environmentally friendly alternative that reduces reliance on private automobiles (Košice City Council, 2022) or play the role of public transportation feeder. The vehicles themselves are highly space-efficient: a single car parking bay can accommodate up to 20 e-scooters, making them an attractive tool for reclaiming urban space from motor vehicles (EIT Urban Mobility, 2021).

In Slovakia several shared mobility service providers operate with Bolt being the largest among them with their e-scooter service provided in 17 cities, followed by Tier in Bratislava the capital city and Antik in Košice the second biggest city in the country. Beyond congestion relief being the main benefit of the shared services is the utilisation of shared e-scooters align with European sustainability objectives, related to climate goals. Micromobility can contribute to climate goals—reducing greenhouse gas emissions, decreasing air pollution, and promoting active travel that benefits public health (EIT Urban Mobility, 2021). Shared e-scooters, when properly implemented, represent an effective tool for reducing greenhouse gas emissions in urban transport. A study of the Voi e-scooter system in Bristol demonstrated that in 2021, it replaced 48,000 km of motorized transport and reduced CO_2 emissions by up to 45% compared to substituted trips (Chaniotakis et al., 2023). Another study of shared micromobility across six global cities (Berlin, Düsseldorf, Paris, Stockholm, Melbourne, Seattle) found that shared e-scooters reduced emissions by 14.8–42.4 g CO_2e/pkm compared to replaced modes, with monthly city-level savings ranging from 3.9 to 66.1 tons CO_2 (Krauss, Doll & Thigpen, 2022). The largest reductions came from replacing ridehailing (-541 g CO_2e/trip) and private ICE cars (-273 g CO_2e/trip). However, when replacing walking or public transit, net emissions increased by up to +110 g CO_2e/trip, highlighting the importance of mode substitution patterns. Also as noted by researchers such as Saltykova et al. (2022), if e-scooters replace public transport (buses, metro) rather than private cars, the environmental benefits are significantly lower—in scenarios with short vehicle lifespans (under 3,500 km) or high operational costs, the net effect may even be negative (Chaniotakis et al., 2023).

Shared e-scooters can improve accessibility for residents unable to afford private vehicles and address the "first/last mile" problem in multimodal transport. This can mitigate issues of high car ownership and limited parking (Bai & Jiao, 2020). Studies in Austin and

Minneapolis showed e-scooters connect peripheral areas to transit stops, enhancing access in underserved neighbourhoods (Bai & Jiao, 2020).

Research shows e-scooter sharing users are typically men with higher education and income (Sanders et al., 2020; Reck et al., 2021). 60–70% of users are men compared to women, reflecting barriers of safety and infrastructure (Verloes et al., 2022). This highlights the need for inclusive infrastructure planning.

However, the rise of e-scooters has not been uniformly celebrated. Rapid, unregulated proliferation across European cities created chaos, with scooters blocking sidewalks and sparking public backlash (EIT Urban Mobility, 2021). Paris banned them after a 2023 referendum (90% voter support) following fleet chaos with multiple operators (BBC News, 2023). Prague announced a full ban citing persistent safety hazards and sidewalk clutter (European Urban Mobility Observatory, 2025). Copenhagen temporarily banned e-scooters in 2021 before reintroducing strict regulations limiting fleets to 3,200 vehicles across four operators. Understanding user behavioural patterns of shared e-scooters is critical for their sustainable integration into urban transport systems, particularly given the regulatory crises observed in European cities such as Paris and Prague. Unlike bikesharing systems with relatively predictable trip patterns, shared e-scooters generate unpredictable spatial flows characterized by high central district concentrations, sidewalk clutter, and hazardous riding behaviours—factors that critically determine net emissions impacts, with mode substitution patterns, emphasizing sensitivity to behavioural factors.

For the city of Košice—where the 2022 Update of the Strategy for Transport Development identifies micromobility (previously Sustainable Urban Mobility Plan) as essential for mitigating urban congestion—localized behavioural analysis is essential. The city's specific context (62% private car ownership, narrow historic core, and critical commuting corridor between the main railway station and Technical University campuses) requires data-driven fleet zoning, transit-integrated parking hubs at DPMK stations, and equity interventions (student pricing schemes, women-targeted safety initiatives) to achieve sustainable outcomes. Without empirical understanding of Košice's e-scooter user behavioural patterns, the city risks replicating regulatory failures observed in Paris and Prague rather than adopting the evidence-based Copenhagen model (3,200 vehicle fleet, four authorized operators, designated parking zones). This study therefore examines the behavioural characteristics and mode substitution patterns of e-scooter users in Košice to provide an empirical foundation for sustainable and equitable micromobility governance.

2 Utilization Pattern Analysis of Shared E-Scooter Users

Behavioural assessments of shared micromobility systems have evolved from basic demographic profiling toward integrated spatial-temporal analyses, though e-scooter research remains substantially less developed than bikesharing literature. Christoforou et al. (2021) conducted foundational analysis of Paris e-scooter users, establishing demographic baselines and revealing preference patterns. Bai and Jiao (2020) employed regression analysis to demonstrate that e-scooters concentrate in short-distance trips within central business districts and near universities. Building on bikesharing spatial research, Mahajan et al. (2024) applied clustering analysis to identify demand concentrations in densely populated areas across 40 global cities. Schimohr and Scheiner (2021) validated spatial relationships between infrastructure and public transit, showing that proximity to universities, restaurants, and shops positively influences usage.

Temporal patterns reveal purpose-driven behavioural differences. Kim (2023) differentiated between long-term subscription patterns (commuting-focused) and short-term casual use (leisure-oriented), establishing that commuting trips exhibit morning (7:00–9:00) and evening (17:00–19:00) peaks. Qin et al. (2023) identified divergent patterns between trip volume, duration, and spatial distribution, with weekend usage concentrating near recreational infrastructure. Critically, Chaniotakis, Johnson, and Kamargianni (2023) advanced temporal-behavioural integration through analysis of 190,932 Bristol e-scooter trips, documenting afternoon usage peaks aligned with rush hours alongside distance distributions (mean 2.1 km) and mode substitution variance (37% walking, 19% car), establishing that temporal patterns fundamentally determine net emissions outcomes.

Spatial-temporal segmentation enables predictive urban planning. Lee and Leung (2023) applied Dynamic Time Warping clustering to analyse demand relationships with neighbourhood characteristics, advancing beyond static spatial approaches. Cantelmo et al. (2020, 2019) proposed integrated models combining quantitative clustering with spatial dimensions. Chen et al. (2022) utilized bikeshare networks to identify urban zone boundaries, while Moore et al. (2023) applied k-means clustering to classify areas as "Central Urban Hub," "Dense Residential," "Connected Outskirts," and "Disconnected Suburbs". Yang et al. (2025) advanced prediction to operational scales through BikeMAN, a multi-level spatio-temporal neural network validated on 10+ million trips, yet such sophisticated modelling remains absent for e-scooter behavioural analysis.

Research gaps persist in Central European contexts. Reck et al. (2022) developed mixed logit models integrating revealed preference data with lifecycle assessment, establishing methodological frameworks. However, research remains concentrated in megacities, while Central Europe, including Slovakia, remains understudied. Gender-equity research by Verloes et al. (2022) documented persistent male-dominated adoption (60–70%) and identified safety and infrastructure barriers—yet few studies link behavioural insights to proactive regulatory design or test whether data-driven interventions prevent governance failures as observed in Paris and Prague. This analytical gap motivates the present Košice-focused investigation, integrating spatial clustering, temporal segmentation, to evidence-based grounds for governance and future spatial analysis.

3 Data and Methodology

The analysis is based on shared e-scooter trip data provided by Antik, one of the operators of shared micromobility systems within the city of Košice. These data comprise records of e-scooter trips for the years 2021, 2022, and 2023, with a total of 403683 records available. The data was processed utilizing the R software, with visualizations compiled using ggplot2 and OpenStreetMap packages based on OSM map data.

The data provided by Antik contained the following information:

•Time when the trip was started, rounded to the nearest hour.

•Latitude of the trip origin.

•Longitude of the trip origin.

•Address of the trip origin.

•Latitude of the trip destination.

•Longitude of the trip destination.

•Address of the trip destination.

Cluster analysis was performed using the K-means approach, with the optimal number of clusters determined by the elbow method using the factoextra package in R. Density analysis and plots were constructed using the stat_density series of functions from the ggplot2 package. Streight-line distances for trips were calculated from the start and end point coordinates using the geodist package.

The main limitations of this study arise from the availability and structure of the underlying data. First, the dataset did not include exact trip dates, only start times rounded to the nearest hour, which precluded a seasonal or day-of-week analysis of e-scooter usage patterns. Second, trip length was approximated using straight-line (Euclidean) distances between origin and destination coordinates, ignoring the actual routes followed along the street network and the influence of topography or infrastructure constraints. This simplification may underestimate effective travel distances, particularly in areas with indirect connectivity. A promising avenue for future research is the integration of public transport data—specifically the spatial distribution of bus and tram stops—and the use of network-based trip distances when identifying utilization clusters. Such an extension would enable a more precise assessment of first-/last-mile functions and the interplay between micromobility and public transport in Košice.

4 Analysis and results

The shared micromobility system operates on a free flow basis, where the vehicles can be freely picked up from their current location and upon ending a trip, can be parked without restrictions, provided they are not blocking traffic or pedestrian movement. The vehicles are then regularly collected by the operator, especially from remote locations, and are redistributed to high demand areas in the city as needed. This can be seen on figure 1, which depicts a sample of the trip start and end points. Due to the size of the dataset, only 5% of all trips are depicted in the figure (20184 trips). As can be seen, many trip ends are located in remote areas or o the outskirts of the city, where they are then collected from, and only a limited number of trips actually start in these areas.

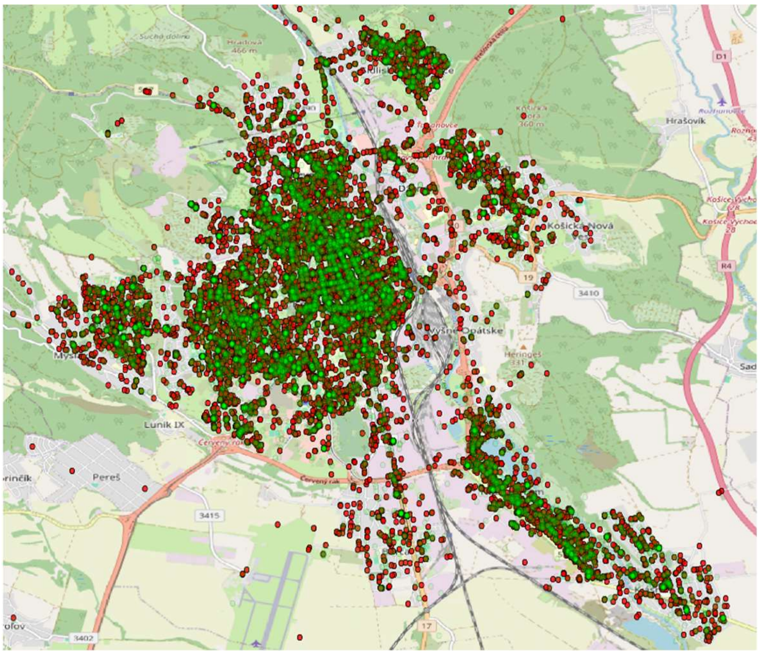

Figure 1: Sample (5%) of trip start (green) and end (red) locations

To analyse the spatial distribution of trips taken, a cluster analysis was conducted using the start and end point locations of the trips, to identify trips with similar origin and destination points. Visualization of the resulting clusters is presented in figure 2, with a 5% sample of all available trips is depicted in the figure for clarity.

The clusters represent separate groups of trips, which largely correspond to the topographical features of the city. Cluster 1, outlined in black, covers the city centre, located on a lowland, and the western part of the city, comprised of city districts located above the city centre on hillsides surrounding the city from the west. Cluster 3, outlined in red, covers the city districts located to the east and north in a similar fashion, with these districts also located in hilly areas. Both of these clusters overlap in the city centre, meaning they are comprised of trips to the city centre from the outlying districts and back, with only minimal travel across the centre to other districts. This can be also seen reflected in the average trip distance, measured as the straight-line distance from the origin to the destination points of each trip, which has been calculated using the geodist package. The distances are presented in table 1, with an average of 1275.005 meters and 1070.837 meters for cluster 1 and 3 respectively. These distances roughly correspond to the straight-line distance of the boundaries of the districts covered by these clusters to the city centre (ranging between 800m up to 1500m for most districts). This would also suggest that many trips are taken within the districts themselves, as they are shorter than these distances. Since the distances between districts covered by cluster 1 and 3 mostly exceed 2500m, this would confirm that the trips are not taken across the centre in most of the cases.

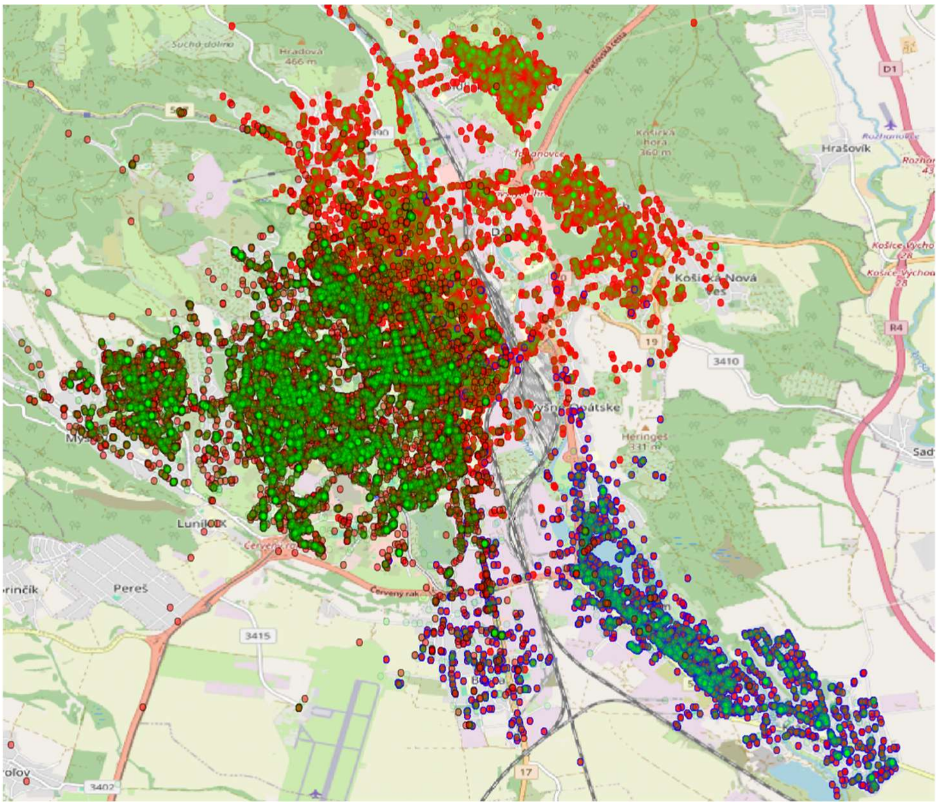

Figure 2: Clusters of similar origin-destination trips. Clusters denoted by outline colour (1 black, 2 blue, 3 red). Fill colour denotes trip start (green) and end (red) points. Sample of trips (5%) visualized per cluster.

Cluster 2 represents a special case, covering the south-east part of the city, which is largely separated from the city centre by a large predominantly industrial zone, meaning trips have to be taken over longer distances, increasing costs for such trips. Most of these trips in this cluster rather originate or end near public transport transfer points, meaning that micromobility is either used for inter-district travel or as a part of a combined travel solution.

Table 1: Statistics for trip clusters

Cluster	No. Trips	% of Trips	Average Length (m)	Median Length (m)
1	171366	42.42%	1275.005	1068.096
2	64652	16.02%	1141.549	747.676
3	167665	41.57%	1070.837	796.45

Source: own calculations

Since user behaviour and utilization patterns can vary across a single day, respecting typical travel behaviour patterns, the data was separated into distinct time slots, presented in table 2.

Table 2: Trip statistics for selected time windows during the day

Time of start	No. Trips	% of Trips	Average Length (m)	Median Length (m)
0:00 - 6:00	15853	3.93%	1315.076	1015.444
6:00 – 10:00	57661	14.28%	1295.011	1039.156
10:00 – 14:00	85408	21.16%	1142.582	870.2651
14:00 – 19:00	156380	38.74%	1152.333	865.8759
19:00 – 0:00	88381	21.89%	1114.844	838.124

Source: own calculations

The number of trips is the lowest for the first time windows, which represents early morning hours, when micromobility is often used to supplement the low number of public transport options available at night, when most bus and tram lines in the city operate at a reduced level, or not at all. The trips taken in this time windows are also the longest on average. The second time window, between 6:00 and 10:00 represents the morning rush hour, with a much higher level of utilization. Notably however, the level of utilization is the highest in the afternoon rush hour time windows between 14:00 and 19:00. The midday and evening time windows have a comparably high level of utilization as well. Overall, micromobility in the city has the highest level of utilization from the midday onwards, with trip length becoming shorter as the day goes on. What is notable however, is that the geographical utilization patterns described earlier hold up throughout the day, with cluster analysis results for the first three time windows (morning rush hour, midday and afternoon rush hour) visualised in figure 3. The results remain the same for the remaining two time windows. This would mean, that overall trip spatial similarity remains consistent throughout the day, irrespective of different character and reasons for individual trips, that can be expected at different times of the day. Rather, the inter-district or district-centre spatial character of most trips is mostly determined by the topology of the city.

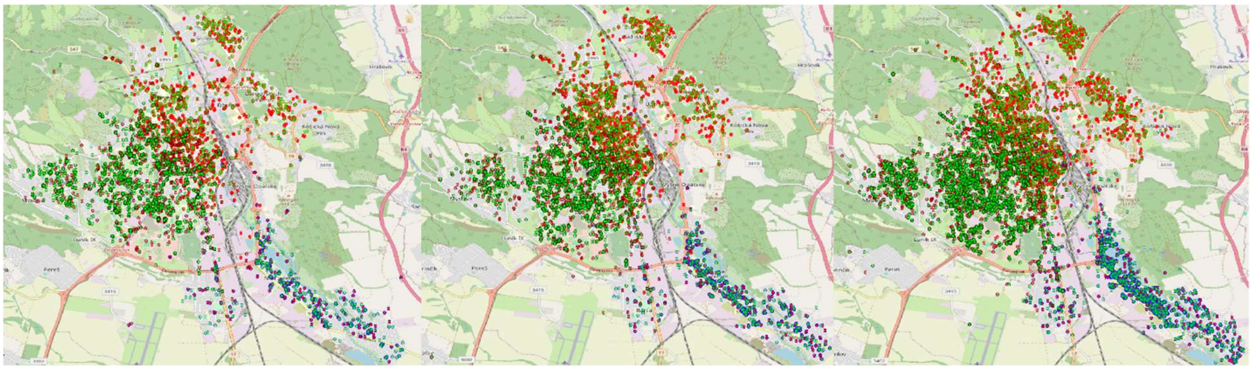

Figure 3: Clusters of similar origin-destination trips for morning rush hour (left), midday (middle) and afternoon rush hour (right). Clusters denoted by outline colour (1 black, 2 blue, 3 red). Fill colour denotes trip start (green) and end (red) points. Sample of trips (5%) visualized per cluster.

What can change throughout the day, however, is the distribution of trip starts, ends and the orientation of trips. For this reason, density plots were constructed for trip start and end points for the different time windows.

Figure 4 depicts the density plot for start and end points for the morning and afternoon rush hours, as well as for the midday time windows. There are notable differences between these time windows. During the morning rush hour, the distribution of start points is more widely spread throughout the city districts, as people utilize micromobility to travel from their residences to possible places of work or study. The end points of these trips are then more densely situated in the city centre and around known public transport transfer points. During the midday, trip start and end points are both more densely condensed in the city centre, suggesting shorter trips between various points of interest and possible transport transfer locations. This condensation trend further continues into the afternoon rush hour, with even more pronounced concentration of trip start and end points at known transport hubs. One possible explanation of this, is that while e-scooters are distributed by the operator during the night, they continue to concentrate at high traffic areas as the day goes on, becoming less available at city and district outskirts.

Figure 5 depicts the same density plots, but this time for the early morning and evening time windows. In the morning, most trips originate in the city centre, with destinations being widely spread throughout the entire city, suggesting that micromobility is widely used during this time window for return trips from the city back to personal residences.

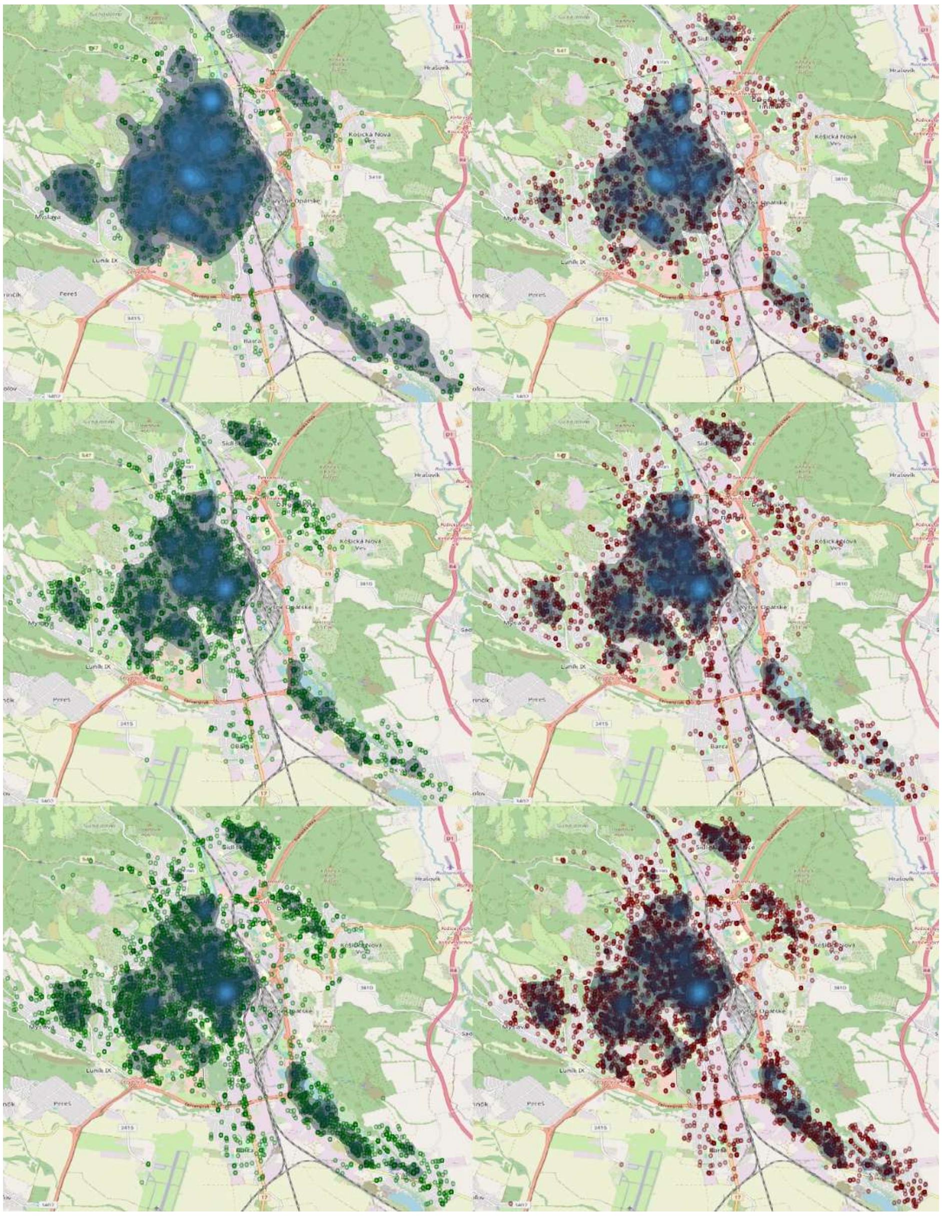

Figure 4: Density plots of trip start (green) and end (red) points for morning rush hour (top row), midday (middle row) and afternoon rush hour (bottom row). Sample of trips (5%) visualized per plot.

Similar trend is observable during the evening hours, but to a much less pronounced extent, again suggesting a possible daily cycle of shared micromobility availability, where the operators distribute e-scooters during the night, as well as some of them becoming available in more remote locations naturally by being used to travel to outlying parts of the city during the night, when public transport availability is limited, and becoming more concentrated at points of interest or transport hubs as the day goes on.

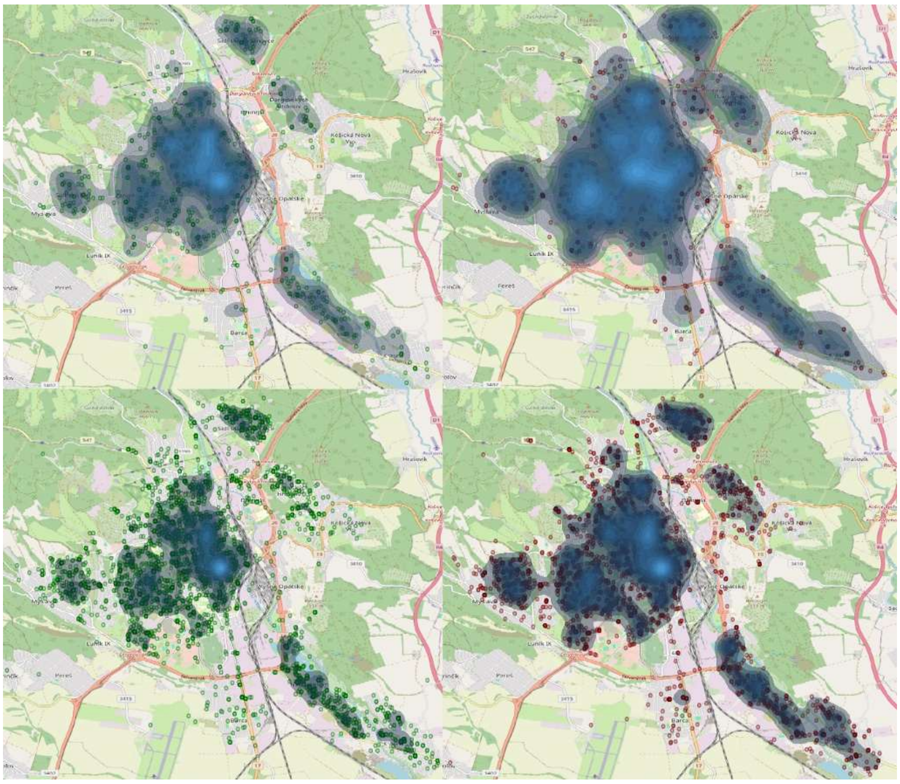

Figure 5: Density plots of trip start (green) and end (red) points for early morning (top row) and evening (bottom row). Sample of trips (5%) visualized per plot.

Conclusion

This spatiotemporal analysis of 403,683 e-scooter trips in Košice reveals critical insights into the behavioural patterns and spatial-temporal dynamics of shared micromobility systems in a Central European mid-sized city. The investigation identified three distinct spatial clusters corresponding to topographical features: Cluster 1 (42.42% of trips, 1,275 m average distance) connecting western districts to the city centre; Cluster 3 (41.57% of trips, 1,071 m average distance) serving eastern and northern districts; and Cluster 2 (16.02% of trips, 1,142 m average distance) representing isolated southeastern areas dependent on longer-distance connections. Critically, these spatial patterns remained remarkably consistent across all temporal segments, indicating that urban topology, rather than trip purpose, is the primary determinant of origin-destination behaviour.

Temporal analysis revealed pronounced temporal variation in utilization intensity and spatial distribution. Early morning hours (0:00–6:00) exhibited the lowest usage (3.93%) but longest average trip distances (1,315 m), indicating supplementary first/last-mile functions during reduced public transit availability. Morning commute hours (6:00–10:00) showed increased activity (14.28%), while peak utilization occurred during afternoon hours (14:00–19:00, 38.74% of trips). Notably, trip length decreased throughout the day (1,295 m to 1,115 m), suggesting progressive concentration of vehicles in central districts and transport hubs. Density analysis documented a critical operational dynamic: vehicle redistribution during night hours resulted in dispersed morning start points, but afternoon and evening peaks showed pronounced clustering around central locations and public transit transfer points, indicating diminishing availability in peripheral districts as the day progressed.

These findings hold substantial implications for multiple stakeholders. For policymakers, the data demonstrate that micromobility integration with public transport operates at distinct temporal scales—morning peaks reflect residential-to-centre commuting patterns, while afternoon peaks indicate secondary mobility for intra-centre trips and transit connections. This time-differentiated relationship suggests targeted transit coordination opportunities. For the service operator, the analysis reveals a structural challenge: current night-time redistribution strategies insufficient to maintain equitable availability throughout the day. Vehicle concentration intensifies from midday onward, particularly around central hubs, while peripheral districts progressively lose access—a pattern that may exacerbate equity barriers and limit adoption among non-central populations.

This study provides empirical foundations for future research directions: longitudinal analysis tracking seasonal variation, correlation of trip patterns with public transit schedules and demand, and integration of mode-choice data to assess substitution effects on emissions and congestion. Additionally, operational simulation modelling could test alternative redistribution strategies to address the identified concentration problem. For Košice specifically, these findings underscore the necessity of proactive fleet management—particularly mid-day rebalancing to outlying districts—to prevent the regulatory crises observed in Paris and Prague, and to achieve the equitable, multimodal transport objectives outlined in the city's Sustainable Urban Mobility Plan.

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