Politecnico di Torino

1859

DIGITAL SKILLS FOR SUSTAINABLE SOCIETAL TRANSITIONS

Transport innovation for a sustainable, inclusive and smart mobility

5 Exercises on shared mobility

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1. Exercise 1 data sets and descriptive analysis

1.1Data description and cleaning process

Operator	Original items number	Items number after cleaning
A（Lime）	1,624,528	1,421,381
B（Voi）	291,765	285,453
C（Bird）	858,020	857,957
Total	2,774,313	2,564,791

Table 1 Number of trip records before and after data cleaning by operator

This cleaning process resulted in the removal of approximately 209,522 records, corresponding to 7.55% of the original dataset.

The following types of rules are applied to remove invalid and inconsistent data:
- Trips with non-positive duration or distance (duration ≤ 0 or distance ≤ 0).
- Records with battery levels outside the valid range (start or end battery not in [0%,100%]).
- Trips with inconsistent timestamps, where end time precedes start time.
- Trips with missing essential fields, such as start time, end time, coordinates, trip id,or vehicle id.

1.2 Mobility trends over time

Common analysis time window：
The three operators do not provide data covering the same calendar period (i.e., the available time ranges differ across Lime, Voi and Bird). To ensure a fair and consistent comparison across operators, all subsequent analyses are restricted to the common overlapping time window: 2024/01/31–2025/04/29.This choice avoids biased comparisons caused by unequal observation lengths.

Figure 1 reports the monthly mobility trend. A yearly aggregation is not presented, as the three operators provide data over different and incomplete 2 calendar years; therefore, annual comparisons would be misleading and less informative than finer temporal analyses.

The monthly trend shows a clear seasonal pattern in scooter usage. From February to June, the number of trips increases steadily, indicating growing demand as weather conditions improve. Usage reaches its highest levels between late summer and early autumn, with a peak around September–October, suggesting that warm and stable weather strongly supports micromobility demand.

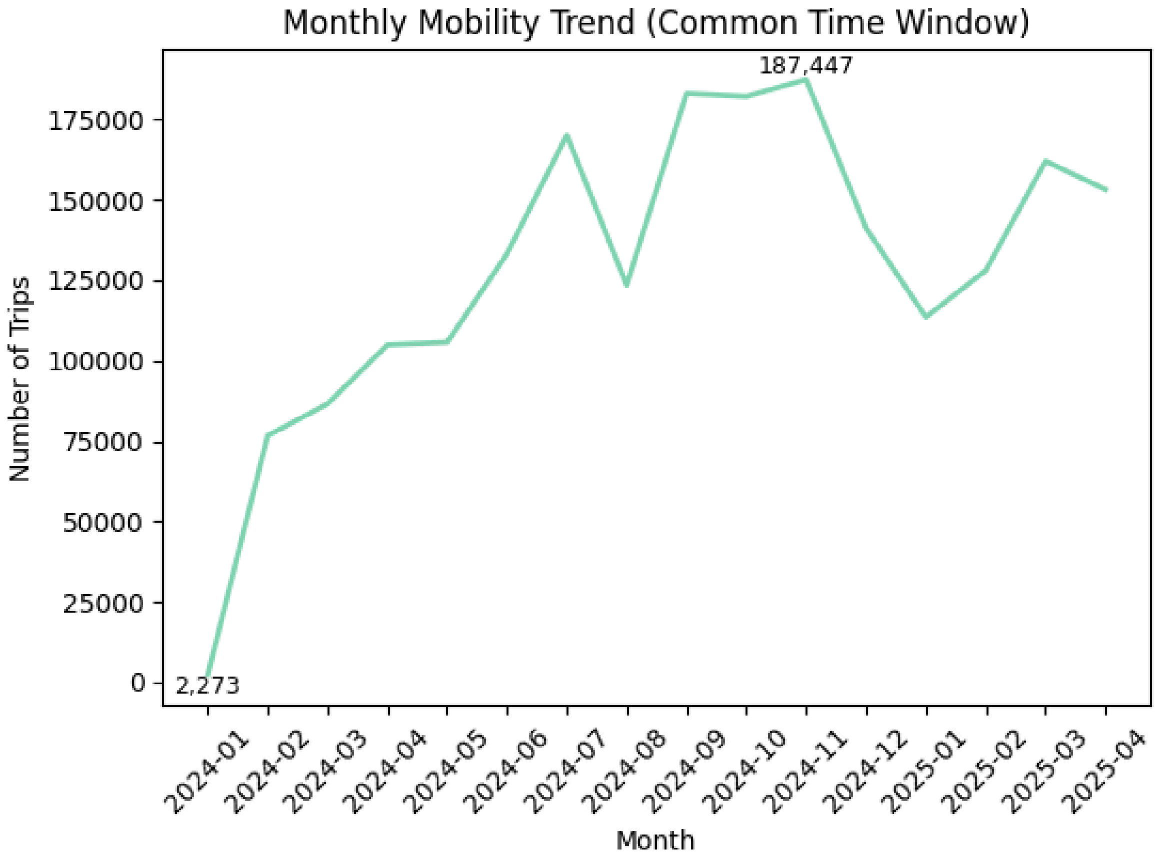


Figure1 Monthly Mobility Trend

From November onward, trips decline sharply, reaching the lowest levels during winter months, reflecting reduced outdoor mobility and adverse weather conditions. A gradual recovery is visible again toward the end of the observation period, indicating the start of a new seasonal cycle.
Overall , the monthly analysis captures seasonality and demand fluctuations effectively.

Figure 2 shows strong week-to-week volatility, but the overall direction is clear: trips rise from late winter into summer, stay high through late summer/early autumn, then drop sharply in late autumn/early winter.

The highest weekly levels occur around September–October (peak weeks close to ~50k trips), consistent with the monthly peak season. After that, weekly trips fall and remain lower during winter, then partially recover in early 2025.

The final sharp drop at the end of the series is a data-window artifact (the last week is incomplete), not a real demand collapse.

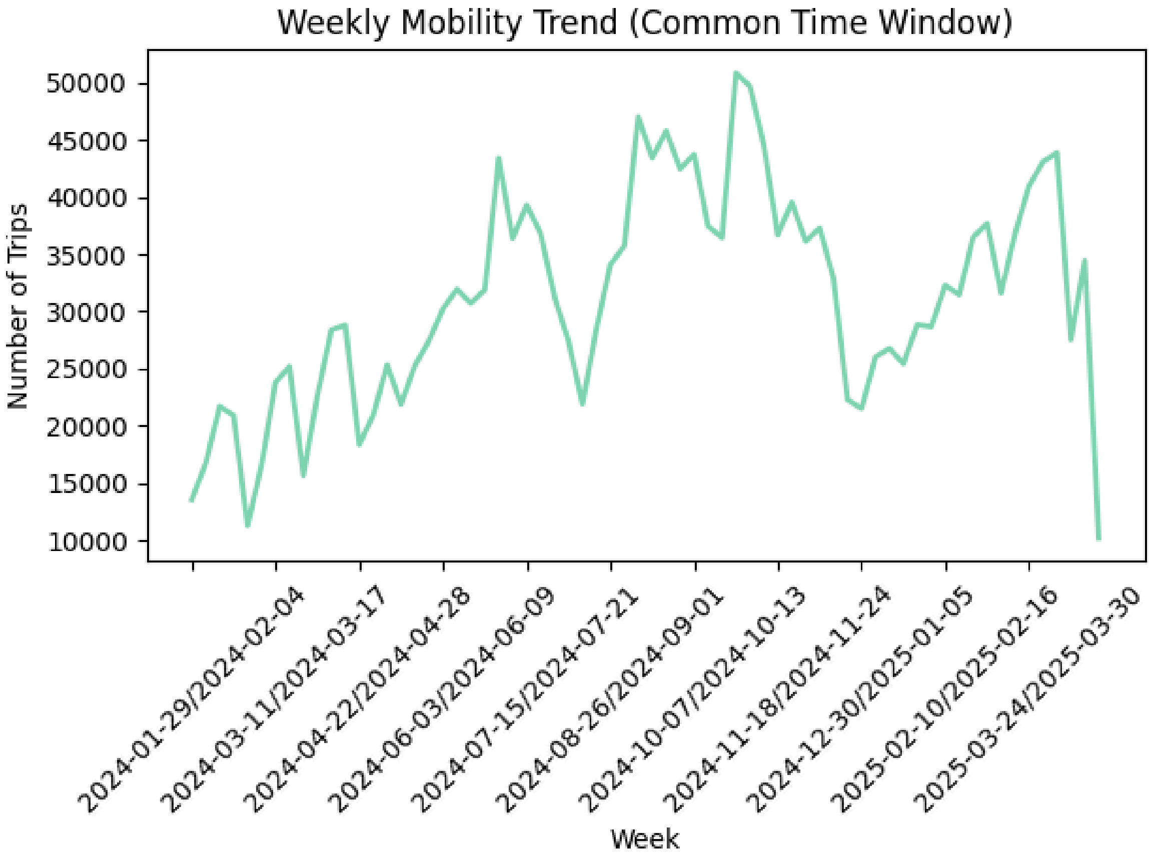


Figure 2 Weekly mobility trend

1.3 Vehicle usage intensity and operational efficiency

Due to differences in data availability across operators, As a result, the figure 3, 4 reported for 2024 and 2025 do not represent full calendar years.approximately 10 months are observed in 2024 and 5 months in 2025.

Although the 2025 data cover only about five months, the number of unique vehicles deployed by all three operators already approaches the 2024 level, which spans roughly 10 months. This indicates a clear linear, and possibly accelerating, growth trend in fleet deployment rather than a stable or declining pattern.

At the same time, vehicle usage intensity does not decrease as the fleet expands. On the contrary, the average utilization per vehicle remains high, suggesting that newly deployed vehicles are effectively absorbed by market demand, with no evident signs of oversupply or idle capacity.

Operator A consistently maintains the largest number of deployed vehicles in both years, indicating a clear market-leading position and a more aggressive expansion strategy. Operator C occupies an intermediate position, reflecting a more balanced and gradual deployment approach. In contrast, operator B operates with a substantially smaller fleet size throughout the period, suggesting a more cautious or constrained deployment strategy in the Turin market and a relatively weaker market presence.

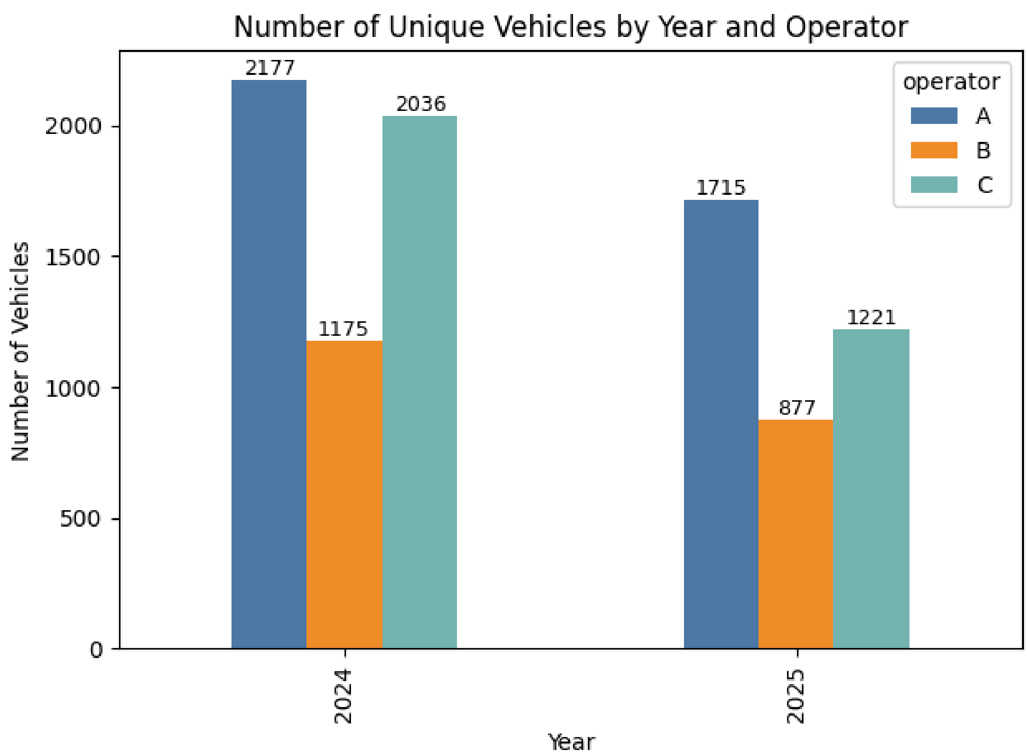


Figure 3 Number of unique vehicles by years and operator

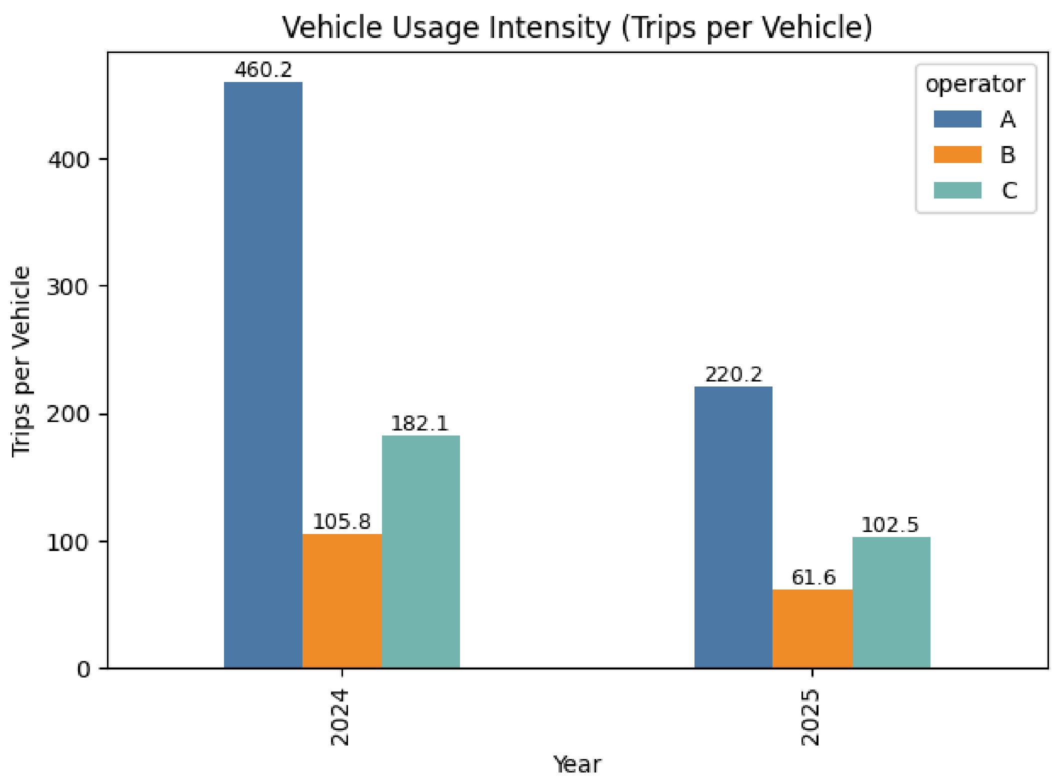


Figure 4 Vehicle usage intensity by year

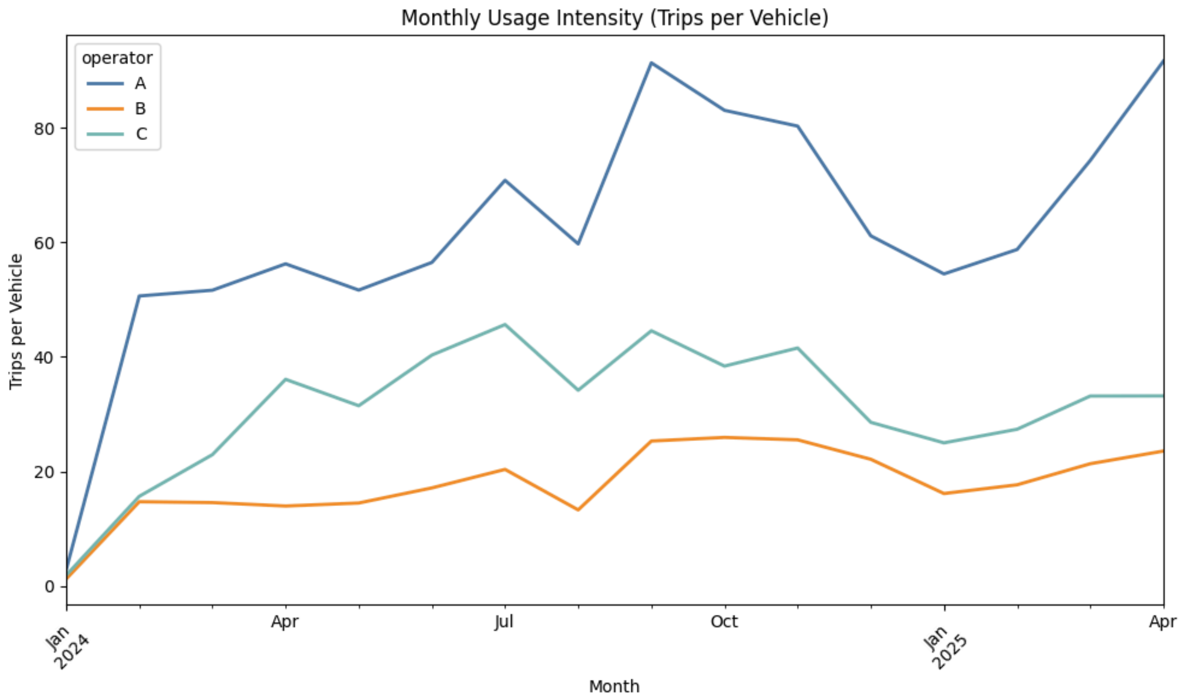


Figure 5 Vehicle monthly usage intensity

Figure 5 reports the three operators exhibit clear and persistent differences in operational efficiency.

[Video–Monthly E-scooter Usage Trends by Operator (Torino)]
To complement the static analysis, an animated visualization of monthly e-scooter trips was produced to illustrate the temporal evolution of demand within the common observation window.

Operator A consistently shows the highest vehicle usage intensity, indicating superior fleet deployment, demand matching, and operational scheduling capabilities. Each vehicle generates more trips for A, implying higher revenue potential and better capital utilization, and demonstrating a strong ability to convert deployed assets into high frequency usage;
Operator C performs significantly better than B and consistently ranks second, suggesting that, under the same market conditions, C is more effective than B at translating fleet size into actual ride demand;
Operator B displays the lowest usage intensity throughout the period, and does not show meaningful convergence even during peak demand months. This suggests that B’s limitations are structural and operational rather than driven by short-term demand fluctuations.

Overall,this figure highlights that operational capability , rather than simple fleet expansion is the key factor differentiating the commercial performance of micromobility operators.

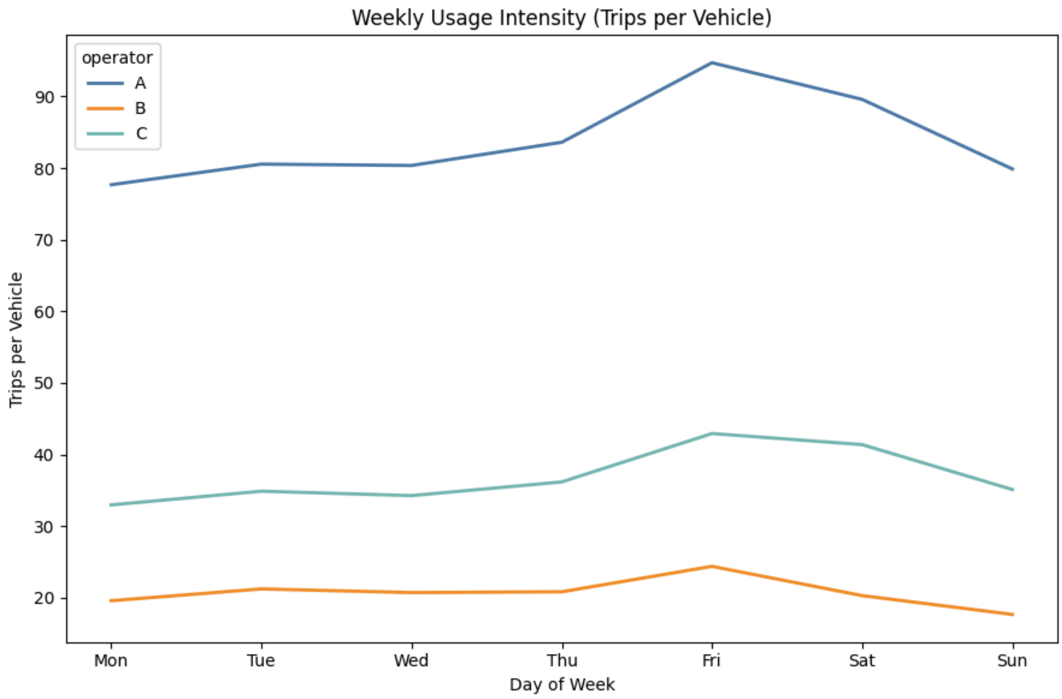


Figure 6 Vehicle usage pattern by day of week

Figure 6 reveals a strongly commute-oriented usage pattern across all three operators, usage intensity per vehicle increases during weekdays, peaks on Friday, and declines over the weekend, which is consistent with typical commuting and daily mobility behavior. Operators with stronger operational capabilities, particularly Operator A , are better positioned to capture weekday demand, leading to higher asset utilization, more stable revenue generation, and superior operational efficiency compared to competitors.

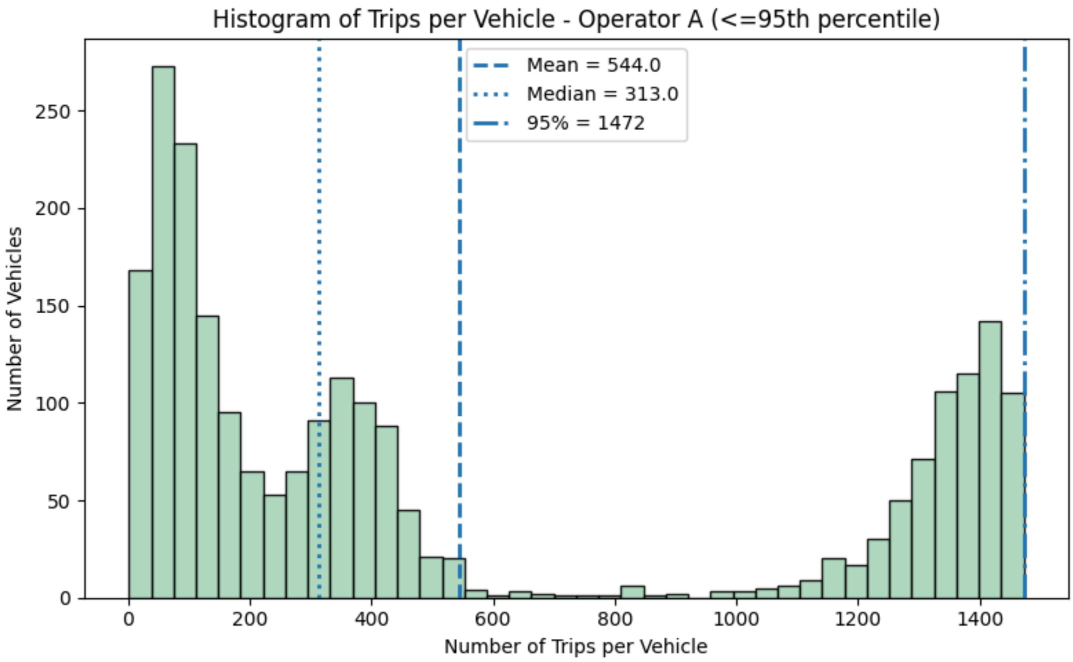


Figure7 Distribution of trips per vehicle for Operator A (Lime)

Operator A exhibits a strongly right-skewed, head-concentrated distribution.
The large gap between the mean (≈544) and the median (≈313), together with a very long right tail (95th percentile ≈1472), indicates the presence of a subset of vehicles with extremely high usage intensity. This suggests that A is able to consistently deploy and maintain vehicles in high demand locations, generating sustained high frequency usage.

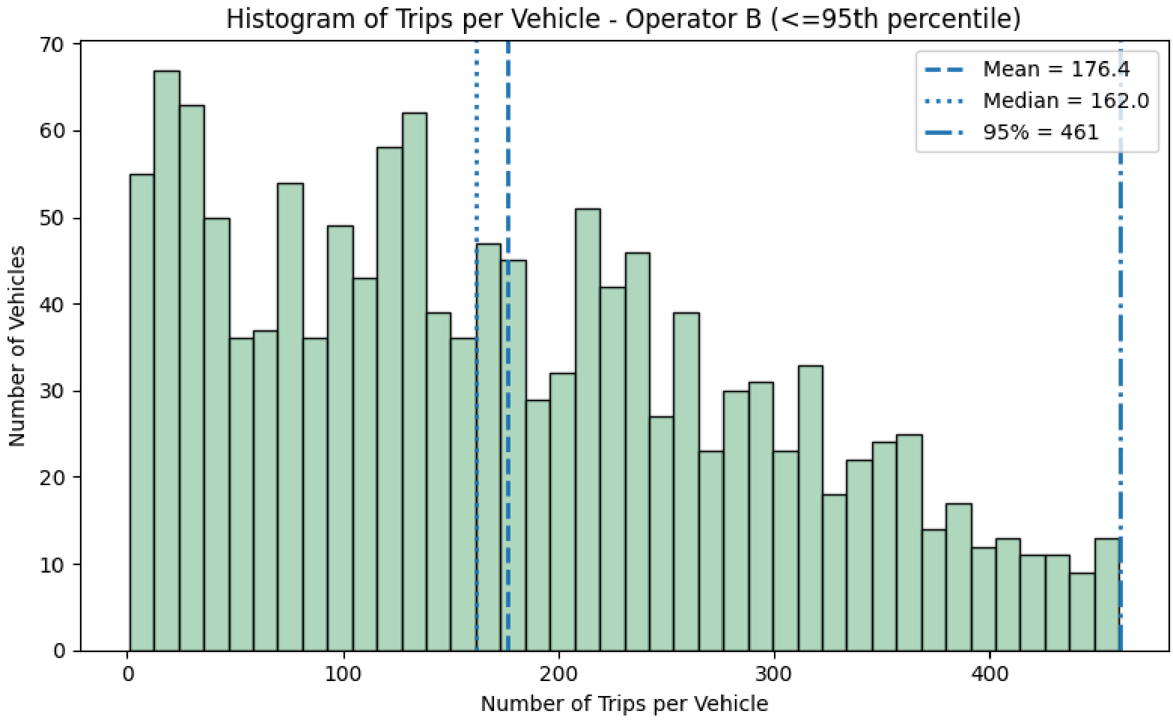


Figure 8 Distribution of trips per vehicle for Operator B (Voi)

Operator B shows a more compact distribution with a clearly lower upper bound.
The mean (≈176) and median (≈162) are close, and the 95th percentile remains limited (≈461), indicating the absence of very high performing vehicles. This pattern reflects a more evenly distributed but less optimized deployment strategy, with limited amplification of demand in high usage areas.

Operator C lies between A and B, with a more heterogeneous structure.
While its mean usage (≈273) exceeds that of B, the lower median (≈154) and a moderate right tail (95th percentile ≈837) indicate the coexistence of many low-usage vehicles alongside a smaller group of high-performing assets. This suggests an intermediate stage of operational optimization.

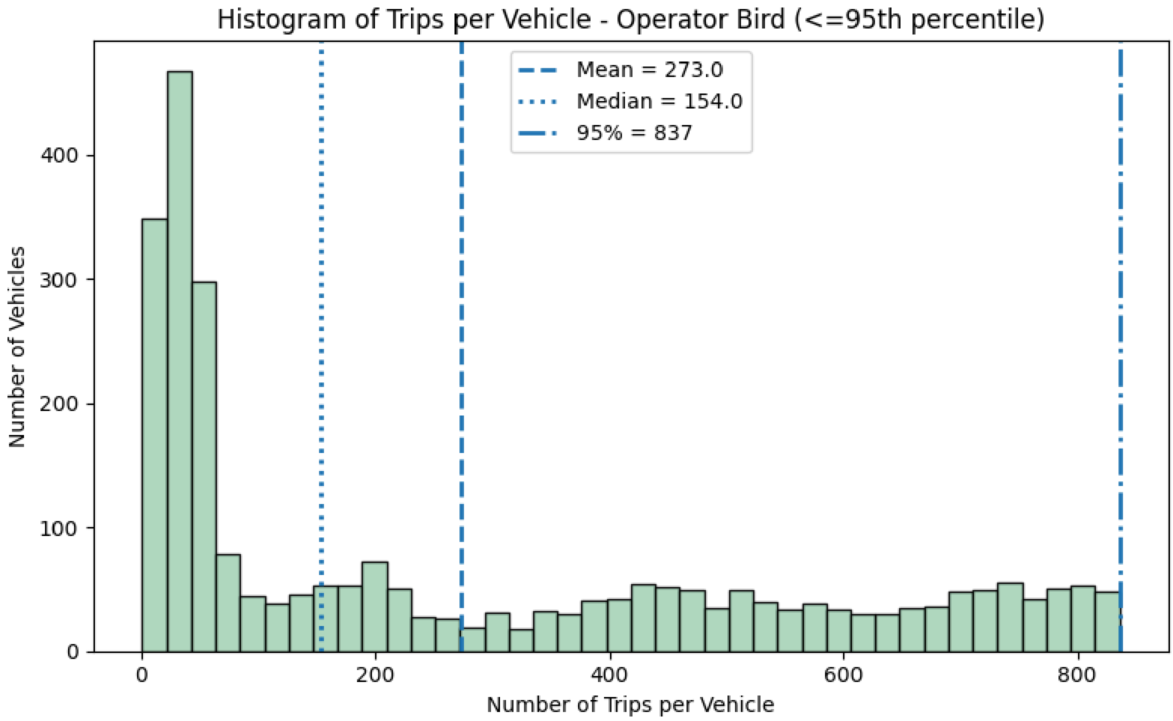


Figure 9 Distribution of trips per vehicle for Operator C (Bird)

The key differentiator among operators is not average usage, but the ability to generate and sustain a right tail of high performing vehicles. Operator A clearly demonstrates this capability, translating fleet deployment into superior asset utilization and revenue potential. Operator B, by contrast, appears constrained by structural operational limitations rather than demand shortages, while Operator C shows partial but incomplete convergence toward a high-efficiency operating model.

2. Exercise 2 O-D matrices

2.1 zoning and O–D matrix definition

This study adopts the official administrative districts of the City of Torino (districts shapefile) as the spatial zoning system, consisting of 27 districts.

- The origin and destination coordinates of each e-scooter trip are spatially matched to their corresponding districts.
- To construct the O–D matrices, all trips are represented as district-to-district flows.

2.2 Overall O–D Flow Patterns Across Districts

The results of figure 10,11,12 derived from zone-level outflows, inflows, and the O–D matrix consistently describe the same underlying spatial mobility structure in Turin. Scooter trips are highly concentrated in a limited number of central districts, which function simultaneously as major trip origins and attraction destinations. This pattern reflects the presence of well-defined urban activity centers and a strong commuting related spatial organization.

The O–D matrix further shows that the majority of trips occur either within the same district or between adjacent districts, while long-distance inter-district movements remain relatively limited. This indicates that scooter usage primarily serves short-distance urban travel needs, particularly for connecting residential areas with employment zones, commercial centers, or major transport nodes, rather than substituting medium- or long-distance public transport.

Overall, these three visualizations jointly confirm a consistent transport insight: micromobility demand in Turin is characterized by strong spatial concentration and localized flows, with e-scooters mainly fulfilling a first and last-mile function within the urban transport system.

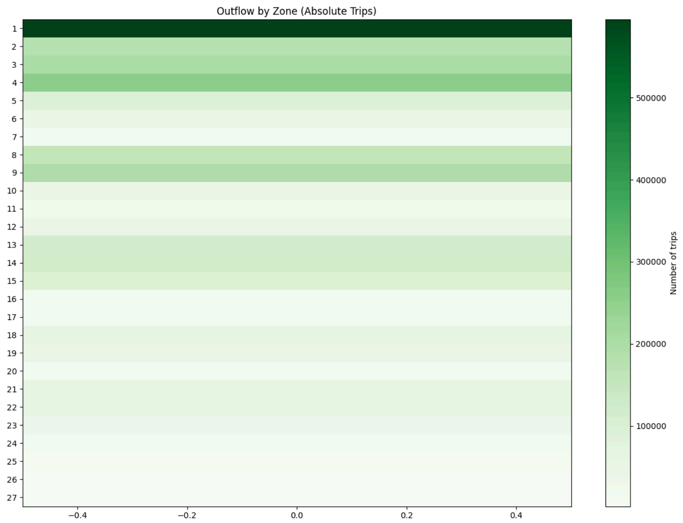


Figure 10 Outflow by district, measured as the total number of e-scooter trips originating from each district. Darker colors indicate districts generating higher volumes of outbound trips

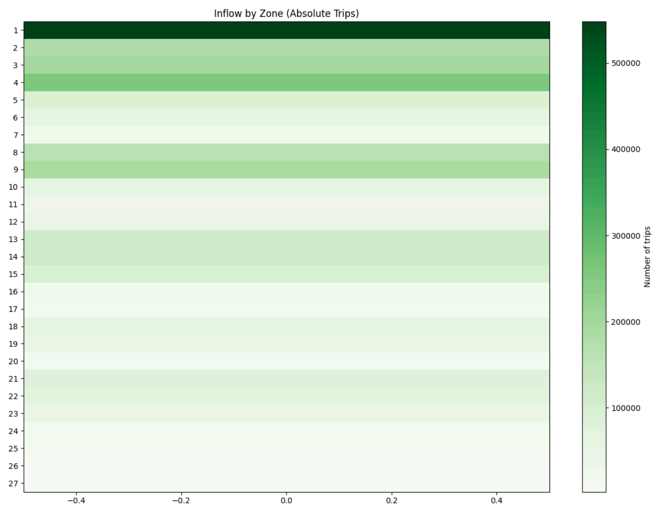


Figure 11 Inflow by district, measured as the total number of e-scooter trips originating from each district. Darker colors indicate districts generating higher volumes of outbound trips

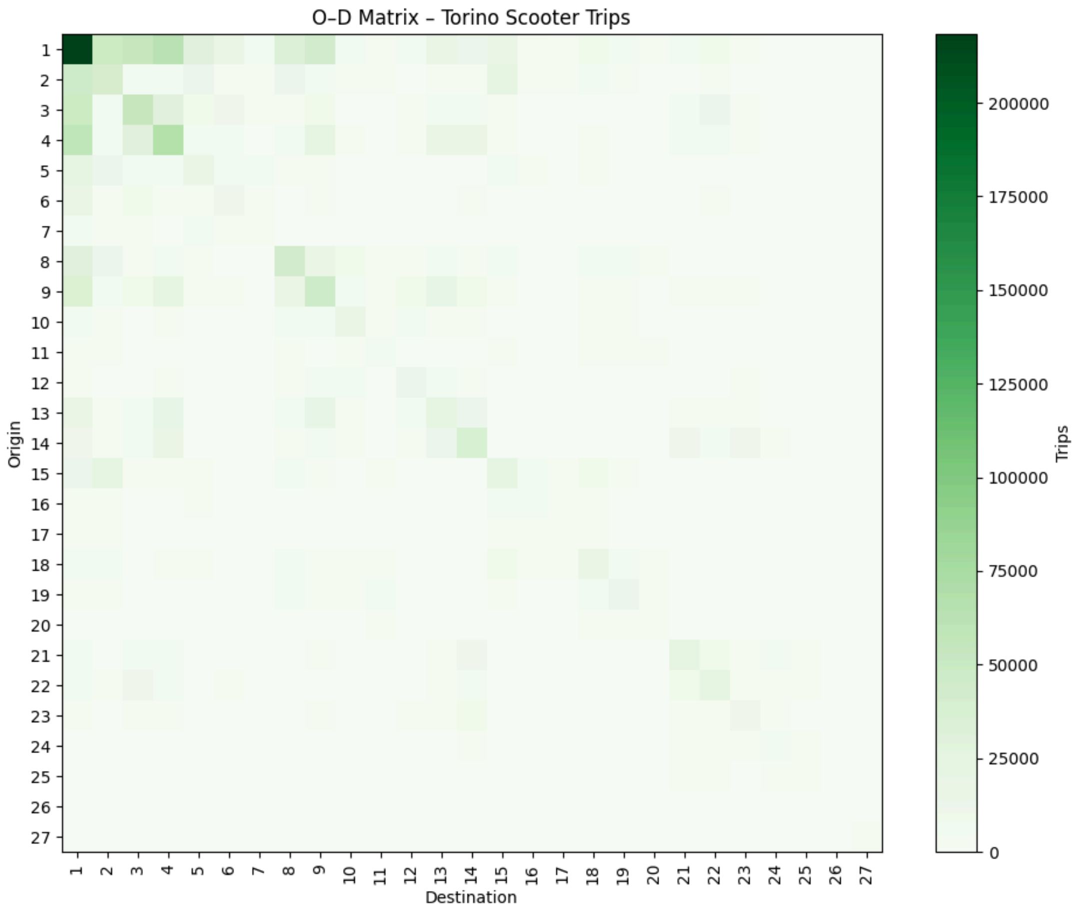


Figure 12 O-D matrix by district, measured as the total number of e-scooter trips originating from each district. Darker colors indicate districts generating higher volumes of outbound trips

2.3 Centralized Spatial Structure of E-Scooter Trips in Torino

The analysis of figure 13, 14, 15, 16 consistently reveals a highly centralized spatial structure of e-scooter trips in the City of Torino, characterized by a clear core-periphery pattern.

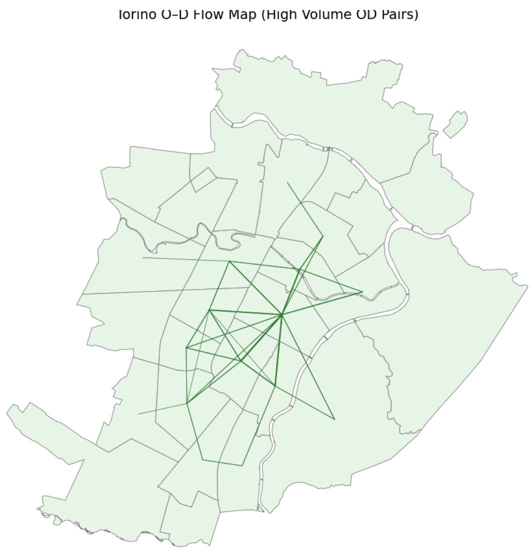
First, both trip origins and destinations are strongly concentrated in a limited number of central districts, while most peripheral districts exhibit substantially lower trip volumes. The strong overlap between high outflow and high inflow zones indicates that these central districts function simultaneously as major trip generators and trip attractors, reflecting their concentration of employment, commercial activities, and urban services.

Second, the O–D matrix and flow maps show that a small number of district pairs account for a disproportionately large share of total trips. These high volume O–D pairs are predominantly centered around the city core, forming a radial and center-oriented interaction structure, rather than a uniformly distributed network. This suggests that e-scooters are primarily used for short-distance trips within the central area or between the center and nearby districts, rather than for long cross-city movements.

A comparison between peak-hour and off-peak-hour O–D flows further highlights temporal differences in spatial organization.

- During comparison between peak-hour and off-peak-hour O–D flows further highlights temporal differences in spatial organization.
- During off-peak hours, flows become more spatially dispersed, although interactions among central districts remain dominant.

Overall, these figures jointly indicate that e-scooters in Torino mainly serve as a high frequency, short distance mobility mode concentrated in the urban core. Their spatial usage pattern closely reflects the underlying urban functional structure.



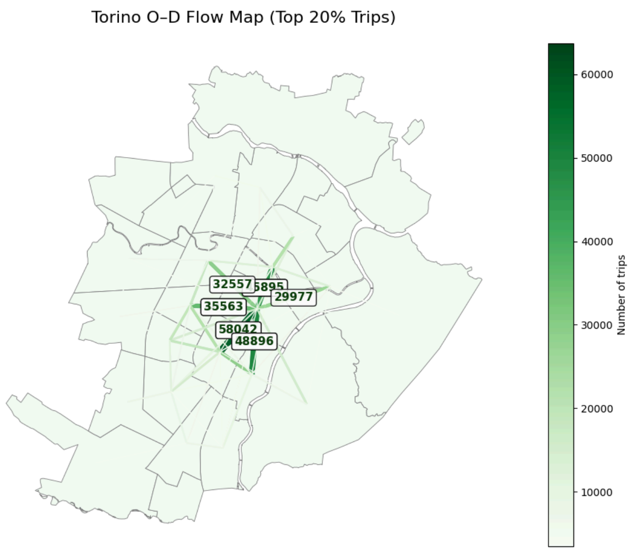
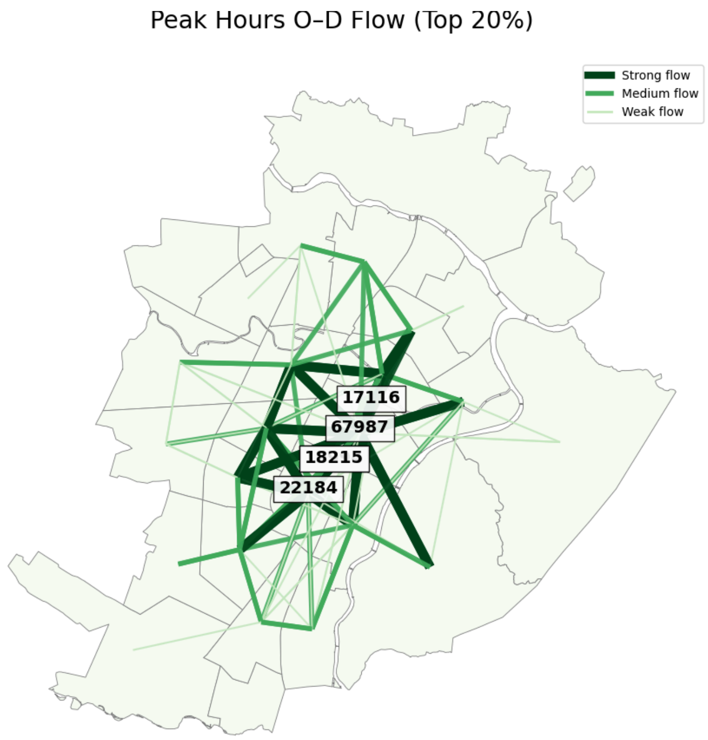


Figure 13,14 spatial distribution of high-volume e-scooter origin–destination (O–D) flows in Torino



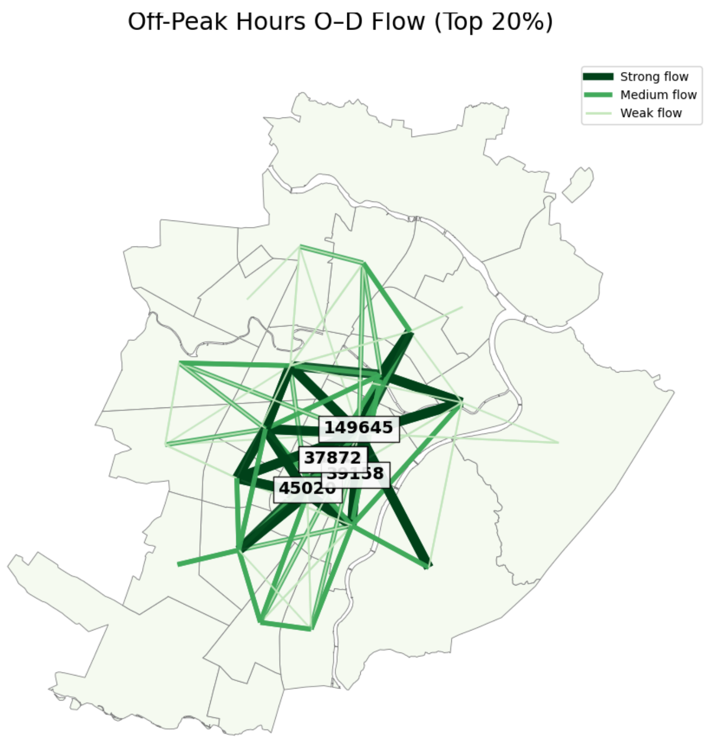


Figure 15,16 Comparison of peak-hour and off-peak-hour e-scooter O–D flows in Torino (top 20% by volume)

3. Exercise 3 comparison between e-scooter sharing use and public transport supply

3.1 Selection of the analysis periods

For exercise 3, the analysis is conducted on two representative months rather than the full dataset, in order to ensure computational feasibility and to allow a clear comparison between e-scooter usage and public transport supply.
Two months were selected to reflect different seasonal conditions and corresponding changes in public transport timetables:

- One summer month(July 2024), characterized by more favorable weather conditions, higher micromobility attractiveness.
- One winter month(January 2025), representing lower temperatures, reduced daylight hours, and a typical winter public transport schedule.

This selection allows the analysis to capture seasonal variations in mobility behavior, while keeping the comparison between e-scooter sharing and public transport supply consistent and interpretable.By comparing these two periods, it is possible to assess whether the spatial relationship between micromobility and public transport remains stable across seasons, or whether patterns of competition and complementarity change over time.

3.2 Seasonal variation in e-scooter spatial density and its relationship with public transport

It should be noted that the e-scooter kernel density maps for July and January are based on separate color scales. Therefore, the color intensity only reflects the relative density distribution within each individual month and cannot be directly used for absolute comparisons between months.

From a spatial distribution perspective, both months exhibit a highly consistent core–periphery pattern. In both July and January, high-density e-scooter activity is persistently concentrated in the central area of Torino, while peripheral districts show significantly lower densities. This indicates that seasonal variation does not substantially alter the main service area of e-scooter usage, which remains strongly dependent on the functional structure of the urban core.

However, differences can be observed in the spatial form of the density patterns. In July, the kernel density distribution covers a wider area and the hotspots are relatively more dispersed, suggesting a greater spatial extensiveness of e-scooter usage during the summer period. In contrast, in January the high-density areas are more spatially concentrated, with hotspots largely contracting toward the city center and a marked reduction in peripheral activity. This suggests that under winter conditions, e-scooter trips are more likely to occur within central areas characterized by higher demand and accessibility.

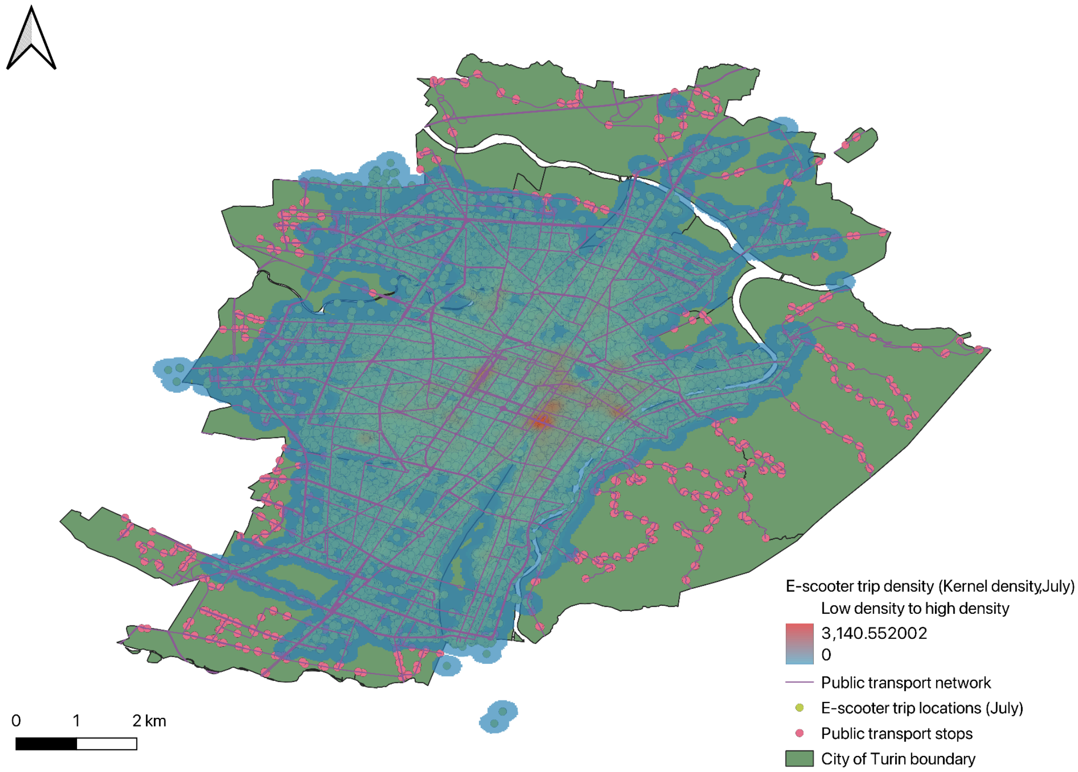


Figure 17 Kernel density map of e-scooter trips in July in Torino, overlaid with the public transport network and stops.

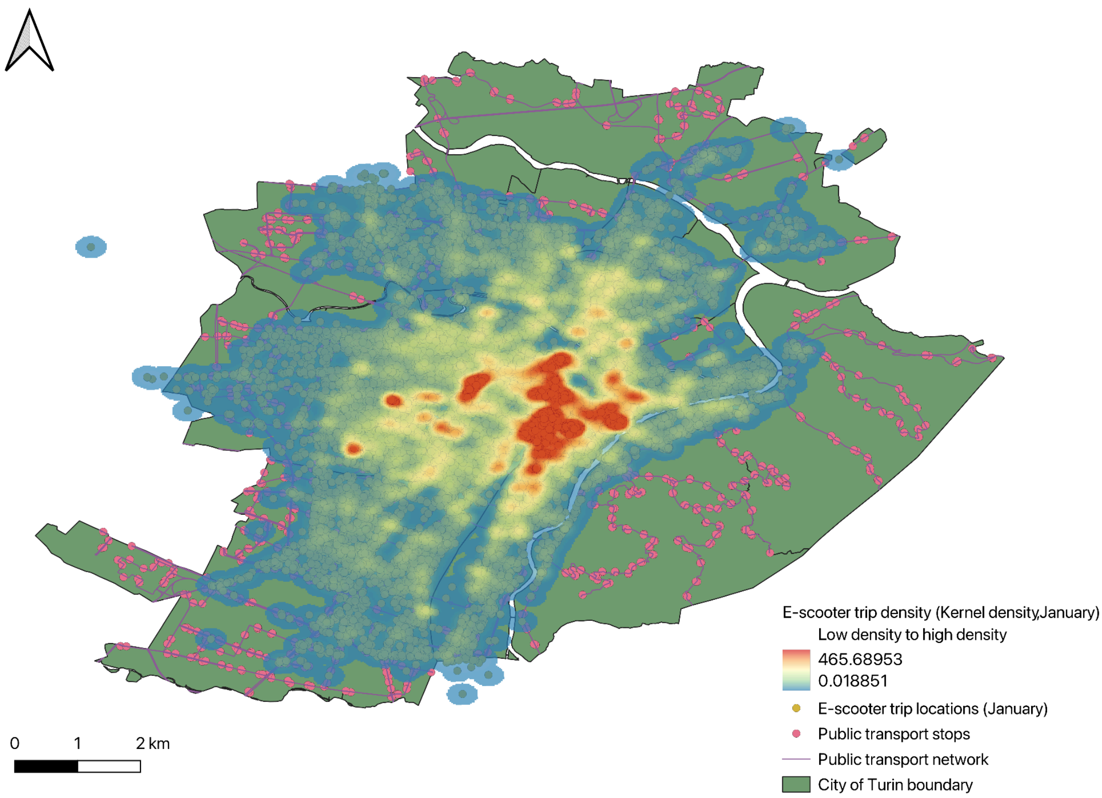


Figure 18 Kernel density map of e-scooter trips in January in Torino, overlaid with the public transport network and stops.

E-scooter usage shows a high degree of spatial overlap with public transport. This overlap indicates the presence of potential travel competition between the two modes in the urban core, particularly for short distance and time sensitive trips.

However, from a spatial perspective, high density e-scooter usage does not diverge from the public transport network, but remains closely anchored to areas with the highest public transport supply. This pattern is stable across seasons. This suggests that e-scooters do not constitute a systematic spatial substitute for public transport, but instead operate within a mixed relationship combining elements of both competition and adduction.

4. Exercise 4 parking duration

4.1 Indicator Definition and calculate method

This exercise calculates the average parking duration of e-scooters across different zones of the City of Torino at the scale of official administrative districts (district zoning), and visualizes its spatial variation using maps.

Specifically：

- For each e-scooter trip, the origin and destination coordinates are spatially matched to their corresponding districts (Origin / Destination zone).
- Using the destination zone as the statistical unit, the parking duration of vehicles within each zone is calculated (in minutes; either mean or median can be adopted, this figure represents zone-level parking duration).
- To capture temporal variations, the dataset is divided into three time periods: Morning peak (07–10), Midday (11–15), and Evening peak (16–19).
- For each time period, zone-level parking duration is displayed using choropleth mapping, and the O–D flow structure of the same period (represented by major O–D pairs / high-volume O–D links) is overlaid, enabling a joint visualization of “parking–flow” patterns.

4.2 Main spatial characteristics

From the three choropleth maps, the following observations can be directly made:

- Parking duration exhibits clear spatial inequality: peripheral districts generally display darker colors, while central districts show lighter colors, indicating longer parking durations in peripheral areas and shorter parking durations in the city center.
- This pattern is observable across all three time periods, suggesting that the spatial structure of “high turnover in the core area and low turnover / long parking in peripheral areas” is relatively stable.

Transport implication: the city center functions more as a "high-frequency use–fast turnover" service area, while peripheral zones function more as "low-frequency use–long parking" areas.

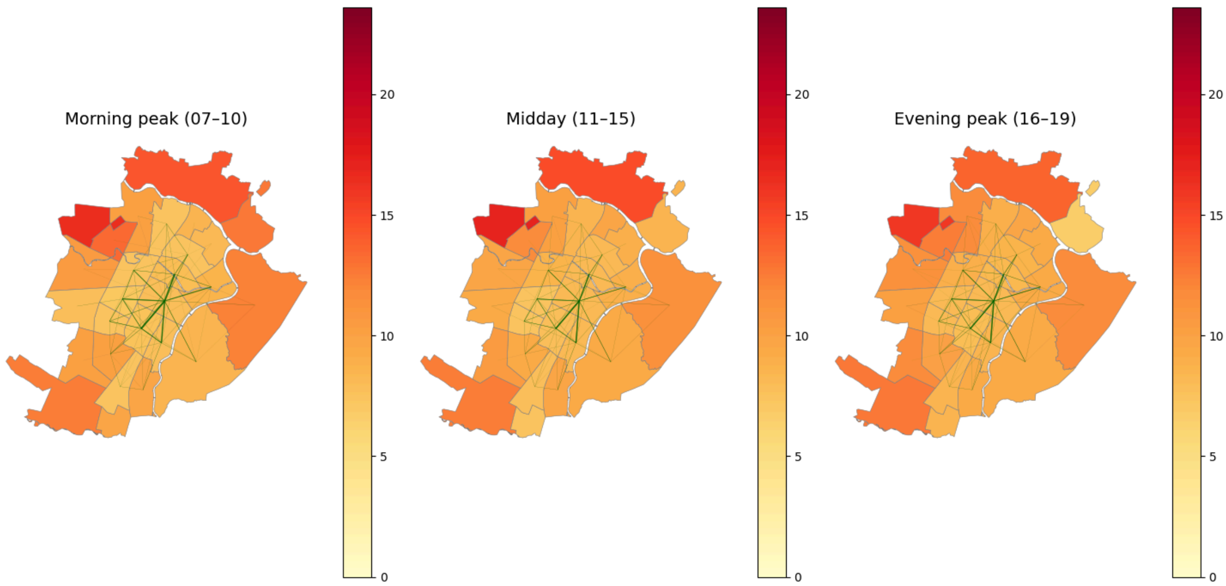


Figure 20 *Average parking duration by district and overlaid high-intensity O–D flows during different periods of the day .The choropleth maps represent zone-level average parking duration, while only high-volume O–D flows are displayed to highlight the dominant movement structure.*

After overlaying O–D links on the parking duration base maps, the patterns become clearer:

- Across all three time periods, O–D flows are mainly concentrated in the central city and adjacent districts (dense links and compact structure), while peripheral areas exhibit fewer O–D connections.
- At the same time, core areas with dense O–D flows generally correspond to lighter parking colors, reflecting a combination of "strong flows–short parking," whereas peripheral areas more often show "weak flows–long parking."

By time period:

- Morning peak(07–10): the O–D structure shows the strongest "commuting-oriented" concentration (more prominent connections involving the city center), while parking duration in the core area is relatively short, consistent with efficiency-oriented usage during peak hours.
- Midday (11–15): O–D flows remain concentrated in the center, but overall usage shifts toward more "daytime activity–oriented" patterns; parking duration increases slightly in some areas, possibly reflecting longer stops associated with errands, consumption, or visits.
- Evening peak (16–19): the concentrated O–D structure persists, with the core area still characterized by relatively short parking durations; peripheral zones continue to exhibit longer parking durations, indicating that vehicles are more likely to accumulate in peripheral areas after the evening peak.

Based on the combined visualization results across the three time periods, e-scooter trips in Torino exhibit a stable core–periphery structure. The city center accommodates the majority of inter-zonal flows and high-turnover usage (dense O–D connections and short parking durations), while peripheral areas are characterized by lower flow intensity and longer parking durations (sparse O–D connections and long parking). This coupling between "high flow–short parking" and "low flow–long parking" indicates that the e-scooter system spatially reflects both commuting / high-frequency short-trip functions in the urban core and peripheral accumulation patterns that may require operational rebalancing.

5. Exercise 5 Business model & profitability

5.1 Preliminary note:reference to financial statements and analytical assumptions

As micro-mobility companies do not disclose detailed financial data at the city level, and in particular do not provide revenue and cost information for the City of Torino, this exercise adopts a combined approach based on "calculable components + financial statement based assumptions" to conduct a structural analysis of the financial performance of the three e-scooter operators.

With regard to cost structure assumptions, this study refers to the **Bird Global 2022 annual financial report** as the main reference for the e-scooter sharing business, for the following reasons:

- Bird's core business is dockless e-scooter sharing, and its cost structure is highly consistent with the operators analyzed in this study;
- The financial report provides a relatively clear distinction between fixed costs (capital expenditures) and variable costs (operational expenses);
- Compared to multi-modal mobility platforms, Bird's financial data more accurately reflect the operational characteristics of a single e-scooter business.

It should be clearly stated that this study does not attempt to replicate Bird's absolute cost levels. Instead, only the cost composition ratios disclosed in the financial report are used as a reasonable reference for formulating assumptions about e-scooter operations in Torino.

5.2 Scope of financial calculation and research limitations

Based on data availability, the financial analysis in this study is explicitly divided into two categories:

- Directly calculable components:
  Ride-based revenues are calculated for the three operators using trip-level data and publicly available tariffs.
- Components that cannot be directly calculated but must be discussed:
  - ❖ Revenues include non-ride income such as unused breakage minutes, subscription packages, and product sales;

❖ Costs include fixed costs such as depreciation, administration, software platforms, and licensing, as well as variable costs such as operations, insurance, and marketing.
These components can only be structurally inferred using cost proportions derived from financial statements.

This classification helps avoid over interpretation of missing data while maintaining transparency in the analytical logic.

5.3 Revenue calculation method and result (calculable component)

Selection of the time window:
To ensure comparability across operators, this study selects the common time window during which data from all three operators are available, and on this basis estimates their equivalent annual ride revenue.
This approach avoids systematic bias caused by differences in market entry and exit timing across operators.

Revenue calculation logic:

- The ride duration (in minutes) of each e-scooter trip;
- The pricing rules are publicly disclosed on each operator's official website (unlock fee + per-minute fee);
- The assumption that all trips are regular paid rides, without considering promotions, coupons, or subscription discounts.

Based on these assumptions, the total ride revenue of each operator within the common time window is calculated and then annualized.

Result:

Operator	Unlock fee	Riding fee/minute	Trips	Travel duration (minute)	Revenue
A (Lime)	1€	0.28€	1,421,381	14,856,750	**5,582,715€**
B (Voi)	1€	0.24€	285,453	2,592,376	919,405€
C (Bird)	1€	0.26€	857,957	11,830,770	3,933,622€

Table 2 Trips, travel duration, and ride-based revenue by e-scooter operator

- Under the same pricing structure, Operator A (Lime) generates significantly higher annual riding revenue than Operators B and C, reflecting its clear advantage in both trip volume and usage intensity.
- In contrast, Operator B (Voi) shows a markedly lower revenue level, indicating substantially weaker market penetration and/or lower per-vehicle utilization efficiency compared with the other two operators.

5.4 Methods for inferring partial revenue and cost structures (parts that cannot be directly calculated)

Note: The table below is for structural inference and not for absolute monetary calculation. The proportions are based on Bird Global's 2022 Annual Report.

Revenue streams

Revenue category	Content	Directly quantifiable	Notes
Ride revenue	A (Lime) **5,582,715€**	yes	Calculated in this study using trip-level data and public tariffs
	B (Voi) 919,405€		
	C (Bird) 3,933,622€		
Subscription / Passes / Promotions	Monthly passes, bundles, discounts	No	City-level subscription usage data are unavailable
Breakage(unused minutes)	Prepaid but unused riding minutes	No	Considered implicit revenue, usually aggregated in financial reports
Subtotal : Sharing revenue contribution	≈ 94.6%		
Products sales		No	Typically marginal at the city level
Subtotal : Sales revenue contribution	≈ 5.4%		

Table 3 Breakdown of e-scooter revenue streams

Fixed/Capital cost

Cost item	Content	City-level interpretation
Depreciation	Vehicle purchase and renewal	Largest cost item; new vehicle purchases included
Asset impairment		
Proprietary hardware		largely amortized across cities
Permits&partnerships	City permits and cooperation agreements	
Subtotal : Fixed cost		≈ 24-30%

Table 4 Breakdown of e-scooter fixed/capital cost

Variable cost

Cost item	Content	City-level interpretation
Charging and battery swapping	Electricity and operational labor	

Maintenance and repairs		
Fleet managers share	Local operators or contractors	
Cleaning and deployment	Cleaning and vehicle repositioning	
Subtotal：Variable cost		≈ 43-45% Strongly linked to ride volume and local operations

Table 5 Breakdown of e-scooter variable cost

Operating expenses include administrative expenses, marketing expenses, and research and development (R&D). According to the financial report, these expenses account for approximately 20.7% of total costs. However, these expenditures are typically incurred at the headquarters level and are therefore diluted when allocated to the city level.

All non-directly quantifiable revenue and cost items are used solely to identify key drivers and relative structural differences.

5.5.Profitability Assessment under Cost Structure Constraints

Under the cost structure assumptions informed by publicly available financial disclosures and industry-level evidence, the operating results of the three e-scooter operators can be assessed as follows.

First, ride revenues are sufficient to cover variable costs, but are not enough to guarantee overall profitability.

According to the financial disclosures, Ride Profit (before vehicle depreciation) is approximately 49–55%. This indicator can be interpreted as an operating gross margin at the single-ride level, reflecting the direct profitability generated by each ride when vehicle depreciation and other fixed costs are excluded. This proportion indicates that, without considering vehicle depreciation, the revenue from a single ride is generally sufficient to cover major variable costs such as electricity, routine maintenance, charging and rebalancing operations, and Fleet Manager revenue sharing. Therefore, at the ride level, shared e-scooter services exhibit a positive cash contribution.

Second, vehicle depreciation represents the core constraint on profitability.

Once vehicle depreciation is included, the Gross Margin declines to approximately 15–19%, indicating that vehicle acquisition and depreciation amortization constitute the most significant source of fixed costs. At the city scale, these costs are difficult to reduce in line with short-term changes in ride volume, thereby exerting persistent pressure on profitability.

Third, there is clear differentiation in profitability potential across operators.Under identical pricing schemes and similar cost structure assumptions:

- Operator A’s annual ride revenue is significantly higher than that of B and C, providing greater capacity to amortize fixed costs such as depreciation and permits after covering variable costs, and therefore a higher likelihood of reaching break-even;
- Operator B’s revenue scale is substantially lower, while fixed costs remain rigid, making its operating results more susceptible to being constrained by depreciation and operating expenses, and thus more likely to remain in a loss-making or low-profit state;
- Operator C lies between the two, with its profit or loss outcome highly dependent on operational efficiency, fleet lifespan management, and fixed cost control.

Fourth, even under conditions of rapid revenue growth, overall losses may persist.
Bird’s financial statements show that despite year-on-year revenue growth exceeding 100%, the company as a whole remained in a net loss position. This outcome is primarily driven by operating expenses beyond depreciation, including insurance, city permit fees, management, and platform costs. This result demonstrates that scale expansion alone is insufficient to ensure profitability; fixed costs and operating expenses are the key determinants of long-term sustainability.