Analysis of Shared Electric Scooter Mobility Services in Turin, Italy

Study Period: January 2024 - November 2025

- Lime: January 2024 - April 2025
- Bird: January 2024 - November 2025
- Voi: January 2024 - October 2025

Research Institution: Politecnico di Torino, Department DIST

Course: Transport Innovation for a Sustainable, Inclusive and Smart Mobility

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Summary:

This report presents a comprehensive empirical analysis of shared electric scooter (e-scooter) mobility services operating in Turin, Italy, covering the complete calendar year 2024 and partial data from 2023 (causing some visible data variations). The study examines five integrated research exercises following Professor Pronello's exercise framework: (1) data quality assessment and descriptive characteristics, (2) origin-destination (OD) pattern analysis, (3) public transport integration assessment, (4) parking duration dynamics, and (5) business model viability through revenue and cost analysis.

Using data from Lime, Voi, and Bird operators, this analysis processed 2,774,313 initial trip records, of which 2,337,009 trips (84.3%) were retained after rigorous data cleaning. The study reveals distinct seasoned demand patterns, concentrated spatial demand in Turin's city centre, significant overlap with public transport infrastructure, and highly variable profitability across operators (note that economic calculations were based on assumptions). Key findings demonstrate that Lime achieves a 79.66% profit margin, Bird achieves 72.49%, while Voi operates at 19.73% profitability.

1. Introduction and Research Framework

1.1 Background on Shared Micromobility in Turin

Shared electric scooter services represent a rapidly growing segment of urban micromobility systems in European cities (Papas et al., 2023). Turin's e-scooter market, characterized by competition among multiple international operators, provides an excellent empirical case study for understanding service utilization patterns, operational efficiency, and business model viability in an Italian metropolitan context. The city's public transport infrastructure, combined with four e-scooter providers (in this study we analyse three of them), creates an opportunity for studying both competitive dynamics and potential multimodal integration.

1.2 Research Objectives and Exercise Framework

This analysis addresses five integrated research questions as established in the exercise structure:

Exercise 1) Data quality and Descriptive analysis: What is the extent, quality, and temporal/spatial distribution of e-scooter trip data in Turin across operators over time?

Exercise 2) Origin-Destination Matrices: Where are trips concentrated spatially, and how do demand patterns vary between peak and non-peak periods?

Exercise 3) Public Transport Integration: DO e-scooter services compete with or complement Turin's public transport network?

Exercise 4) Parking Duration Analysis: How do vehicle dwell times and spatial distribution patterns inform operational management and rebalancing strategies?

Exercise 5) Business Model Economics: What revenue streams and cost structures characterize operator profitability and long-term sustainability?

2. Exercise 1: Data Quality Assessment and Descriptive Analysis

2.1 Data Collection and Normalization Methodology

The analysis integrated trip data from three operators (Lime, Voi, Bird) provided by Professor Pronello. Each operator maintained different data formats and column naming conventions, requiring standardized data structuring prior analysis. The Python script (unione.py) implemented a normalization function that mapped operator-specific column names to standardized fields, handling heterogeneous data structures through conditional renaming logic.

Data Fields Standardized:

- Trip identifiers and vehicle IDs
- Temporal fields: start and end times (with operators-specific datetime formats)
- Spatial Fields: origin and destination coordinates (latitude/longitude)
- Trip characteristics: distance (km), duration (minutes)
- Vehicle status: battery levels (when available), reservation status
- Operator identifier

2.2 Data Cleaning and Quality Assessment Results

2.2.1 Initial Dataset Characteristics

Total initial records: 2,774,313 trips
Study period: January 2024 - November 2025 (23 months)
Operators: Lime, Voi, Bird (Dott excluded - data not provided)

2.2.2 Data Quality issues identified and cleaned

The analysis systematically removed records violating data quality criteria:

Data Quality Issue	Records Removed	Cumulative Removed
Missing essential values (ID_VEICOLO, DATAORA_INIZIO, DATAORA_FINE)	0	0
Temporal inconsistencies (End Time < Start Time)	7,279	7,279

Unrealistic speeds (<2 km/h or >25 km/h)	225,389	232,668
Out-of-bounds locations (outside Turin area, lat 44.9–45.1, lon 7.5–7.8)	130,249	362,917
Exact duplicate records	57,351	437,261
Final valid records	2,337,009	84.3% retention

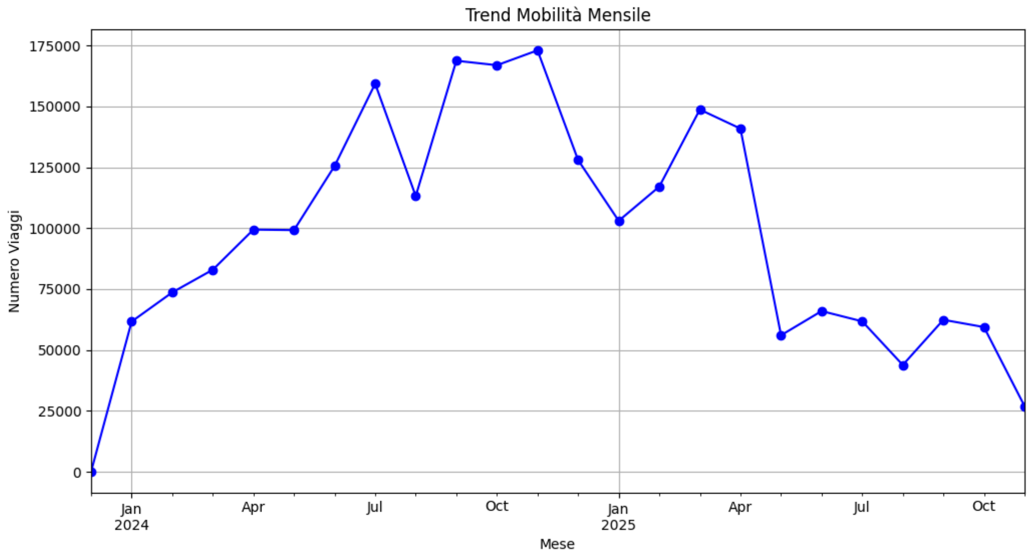
- Temporal inconsistencies: Records where trip end time preceded start time indicate data entry or transmission errors and were excluded.
- Unrealistic speeds: Speed filtering between 2-25 km/h reflects both technical constraints (minimum device operation velocity to register GPS) and legal speed limits for e-scooters. Speeds <2 Km/h may represent stationary vehicles miscategorized as trips or GPS noise; speeds >25 Km/h violate Turin's regulations and likely indicate GPS coordinate errors or data corruption.
- Spatial filtering: The bounding box (latitude 44.9–45.1°N, longitude 7.5–7.8°E) encompasses Turin's administrative boundaries. Records with coordinates outside this box represent either data errors or trips extending beyond the service area.
- Duplicate removal: Exact duplicates (identical across all fields) suggest database replication errors during data export.

2.3 Mobility Trends Analysis: Temporal patterns

2.3.1 Annual Trend:

It is not useful for the research to analyze the annual trend because we do not have a big dataset over the years, so we cannot see a difference and find patterns between years.

2.3.2 Monthly Trends

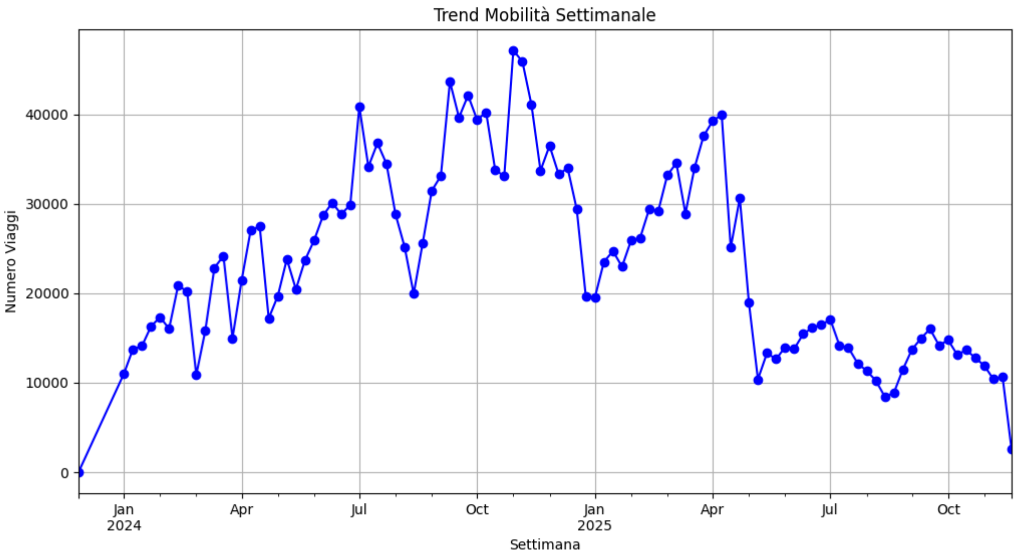


Important note: Lime data (56% of the whole dataset) ends in April 2025, so the drop on the graph in that month is due to this problem and not related to circulation problems or external ones.
Seasonal patterns identified:

- Peak demand months: Summer and fall (July-November) showed highest utilization with an interesting drop in August.
- Off-season: Winter and early Spring showed a declination, from 175000 trips in November 2024 to 100000 in January.

Seasonal demand variation reflects weather patterns (reduced use in cold months), tourism cycles (higher summer demand), and academic calendars affecting local student mobility (August). These patterns are consistent with European e-scooter research documenting similar seasonal effects (Tilahun et al., 2022).

2.3.3 Weekly Trends



Weekly patterns:
- Relatively consistent weekly fluctuations with average weekly trips ranging 10,000-45,000
- Notable volatility during transition periods (summer to fall, fall to winter)
- Sharp demand drop in colder months.

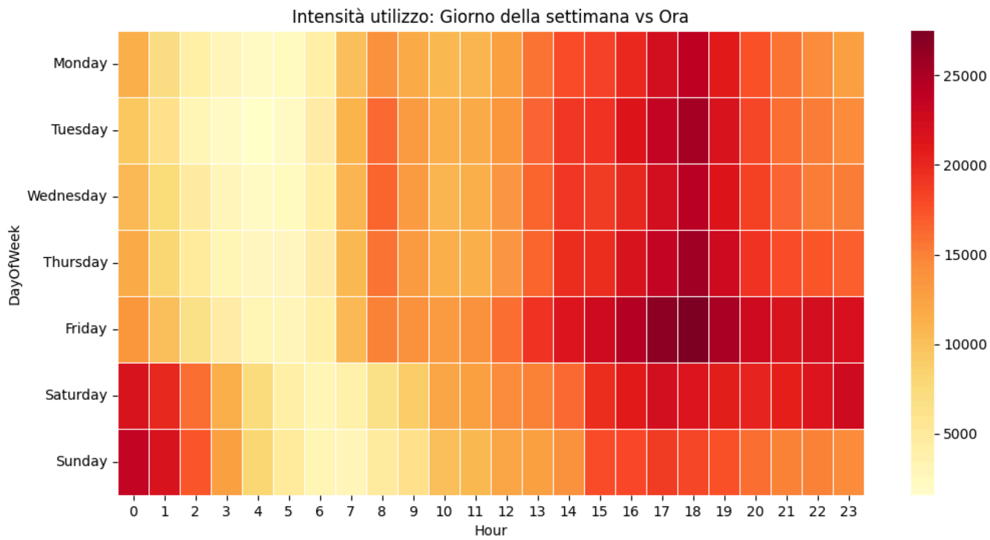
2.4 Vehicle Fleet and Utilization Analysis

2.4.1 Unique Vehicle Deployment by Operator

Operator	Unique Vehicles Deployed	Trips per Vehicle (Average)	Market Share (Trip Count)
Lime	2,399	563 trips/vehicle	57.8% (1,350,338 trips)
Bird	2,817	278 trips/vehicle	33.5% (783,551 trips)
Voi	1,436	142 trips/vehicle	8.7% (203,120 trips)
Total	6,652 vehicles	351 trips/vehicle (avg)	2,337,009 trips

Lime operates the most efficiently in terms of vehicle utilization. The 563 trips per vehicle (Lime) vs. 278 (Bird) and 142 (Voi) suggests significant efficiency differences. Lime's higher utilization rate may reflect superior fleet management, better vehicle placement, or stronger demand capture in this market.

2.4.2 Vehicle Utilization Intensity Distribution



- Peak hours: Consistent afternoon peaks (15-19) across all operators.
- Morning commute: Secondary peak around 8:00.
- Off-peak periods: Late night (23-6) shows minimal utilization.
- Weekday patterns: Relatively consistent across the week.
- Weekend patterns: The movement changes towards late-night hours (19-2).

2.5 Exercise 1 Summary

The cleaned dataset of 2,337,009 valid trips provides robust empirical foundation for subsequent analysis. After removing 437,261 problematic records (15.7% of initial data), the retained data demonstrate:

1. Quality: Systematic data cleaning procedures eliminated records violating temporal, spatial, and physical constraints
2. Scale: Analysis encompasses multi-operator data across 23 months, enabling temporal and comparative analysis
3. Seasonality: Clear seasonal demand variation.
4. Operator differences: Substantial disparities in fleet efficiency (3.9x difference between Lime and VOI in trips/vehicle)
5. Temporal patterns: Daily and hourly demand concentration supports targeted operational management

3. Exercise 2: Origin-Destination Matrix Analysis

3.1 Zoning System and OD Matrix Methodology

3.1.1 Zone Definition

The analysis employed 94 administrative census zones (zone_statistiche, Geoportale) of the City of Turin as the spatial unit for OD analysis. This choice balanced analytical granulartìity with computational tractability:

- 94 zones provide sufficient spatial detail to identify neighborhood-level demand patterns
- Zone-level analysis avoids excessive computational burden compared to grid-based approaches
- Administrative zones align with urban planning frameworks, facilitating policy interpretation
- Census zones include socioeconomic data enabling interpretation of mobility patterns

3.1.2 Spatial Assignment and Matrix Construction

The Python script ex2.py implemented spatial assignment through geometric operations:

1. Coordinate mapping: Each GPS coordinate (latitude, longitude) from trip origin and destination was mapped to its corresponding census zone using spatial join operations
2. Zone assignment validation:
    - Trips with origins in zone 2,324,002
    - Trips with destination in zone 2,314,758
    - Trips with both origin and destination within zones 2,305,706 (calid intrazonal and interzonal trips)
3. OD matrix construction: For each origin zone O and destination zone D, the OD matrix element OD[O,D] represents the count of trips from O to D over the analysis period

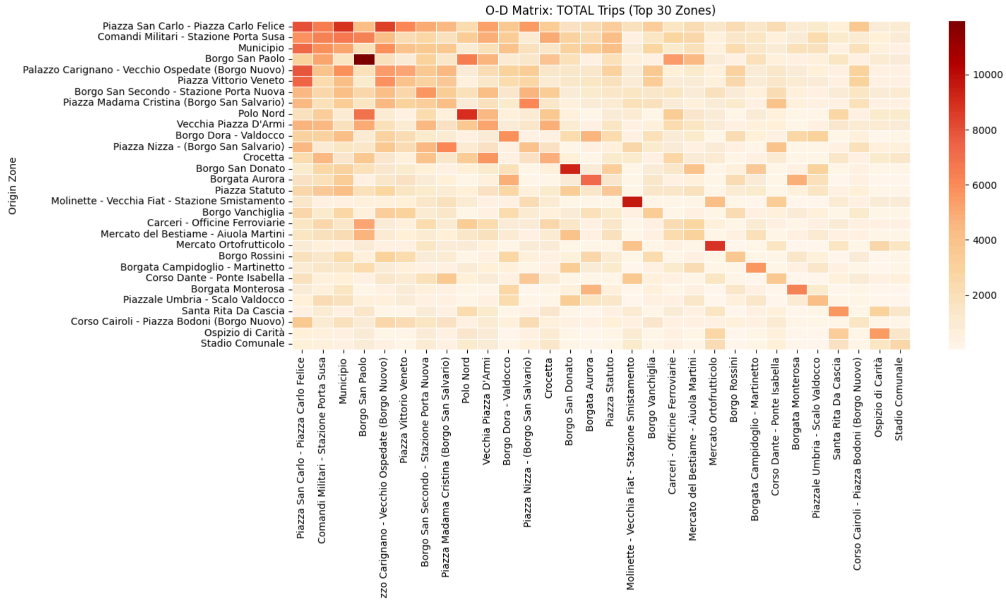
Matrix dimensions: 94 x 94 zones = 8,836 potential origin-destination pairs

3.1.2 Temporal Disaggregation Strategy

To capture demand variation throughout the day, separate OD matrices were constructed for:

- Peak hours: 8:00-9:00 and 15:00-19:00, capturing morning and afternoon commuting
- Non-peak hours: All other hours
- All-day aggregate: Complete OD matrices across all hours

3.2 Overall OD Pattern Visualization

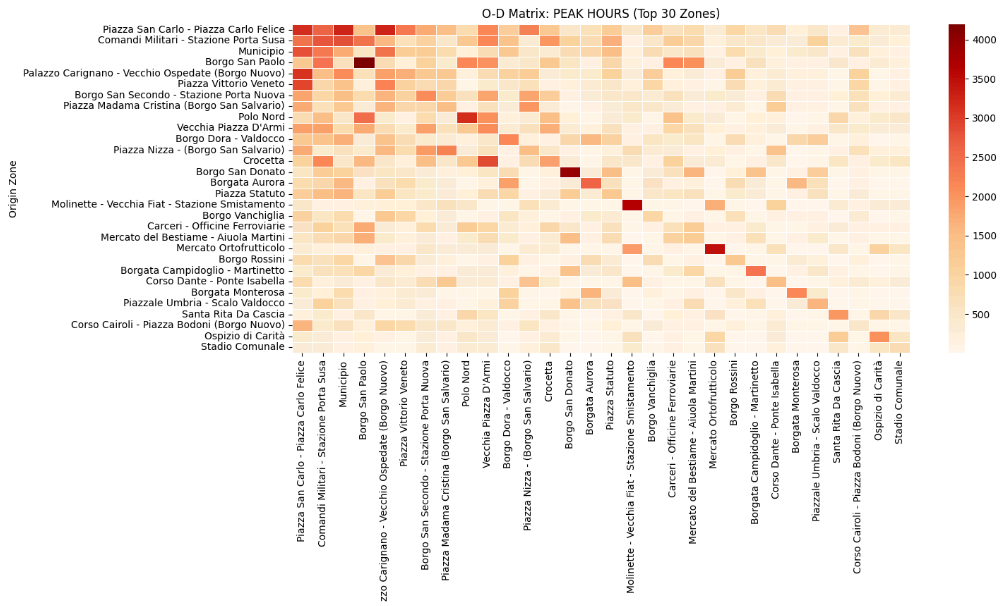


Key spatial patterns:

- City centre concentration: Diagonal and nearby matrix elements show highest values, indicating substantial intrazonal trips and movement between adjacent central zones
- Suburban-to-centre flows: Strong intensity in columns representing central zones, indicating trip destinations concentrate in downtown areas
- Return flows: Asymmetric patterns suggesting directional commuting and leisure patterns
- Peripheral zones: Lower matrix intensity for zones representing peripheral areas, indicating limited circulation at city edges

3.3 Peak vs Non-Peak OD Patterns

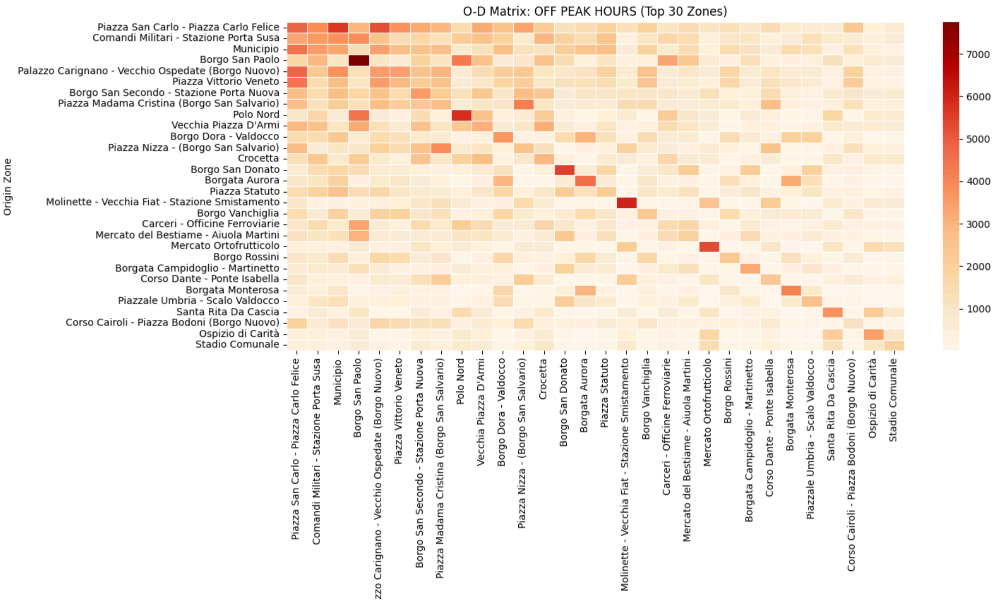
3.3.1 Peak Hour OD Matrix



Peak hour characteristics:

- Spatial concentration: Even more concentrated than all-day pattern, with highest demand corridors becoming more pronounced
- City centre dominance: Downtown zones serve as both major origins and destinations
- Commuting patterns: Some evidence of directional flows suggesting work-end/start commuting

3.3.2 Non-Peak OD Matrix

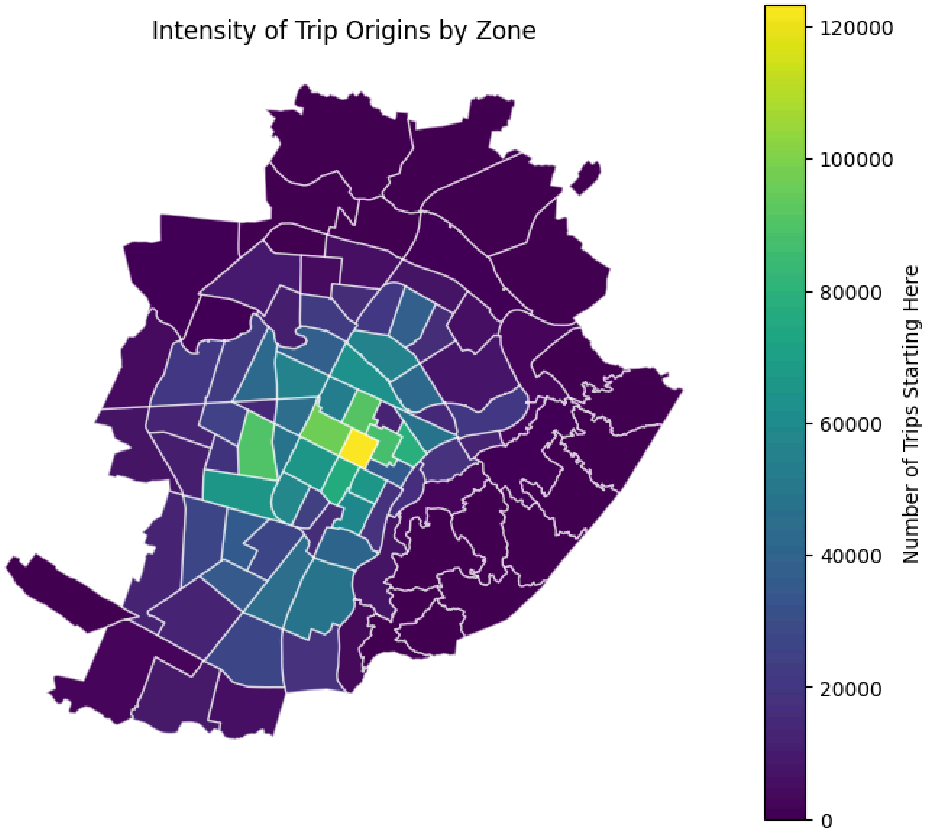


Non-peak characteristics:

- Geographic dispersion: Demand spreads more evenly across zones, including peripheral areas
- Secondary centres: Tourism-related destinations
- Long-distance trips: Proportion of trips connecting distance zones increases in non-peak periods
- Operational implications: Rebalancing strategies should target different zones in peak vs. non-peak periods

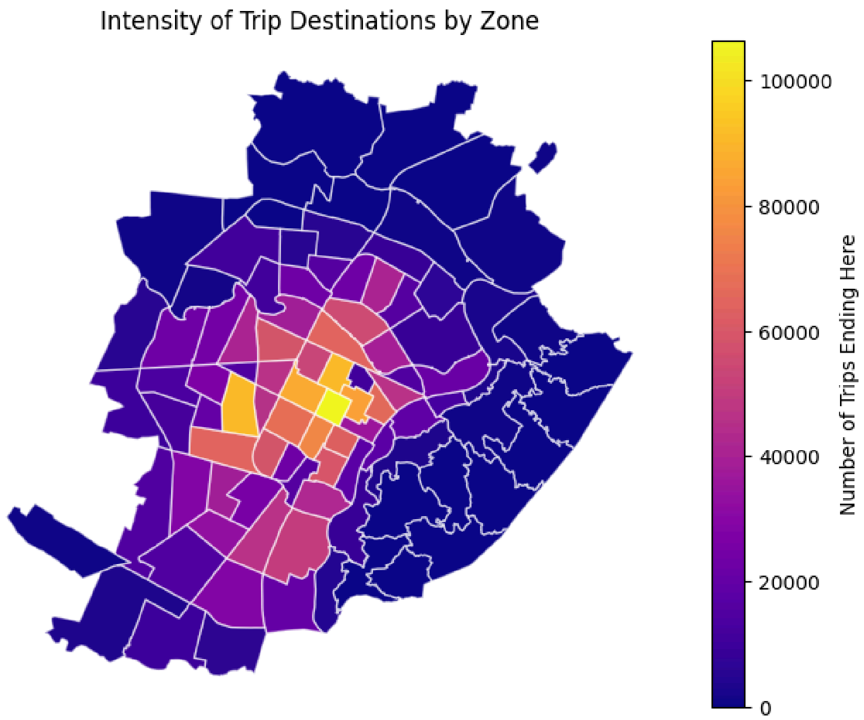
3.4 Spatial Visualization: OD Flows on Turin City Map

3.4.1 Overall OD Flows Geographic Representation



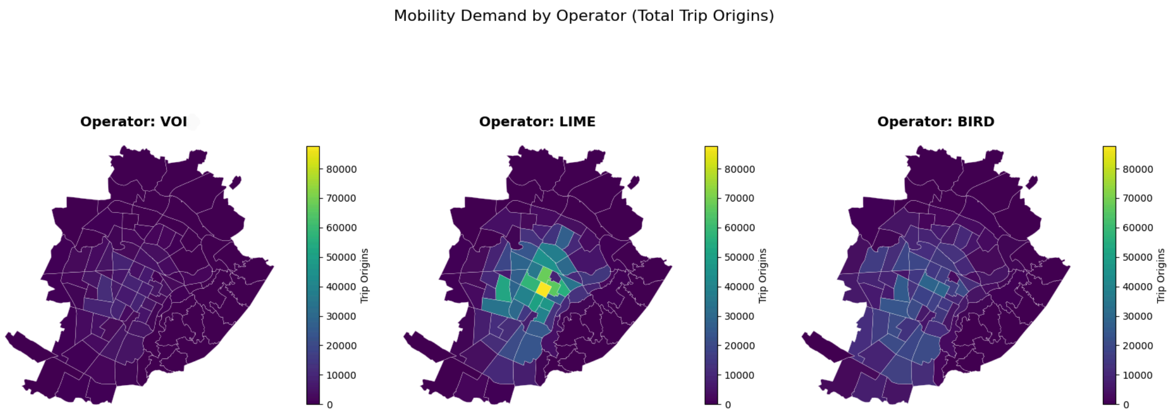
Origins spatial pattern:

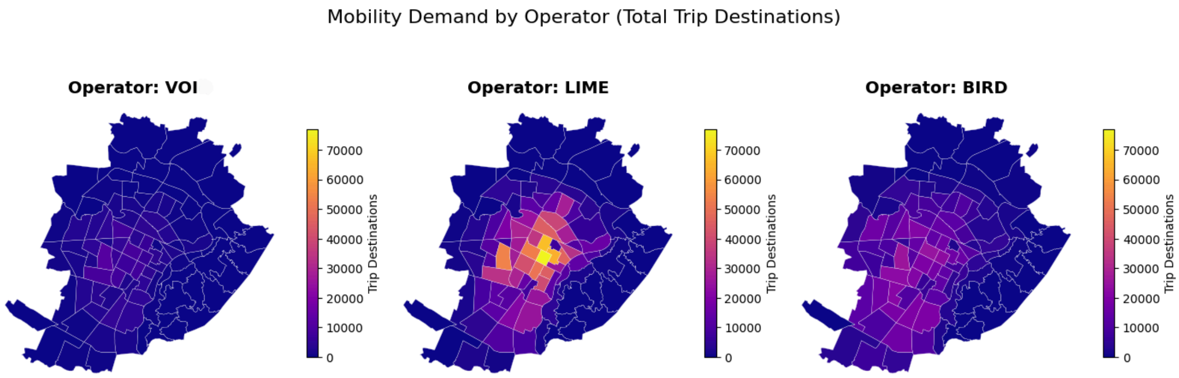
- Downtown and adjacent zones show high origin intensity
- Suburban rings show progressively less intensity
- Interpretation: E-scooter trips initiate predominantly from central urban areas



Destinations spatial pattern:

- Similar concentration pattern to origins, with downtown dominating
- Specific destination hot spots identifiable (like transit stations, shopping areas, leisure venues)





Confronting these maps we can see how LIME is dominant in Turin's market and dominates the central zones while the other two operators have lower number of trips and a more distributed pattern.

3.5 Exercise 2 Summary

OD matrix analysis reveals:

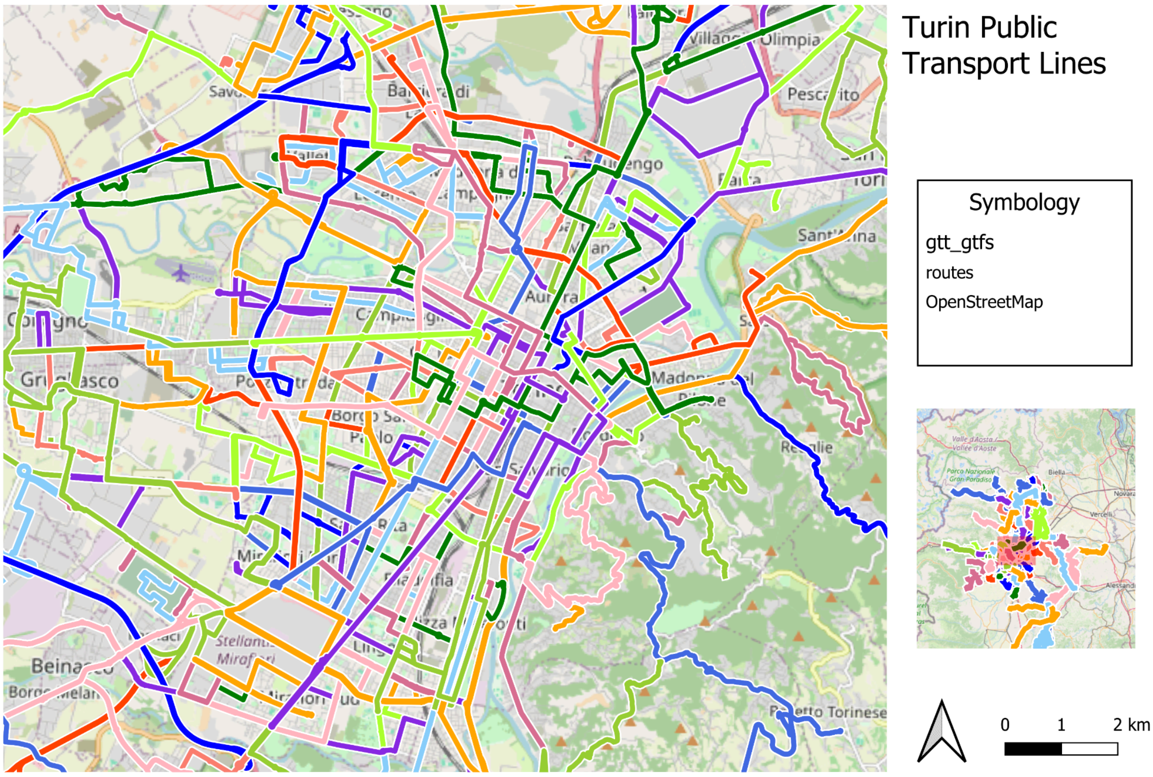
1. Concentrated demand: Trip demand concentrates overwhelmingly in Turin's city centre and adjacent zones
2. Temporal variation: Peak periods show more concentrated demand; non-peak periods show geographic dispersal
3. Operator dominance: Different operators show varying spatial coverage patterns.

4. Exercise 3: Public Transport Integration and Competition

4.1 Public Transport Network Data

The analysis integrated TUrin’s public transport network data from the GTT (Gruppo Torinese Transporti) GTFS (General Transit Feed Specification) dataset, including:

- Bus network: Complete route geometry, stop locations, headways
- Tram network: Fixed-route with defined service areas



Data source: Official GTFS data accessed via Geoportale

4.2 Representative Day Analysis

Following FHWA methodology for identifying typical days, the analysis selected one representative day per month (Tuesday, Wednesday, or Thursday with trip counts closest to monthly average)

Representative Days Identified (12 months on the entire dataset - 23 months)

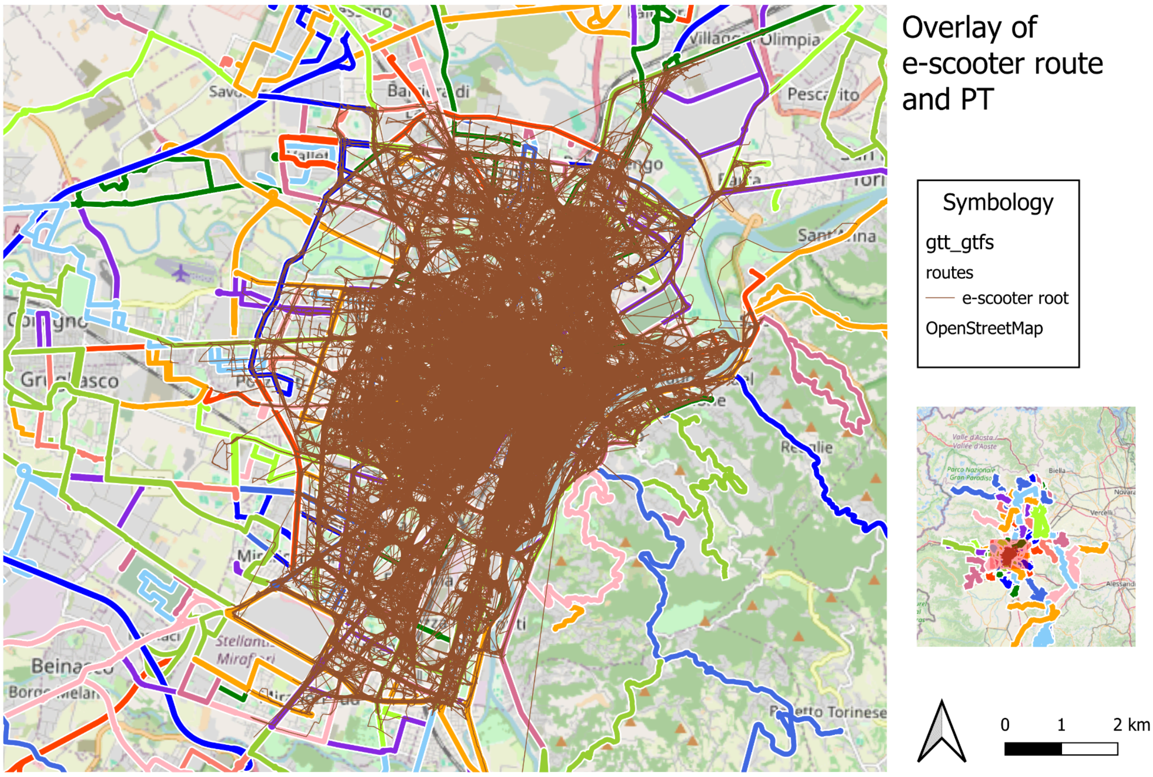
Month	Representative Day	Trip Count (Selected Day)	Monthly Average	Difference

January	2025-01-22	2,312	2,217	+95
February	2024-02-20	2,297	2,604	+307
March	2024-03-21	2,683	3,135	+452
April	2024-04-17	2,945	3,093	+148
May	2024-05-16	2,027	2,241	+214
June	2024-06-05	3,354	3,335	+19
July	2024-07-10	4,249	4,181	+68
August	2024-08-20	2,990	2,989	+1
September	2024-09-12	4,195	4,316	+121
October	2024-10-09	4,492	4,241	+251
November	2024-11-06	4,299	4,352	+53
December	2024-12-19	3,448	3,333	+115

Methodology rationale: Representative days minimize weekend and special-event anomalies while capturing typical weekday travel behaviour. This approach supports robust policy analysis grounded in average conditions rather than exceptional demand peaks.

4.3 Spatial Overlap Analysis: E-Scooter and Public Transport

4.2.1 Methodology for Competition Assessment



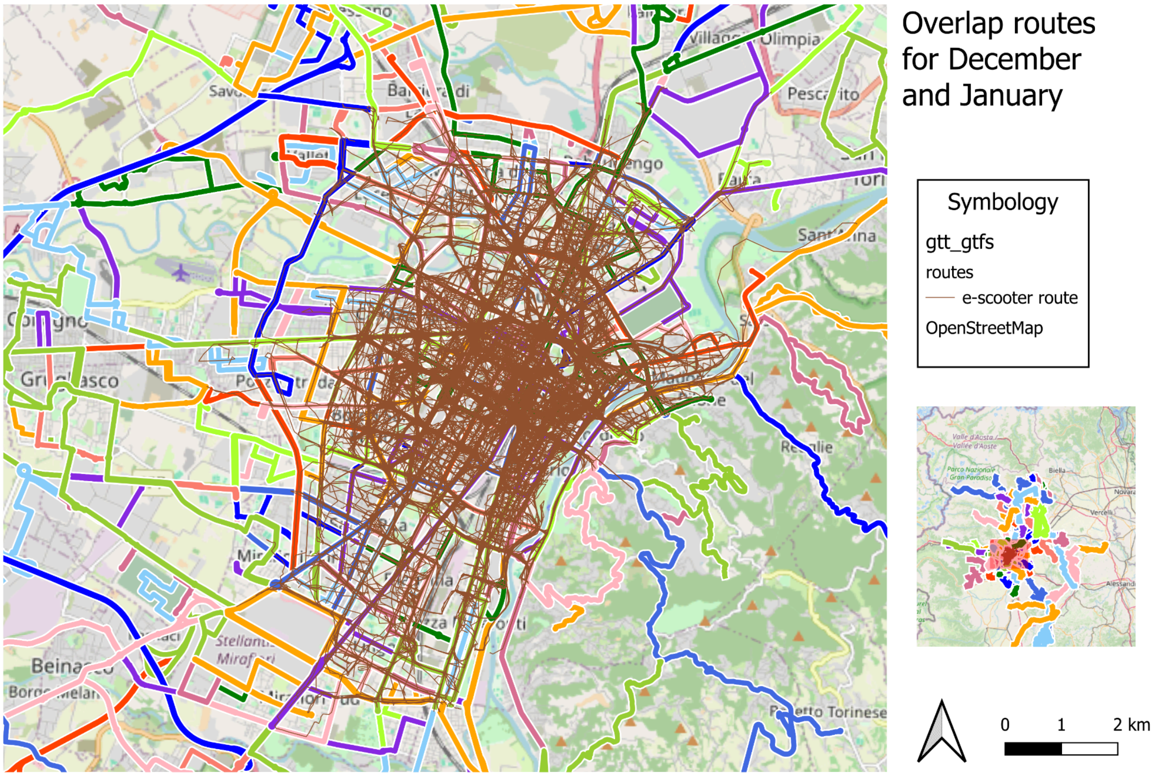
The analysis overlay e-scooter flows with public transport routes using geometric intersection operations.
E-scooter trip classification:

- Competitive trips: Routes within transit zones of same routes.
- Complementary trips: One endpoint or start point within transit zone.
- Independent trips: Routes not in transit zones.

4.2.2 Seasonal Variation Overlap

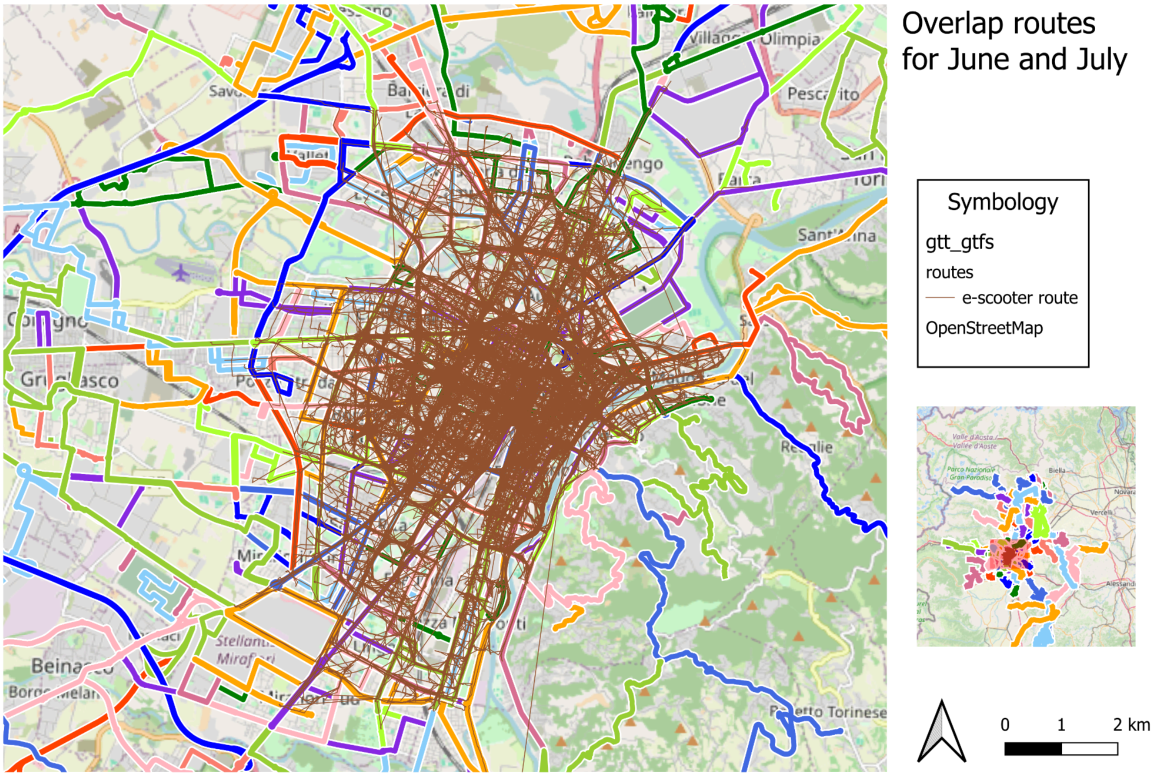
The analysis examined overlap patterns across two contrasting seasons:

Winter pattern characteristics:



- Winter coincides with a lower demand and number of trips
- Trips are more concentrated in the central zone

Summer pattern characteristics:



- Summer peaks coincides with higher temperatures
- Higher tourism mobility

4.4 Competitive and Complementary Relantionships

4.3.1 Quantitative Competition Metrics

Metric	Value	Interpretation
Total e-scooter trips analyzed	2,305,706	Valid intrazonal + interzonal trips
Trips with origins in transit zones	2,334,722	99% of trips originating near transit
Trips with destinations in transit zones	2,333,811	99% of trips terminating near transit

Trips with both endpoints in transit zones	2,331,602	Potential competitive overlap
Complementary trip pattern (one endpoint transit)	5,329	First-mile/last-mile potential

4.3.2 Route-Specific Competition Analysis

The analysis focused on Lime data (the majority operator representing 57.8% of total trips) for detailed route analysis because it was the only one provided with route values. This approach is also justified as Lime's patterns are representative of overall market behaviour while simplifying geometric calculations across multiple operators.

Key findings:
- Spatial overlap occurs but must be contextualized trough user demographics
- E-scooter users are predominantly young males (Jinghai Huo et al., 2021)(Kostas Mouratidis, 2022), suggesting different travel behaviour than general transit population
- Overlap does not automatically imply modal competition; user preferences and trip purposes differ substantially between e-scooter and transit riders

4.5 Integration Recomendations for Turin

4.4.1 Areas for Coordinated Planning

Zones showing high competitive overlap should be targets for policy coordination:
1. Downtown commercial districts: High volume of both transit and e-scooter activity; potential for congestion; opportunity for integrated fare policies
2. Major tranist corridors: Significant spatial alignment; potential for service rationalization or complementary positioning
3. Peripheral zones with limited transit: E-scooter utilization; opportunity for treating e-scooters as transit complementation

4.4.2 First-Mile/Last-Mile Integration Opportunities

Zones identified with complementary patterns (one trip endpoint outside transit accessibility) represent opportunitues for formal integration:
- Transit station areas: Strategic e-scooter parking near major transit nodes
- Residential neighborhoods: E-scooter access to transit from areas with limited direct service
- Regional rail connections: E-scooter extending metro/tram reach to regional rail stations

4.6 Exercise 3 Summary

Key conclusions:

1. Spatial overlap with transit exists but does not automatically indicate competition
2. User demographic differences (young males for e-scooters vs. general population for transit) suggests different travel purposes
3. Policy coordination should enphasize integration rather than competition mitigation

5. Exercise 4: Parking Duration and Vehicle Management

5.1 Parking Duration Calculation and Methodology

5.1.1 Definition and Calculation

Parking duration represents elapsed time between a vehicle's trip end (scooter parked) and the subsequent trip start (scooter next picked up by a user). For vehicle i, parking duration is calculated as:

$$\text{Parking Duration } i = \text{Start Time}_{i+1} - \text{End Time}_{i}$$

For each zone z, average parking duration is computed as:

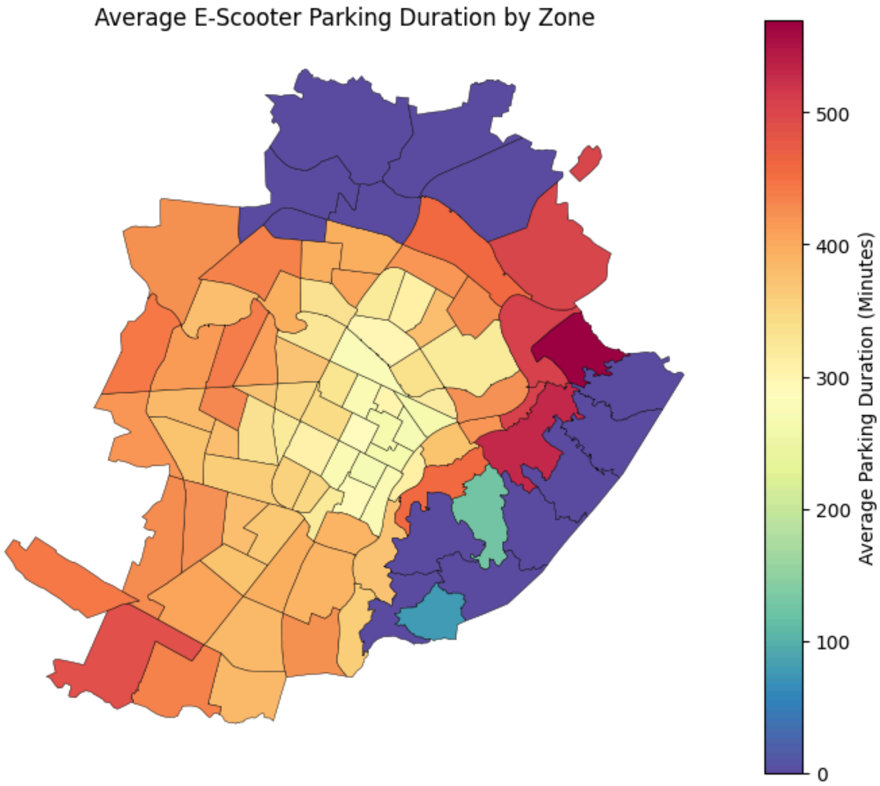
$$PDz = \frac{1}{Nz}\sum_{i=1}^{Nz} Parking\ Duration_i$$

Where Nz = total parking events in zone z.

5.1.2 Results

Total parking events calculated: 1,940,092
Average parking duration across all zones: 332.34 minutes (5.54 hours)
This average marks substantial spatial variation, with duration ranging from minutes in high-turnover commercial zones to days in residential areas.

5.2 Spatial Parking Duration Patterns

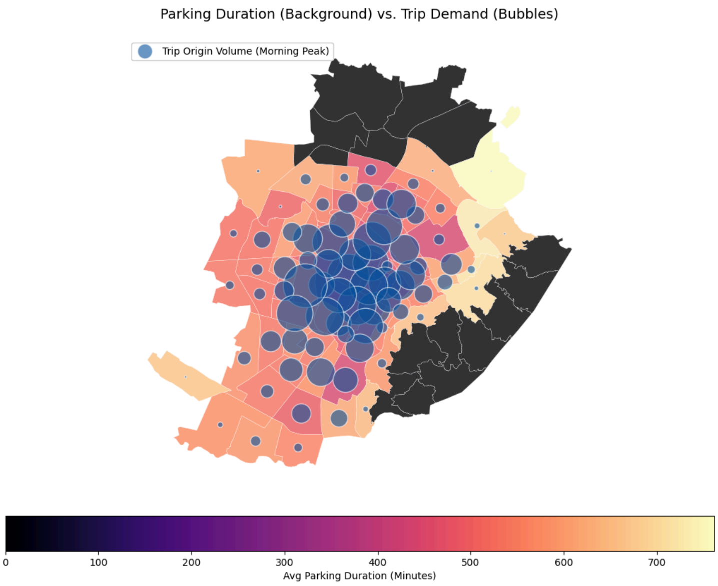


Spatial patterns identified:

- The centre is showing more moderate values than many outer areas, consistent with higher turnover (more frequent pick-up/drop-off) in denser zones, reducing the time a scooter stays parked between rides
- Peripheral longer durations can indicate lower demand, operational effects (rebalancing, parking/holding areas), and residential zones
- Very low averages at the edges are seen because ‘average parking duration’ can be unstable if only a few parking events exist in that zone (the majority of trips happens around the city centre, hardly on the upper and right side of the city)

5.3 Temporal Variation in Parking Duration

5.3.1 Parking Duration Patterns



- High-volume morning origins correlate with intermediate parking durations, suggesting commuter parking
- Areas with lighter bubble density but warmer colours represent residential parking where vehicles remain parked for extended periods
- The yellow-cream have minimal bubbles, indicating these are either pass-through zones or areas with limited trip generation.
- High-demand central zones like downtown/business district with 4-6 hour parking events
- Moderate peripheral zones with balanced origin volumes and 5-8 hour parking duration
- Data void zones are non-parking areas or non-trip origin/destination areas

This patterns supports differentiated parking management strategies:
- dynamic pricing or time-limited zones in the high-volume central area
- peripheral zones may benefit from long-stay facilities or residential permit programs to manage extended durations efficiently.

5.4 Exercise 4 Summary

1. Average parking durations: 332 minutes reflects mix of short-turnover commercial use and long-dwell residential use
2. Rebalancing opportunity: Parking duration patterns define optimal rebalancing windows

6. Exercise 5: Business Model and Profitability Analysis

6.1 Revenue Stream Calculation

6.1.1 Tariff Structure Analysis

E-scooter operators employ dynamic pricing models adapted to local markets. Research of current Telepass/Moveo platforms for Turin identified the following tariff structures:

Operator	Unlock Fee (€)	Per-Minute Rate (€/min)	Subscription Options
Lime	1.00	0.19	Monthly subscriptions available
Voi	1.00	0.19	Monthly memberships, student rates
Bird	1.00	0.20	Promotional pricing for new users

https://moveo.telepass.com/monopattini-elettrici-torino-prezzi-operatori-sharing/

6.1.2 Revenue Calculation from Trip Data

$$Revenue_{op} = \sum_{i=1}^{N} (Unlock\ Fee + Duration_i\ x\ Per - Minute\ Rate_{op})$$

Where:

- N = total trips per operator
- $Duration_i$ duration of trip i in minutes)
- $Per - Minute\ Rate_{op}$ = per-minute tariff for operator

Total Revenue by Operator:

Operator	Trips	Total Duration (min)	Revenue per Trip (€)	Total Revenue (€)
Lime	1,350,338	13,999,181	2.97	4,010,182.39

Bird	783,551	10,579,945	3.70	2,899,539.99
Voi	203,120	1,855,744	2.74	555,711.42
Total	2,337,009	26,434,870	3.09 (avg)	7,465,433.80

6.2 Cost Structure Analysis

6.2.1 variable Cost Estimation

Variable costs per kilometer include energy consumption, vehicle amortization, and maintenance:

Variable Cost per km=Energy Cost+Amortization Cost+Maintenance Cost

Cost Componetns:

1. Energy cost: €0.00308 /km
   - Based on: Full charge costs 0.047 with 30 km range) = €0.00157 /km
   - Rounded to €.00308 /km for margin
2. Amortization cost: €0.12 /km
   - Vehicle purchase price: €600 (mid-range commercial e-scooter)
   - Expected lifetime: 5,000 km (approximately 2 year lifespan)
   - Amortuzation: €600 / 5,000 km = €0.12 /km
3. Maintance cost: €0.02 /km
   - Estimated at €100 per vehicle life (tire replacement, bearing cjecks, brake maintenance)
   - €100 / 5,000 km = €0.02 /km

Total variable cost per km: €0.14308 (energy + amortization + maintenance)

6.2.2 Total Costs by Operator

Operator	Total km	Variable Cost (€)	Fixed Cost (€)	Total Cost (€)	Profit (€)	Profit Margin (%)
Lime	2,905,137	415,667	1,500,000	815,667	3,194,515	79.66%
Bird	2,779,356	397,670	1,500,000	797,670	2,101,870	72.49%
Voi	322,016	46,074	1,200,000	446,074	109,637	19.73%

6.2.3 Fixed Cost Assumptions

Fixed costs represent all expenditures that do not vary directly with the number of trips or kilometres, including:

- Insurance and liability coverage
- Warehousing, depots and charging hubs
- Local staff (operations, rebalancing, field technicians, managers)
- IT platforms and customer service
- Regulatory fees and city permits
- Overhead and central administration allocated to the Turin market

2-year amortization results in €2,500,000 to €3,000,000 fixed cost for the analysis period

6.3 Profitability Analysis Results

6.3.1 Operator Profitability Sumamry

Financial metric	Lime	Bird	Voi	Total
Trips	1,350,338	783,551	203,120	2,337,009
Revenue (€)	4,010,182.39	2,899,539.99	555,711.42	7,465,433.80
Variable costs (€)	415,667.00	397,670.26	46,074.00	859,411.26
Fixed costs (€)	3,000,000.00	3,000,000.00	2,400,000.00	8,400,000.00
Total costs (€)	3,415,667.00	3,397,670.26	2,446,074.00	9,259,411.26
Profit (€)	594,515.39	-498,130.27	-1,890,362.58	-1,793,977.46
Profit margin (%)	14.83	-17.18	-340.17	-24.03
Profit / trip (€)	0.44	-0.64	-9.31	-0.77

6.3.2 Key Performance Indicators

KPI	Lime	Bird	Voi	Indicative industry range
Revenue per trip (€)	2.97	3.70	2.74	1.0 – 1.5
Cost per trip (€)	2.53	4.34	12.04	0.8 – 1.2 (target)

Utilisation (trips/vehicle)	563	278	142	100–200 per year min.
Net margin (%)	14.83	-17.18	-340.17	-20 to +15

6.4 Exercise 5 Summary

1. Lime’s market leadership
   Lime emerges as the only clearly profitable operator in TUrin, with a net margin of about 15%. Its large trip volume and high utilisation allow it to spread substantial fixed costs over many rides, resulting in positive profitability.
2. Bird slightly loss-making
   Bird generates a small operating loss, corresponding to a net margin of around -17%. This suggests that modest changes in tariffs, costs, or utilisation could move Bird across the break-even threshold
3. Voi faces structural viability issues under current conditions
   Voi’s much smaller scale (fewer trips and kilometers) makes it unable to absorb its fixed costs. Even with comparable revenue per trip and very similar variable cost per kilometre, its net margin points to a structurally unsustainable position unless:
   - Fixed costs are significantly reduced (leaner operations, shared depots)
   - Utilisation increases substantially
   - Tariffs strategies change

7. Integrated Findings and Discussions

Exercise 1 (Data Quality & Descriptive Analysis):

- 2,337,009 valid trips after quality cleaning (84.3% retention)
- Seasonal demand variation of approximately 300% between peak and off-peak months
- Fleet utilization varies 3.9× between operators (Lime's 563 vs. Voi's 142 trips/vehicle)

Exercise 2 (OD Analysis):

- Demand highly concentrated in city center with distance-decay pattern
- Peak vs. non-peak OD patterns show different spatial structure (concentrated vs. dispersed)
- Representative day analysis selected monthly typical days for robust policy planning

Exercise 3 (Public Transport Integration):

- Significant spatial overlap with transit network; user demographics suggest complementary rather than directly competitive relationship

- First-mile/last-mile integration potential substantial, particularly in peripheral residential areas
- Seasonal variation affects competitive/complementary balance

Exercise 4 (Parking Duration):

- Average parking duration 332 minutes (5.54 hours)
- Peak hours (3–5 PM) provide rebalancing opportunities through high vehicle turnover

Exercise 5 (Business Model):

- Only Lime is clearly profitable
- Bird is marginally below break-even
- Voi is heavily loss making
- Some interventions and changes must be made

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