DIGITAL SKILLS FOR SUSTAINABLE SOCIETAL TRANSITIONS

Transport innovation for a sustainable, inclusive and smart mobility

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Exercise on Bigdata analysis

Exercise on generalized cost

Exercise on MaaS (Mobility as a Service)

a.y. 2024/2025

Statement Regarding Submission

This report has been prepared jointly with my husband (**Alireza Soleiman Bejarpasi** with student number **s327773**), and our colleague (Masoud Momeni with student number **S324829)**, as we all reside in the same apartment. As confirmed by Professor Pronello, the same report has been submitted individually by each of us in accordance with her instructions.
Thanks

Exercise 1 - Preliminary analysis

Introduction

The rapid growth of micromobility solutions, including scooters and bicycles, has transformed urban transportation, offering sustainable and efficient alternatives to traditional modes of travel. This analysis examines micromobility usage patterns in **Austin, Texas**, using trip data collected between August 2021 and March 2022. By analyzing Origin-Destination (OD) flows, peak hour trends, seasonal variations, and vehicle usage distributions, the study provides valuable insights into how these services are utilized and identifies opportunities for optimization.

Objectives of the Analysis

The primary goals of this analysis are:

1. **Understand Usage Patterns**: Identify dominant hubs and key inter-district flows to assess the role of micromobility in meeting urban transportation needs.
2. **Address Outliers and Imbalances**: Examine and mitigate the impact of outlier data, such as disproportionate self-loops in high-demand districts, to ensure balanced insights.
3. **Evaluate Temporal Trends**: Analyze micromobility usage across peak hours and seasons to understand variations in demand.
4. **Highlight Underutilized Areas**: Identify districts with low activity levels to explore potential improvements in service coverage.
5. **Inform Policy and Infrastructure**: Provide actionable recommendations for enhancing micromobility services and infrastructure in Austin.

Case Study: Austin, Texas

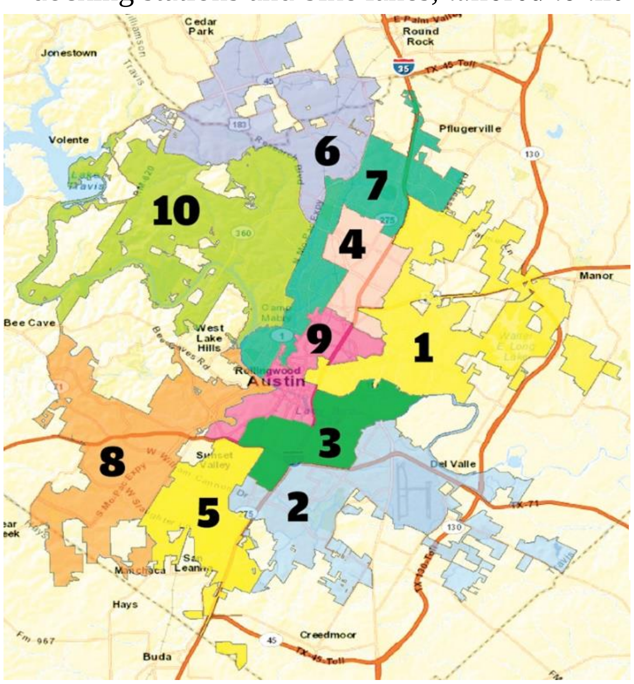
Austin is an ideal case study for micromobility analysis due to its dynamic urban environment and early adoption of shared transportation services. Key characteristics of the case study include:

1. **Diverse Urban Landscape**: Austin features a mix of dense urban areas, residential neighborhoods, and recreational zones, making it a rich context for analyzing micromobility usage.
2. **Council District Framework**: The city is divided into **10 council districts**, which provide a clear geographical structure for analyzing trip patterns.
3. **Seasonal Variability**: The data spans late summer, fall, and winter months, enabling an exploration of how seasonal factors influence micromobility trends.
4. **Availability of Comprehensive Data**: The dataset includes key attributes such as trip duration, trip distance, time of day, and starting/ending districts, supporting detailed analysis.

Importance of the Analysis

Micromobility services hold the potential to address critical urban challenges, including congestion, air pollution, and the last-mile connectivity gap. However, their success depends on understanding how, when, and where they are used. This analysis is vital for:

1. **Improving User Experience**: By identifying high-demand areas and peak usage times, operators can allocate resources more effectively.
2. **Enhancing Accessibility**: Highlighting underutilized areas helps guide efforts to expand service coverage and equity.
3. **Supporting Sustainable Mobility**: Insights from this analysis contribute to promoting environmentally friendly transportation solutions.
4. **Guiding Urban Planning**: The results can inform infrastructure investments, such as docking stations and bike lanes, tailored to the city's needs.



10 council districts of Austin

Preliminary Analysis

1-Data Cleaning

Objective:

The objective of this step is to clean the raw micro-mobility data for Austin, Texas, and prepare it for analysis. This involves:

- Identifying and removing bad or missing data.
- Comparing the dataset size before and after cleaning.

Types of Bad Data Identified

During the data cleaning process, I inspected the dataset for various types of potential bad data, including:

Empty Rows:

- Rows where all fields were empty, possibly due to errors during data collection or export.

Missing Essential Fields:

- Rows with missing values in critical columns that are required for analysis, such as:
  - Trip Duration or Trip Distance: Key metrics for analyzing trip behavior.
  - Council District (Start) or Council District (End): Necessary for spatial analysis.
  - Month, Hour, Day of Week, or Year: Essential for temporal trends.
  - Census - Tract Start or Census - Tract End: Important for demographic analysis.

Invalid or Out-of-Range Values:

- Trip Duration: Negative or extremely high durations (e.g., trips lasting days).
- Trip Distance: Negative distances or excessively large distances (e.g., hundreds of miles for a scooter trip).
- Month, Hour, Day of Week, or Year: Values outside the valid range:
  - Month: Should be between 1 and 12.
  - Hour: Should be between 0 and 23.
  - Day of Week: Should be between 0 (Sunday) and 6 (Saturday).
  -

Types of Bad Data Removed

Upon analyzing the dataset, I found the following issues:

- **Empty rows ,Null or NaN Values:** Certain fields, such as Trip Duration, Trip Distance, and Council District, contained missing data that needed to be removed.
- **Trips Below Thresholds:**
    - Trips with a distance of less than 100 meters were removed as they are too short to be meaningful.
    - Trips with a duration of less than 60 seconds were removed as they are likely erroneous or incomplete.
- **Outliers:** Records were filtered using statistical bounds:
    - The lower 1% and upper 1% of Trip Duration values were removed to eliminate extreme outliers.

These cleaning steps ensured that the dataset was free from incomplete, irrelevant, or distorted data points, making it suitable for analysis.

Records Before and After Cleaning

- Number of records before cleaning: 514767
- Number of records after cleaning: 453962
- Number of records removed: 60805

2-Data Collection Timeline

Objective:

Determine the range of the data collection period by identifying:

- The earliest recorded date and time in the dataset.
- The most recent recorded date and time in the dataset.

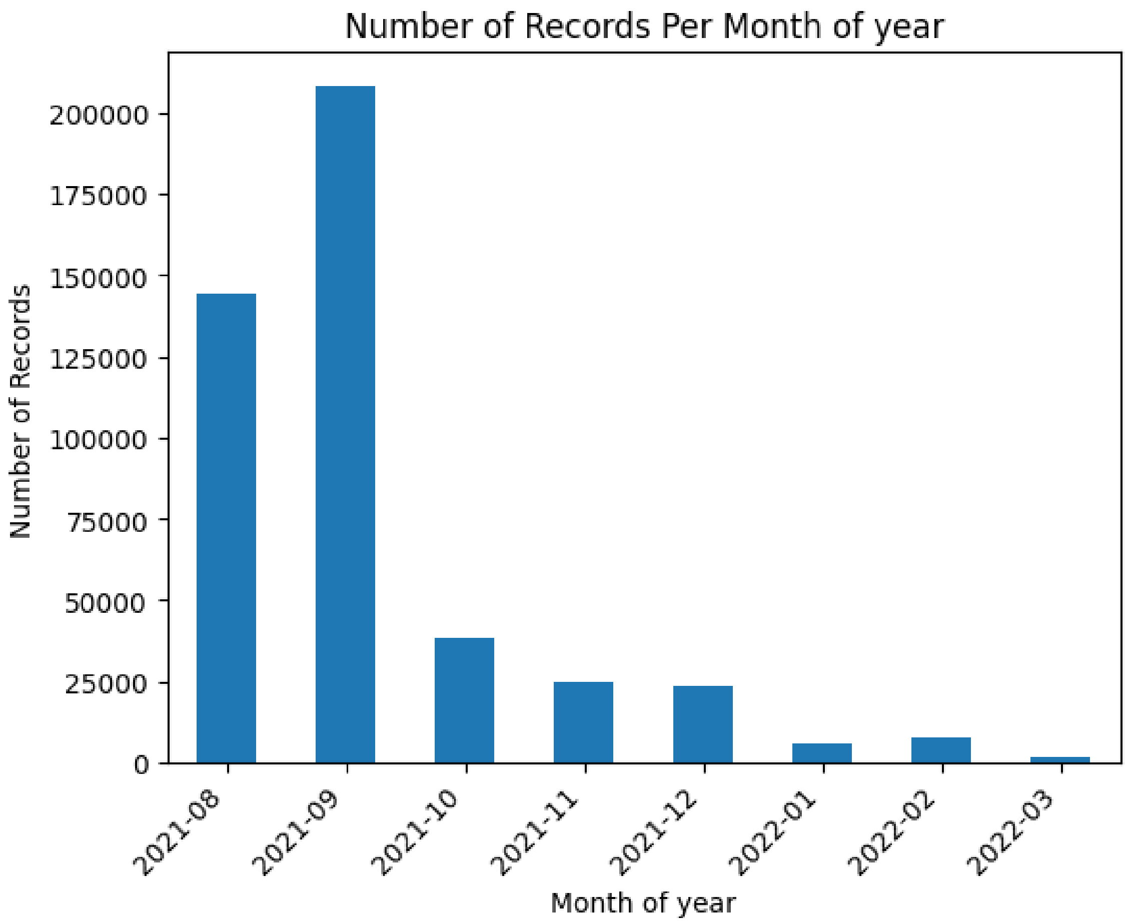
Results:

- **Start Date and Time:** 2021-08-19 05:30:00
- **Most Recent Date and Time:** 2022-03-25 01:00:00

3-Number of Records Per Year and Month

Objective:

Analyze the dataset by year and month to identify usage patterns.



Insights:

- Micro-mobility usage peaked in late summer and early fall of 2021 (August–September) but declined sharply after October 2021.
- Peak usage is September 2021 with 208,086 records and lowest in January 2022 (5,914 records).
- Usage in early 2022 is minimal, likely due to seasonal or operational factors.

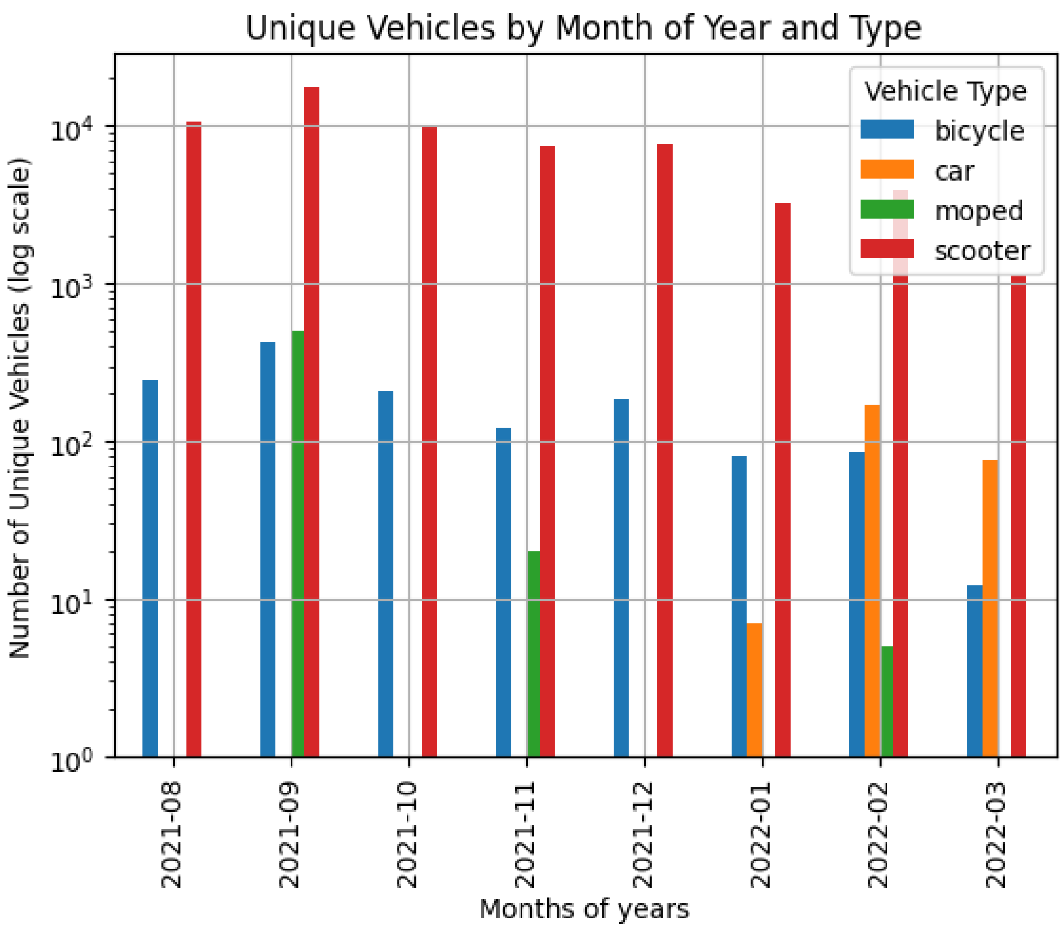
4-Analysis of Unique Vehicles by Month and Day of the Week

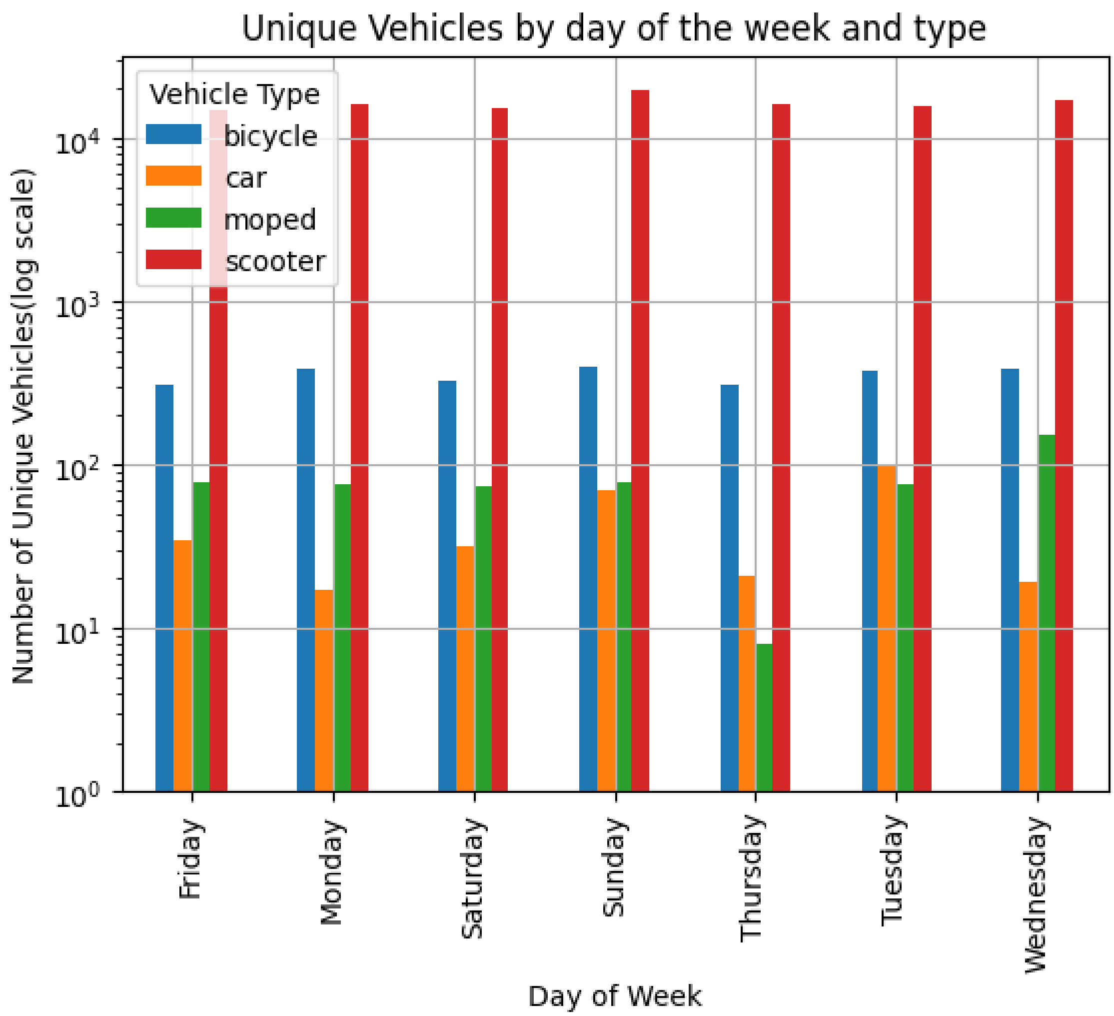
Handling Differences in Record Counts

The number of records varies significantly across vehicle types. For example:

- **Scooters** dominate the dataset with **446,511 records**.
- **Bicycles** account for **6,584 records**.
- **Cars** and **mopeds** have **326** and **541 records**, respectively.

Due to this disparity, a **logarithmic scale** was applied to the visualizations, ensuring all vehicle types are represented in a meaningful and comparable way.





Insights and Conclusion

Monthly Trends:

- Scooters: Usage peaked in September 2021 (17,552 unique scooters) and declined steadily, with a low in March 2022 (1,134 unique scooters).
- Bicycles: Followed a similar trend, peaking in September 2021 (423 unique bicycles) and declining to 11 in March 2022.
- Cars and Mopeds: Limited data with sporadic activity; cars peaked in February 2022 (172 unique cars), and mopeds peaked in September 2021 (505 unique mopeds).

Day-of-Week Trends:

- Scooters and Bicycles: Usage was highest on Sundays and weekends, indicating recreational or leisure use. For example, 19,497 unique scooters were used on Sunday.
- Cars and Mopeds: Showed inconsistent patterns, with mopeds peaking on Wednesdays (152 unique mopeds) and cars on Tuesdays (98 unique cars).

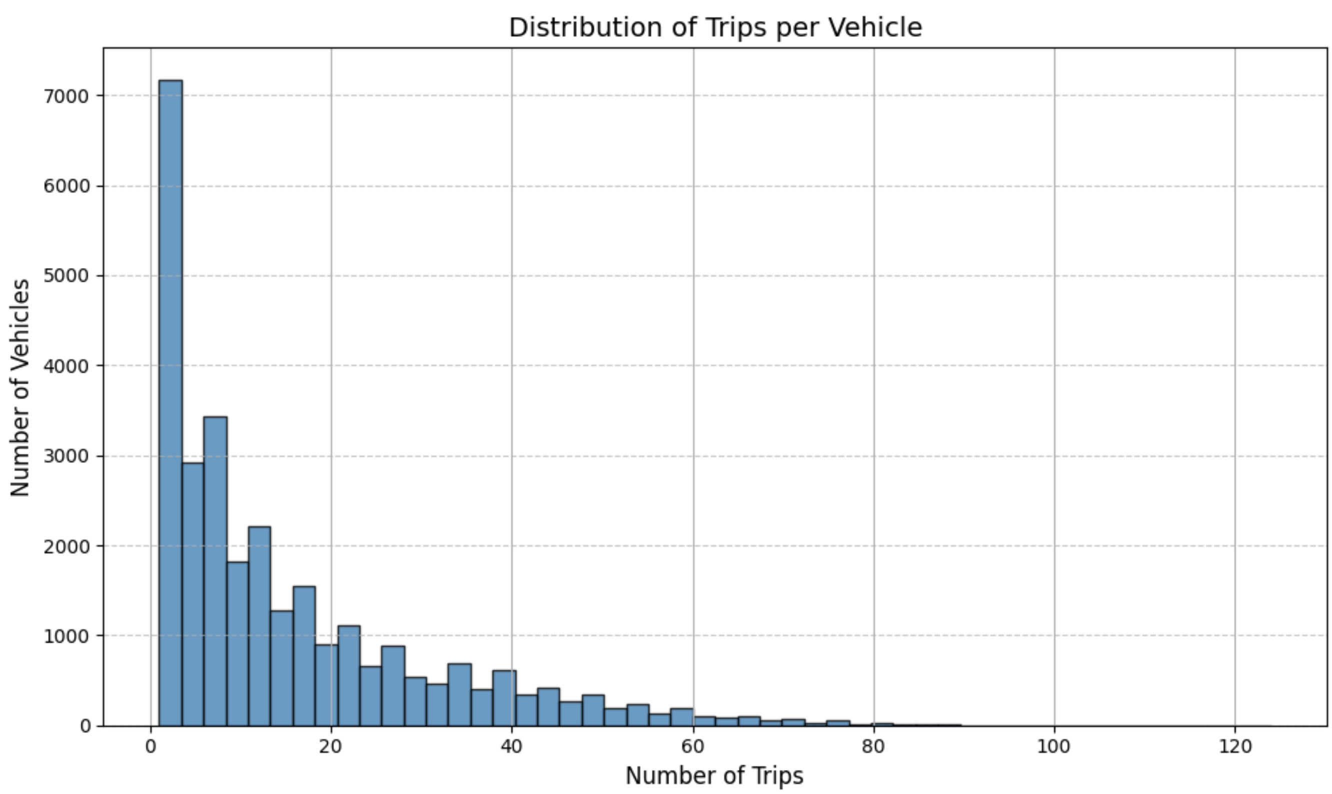
Seasonal Trends:

- Late Summer/Early Fall (August - September 2021): Highest activity across all vehicle types, likely driven by favorable weather and demand.
- Winter (December 2021 - February 2022): Significant reductions in activity, particularly for bicycles and mopeds.
- Spring (March 2022): Slight recovery, especially for scooters.

5-Number of Trips Per Vehicle

Analysis

- The dataset was analyzed to calculate the number of trips made by each vehicle.
- A histogram was created to visualize the distribution of the number of trips per vehicle.



Insights and Conclusion

Skewed Distribution:

- The histogram indicates that the majority of vehicles are associated with a small number of trips (less than 20).

- A few vehicles contributed to a significantly larger number of trips, though their frequency is much lower.

Key Observations:

- Over **7,000 vehicles** were used for fewer than 5 trips, suggesting many vehicles had limited usage.
- The number of vehicles decreases steadily as the number of trips increases.

Long-Tail Effect:

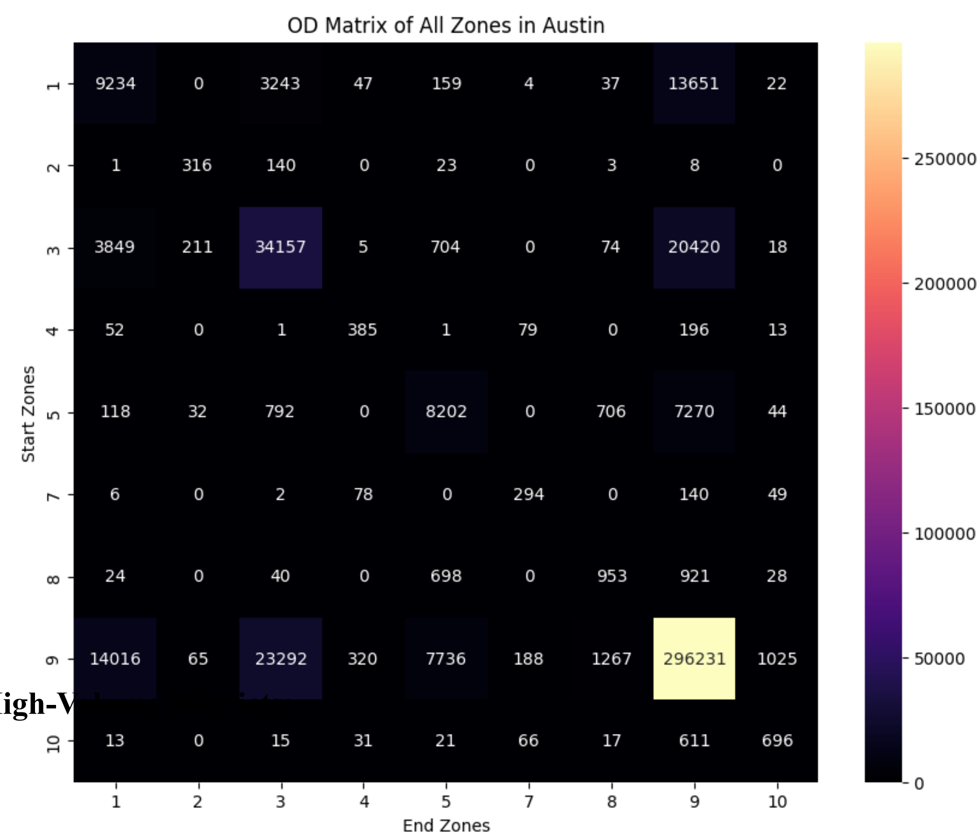
- A long-tail pattern is observed where a small proportion of vehicles are responsible for the majority of trips.

Exercise 2 - The where and when of the mobility - OD matrices

1- Origin-Destination (O-D) Matrix for Council Districts

Analysis

- An **O-D matrix** was computed to show the number of trips starting in council district i and ending in council district j.
- The rows represent the **origin council district**, while the columns represent the **destination council district**.
- The matrix highlights the spatial travel patterns across council districts.



High-V

- **District 9** had the highest number of trips originating and ending in its own area, with **296,231 trips** staying within District 9.
- District 1 also exhibited significant activity, with **13,651 trips ending in District 9** and **9,234 trips staying within itself**.

Low-Volume Districts:

- Minimal inter-district movement was observed in districts like **2**, **4**, **7**, and **10**, reflecting localized or sparse activity.
- Some cells in the matrix (e.g., District 2 to most other districts) have near-zero trip counts.

Notable Inter-District Movements:

- High trip flows were observed between **District 3** and **District 9**, with **20,420 trips** ending in District 9 and **34,157 trips** staying within District 3.
- Movement between districts like **5 and 9**, **1 and 3**, and **9 and 3** also featured prominently.

Insights: Self-Loops:

- Districts 9, 3, and 1 had significant **self-loops**, where most trips originated and ended in the same district. This indicates high local activity, possibly due to popular hubs, recreational areas, or dense urban zones.

2-Peak Hour Travel Pattern Analysis

This section examines the travel patterns during peak hours across selected months.

- Data for cars and mopeds were excluded due to insufficient availability. This decision ensures the analysis focuses on trends in bicycles and scooters, which represent the majority of the dataset and provide more reliable insights
  (Scooter: 446,511 records **Bicycle**: 6,584 records **Car**: 326 records **Moped**: 541 records)

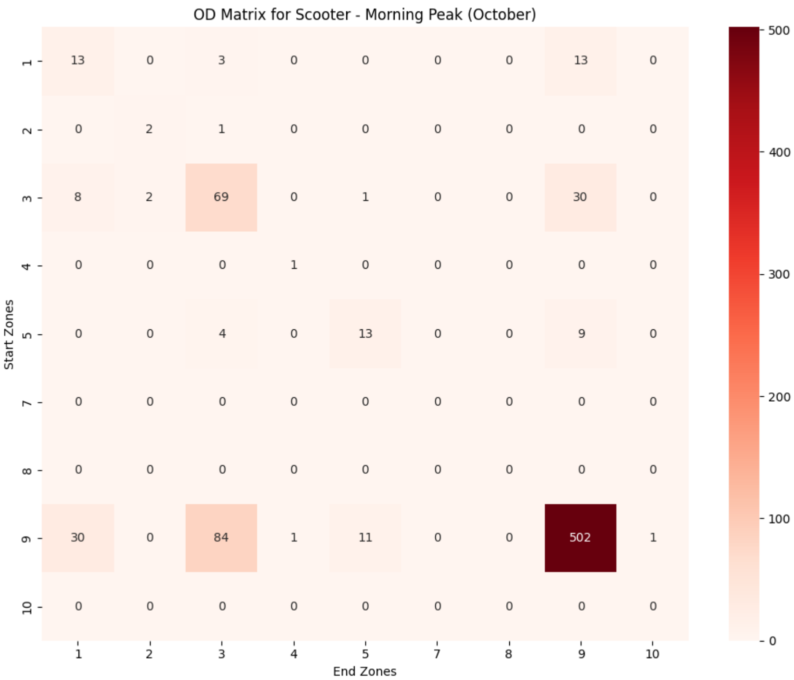
Time Periods:

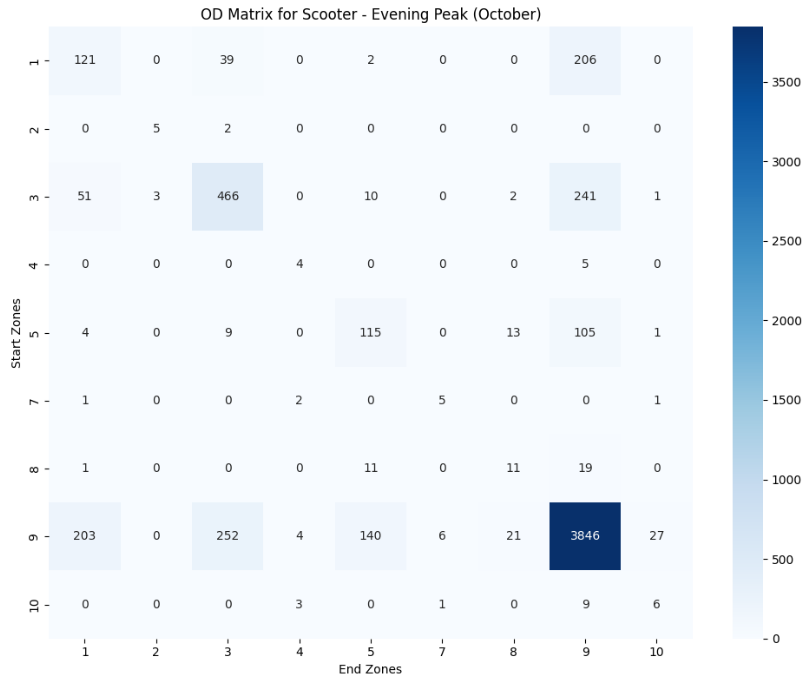
- Morning Peak: 7:00 AM to 9:00 AM
- Evening Peak: 5:00 PM to 7:00 PM

Months Analyzed:

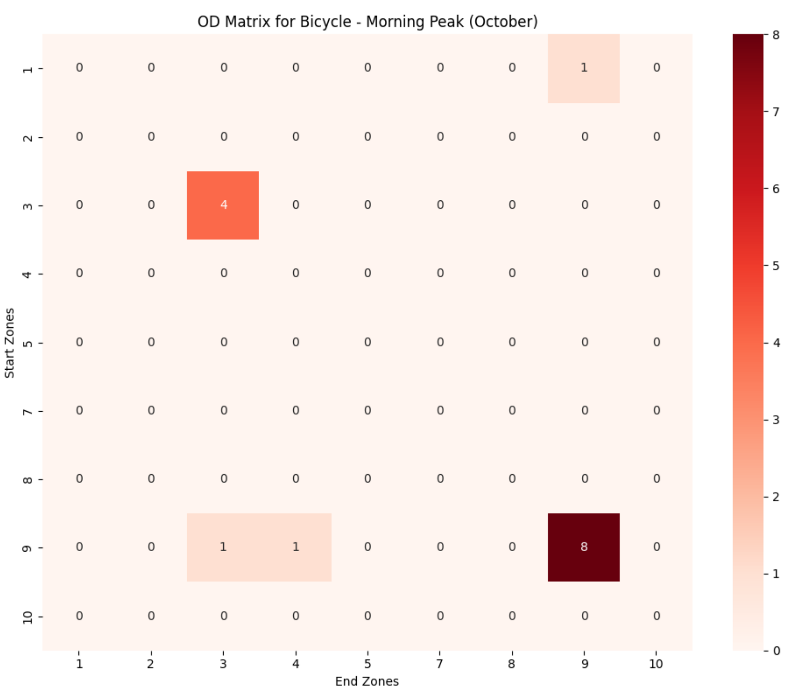
- October (Month 10)
- December (Month 12)
- February (Month 2)

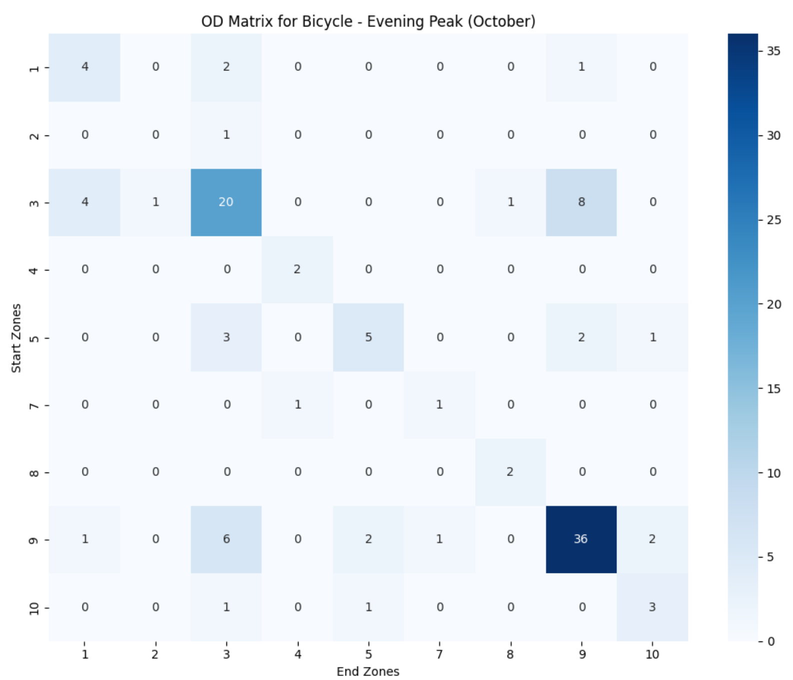
Scooter- October



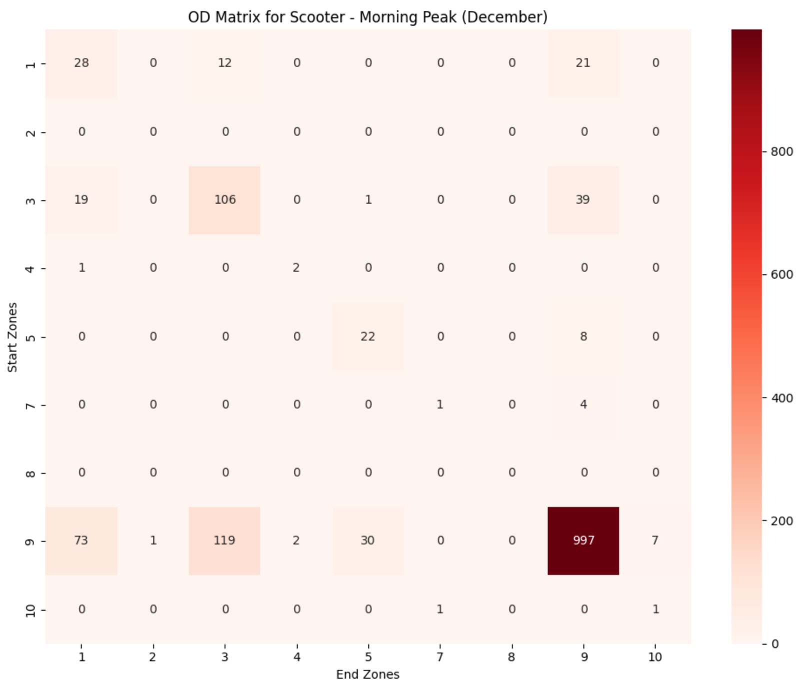


Bicycle- October

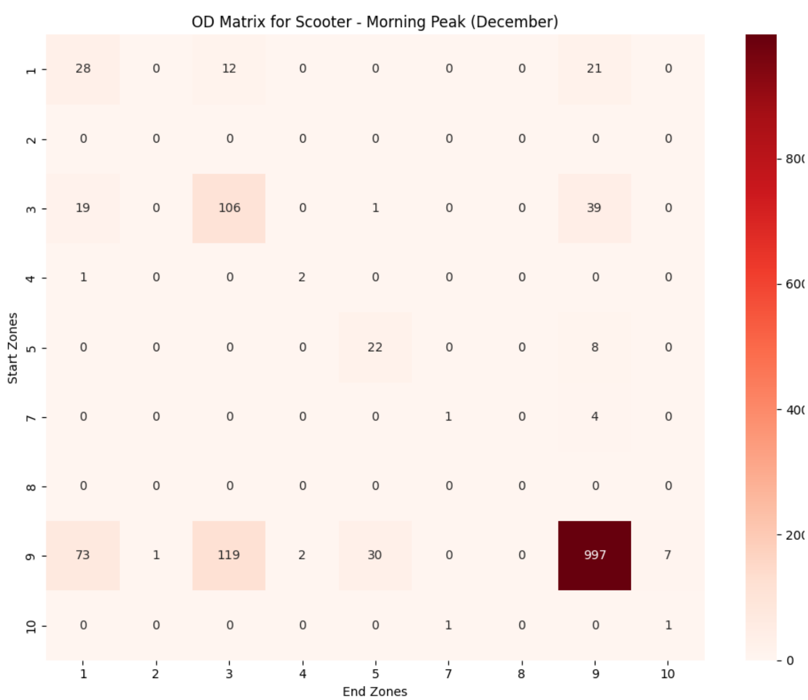


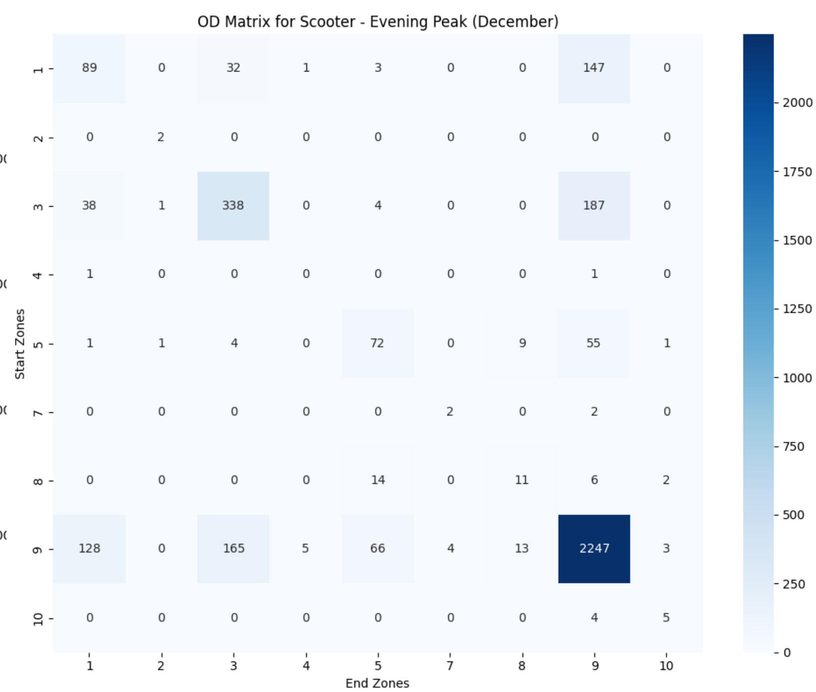


Scooter- December

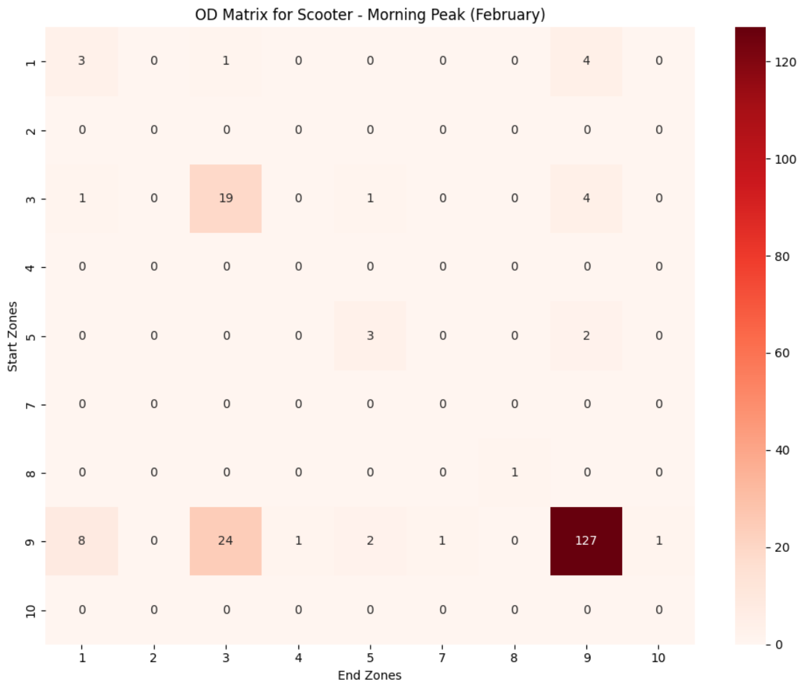


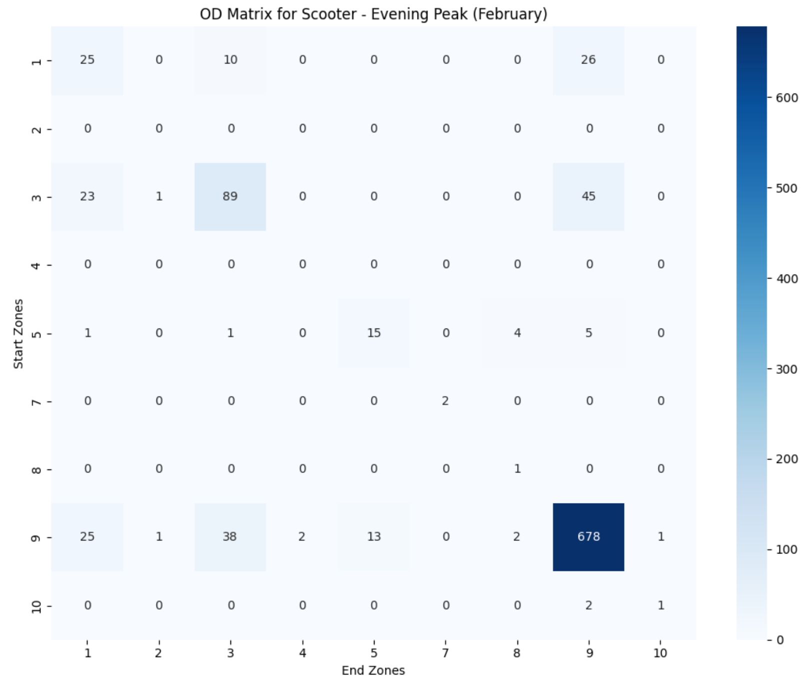
Bicycle- December



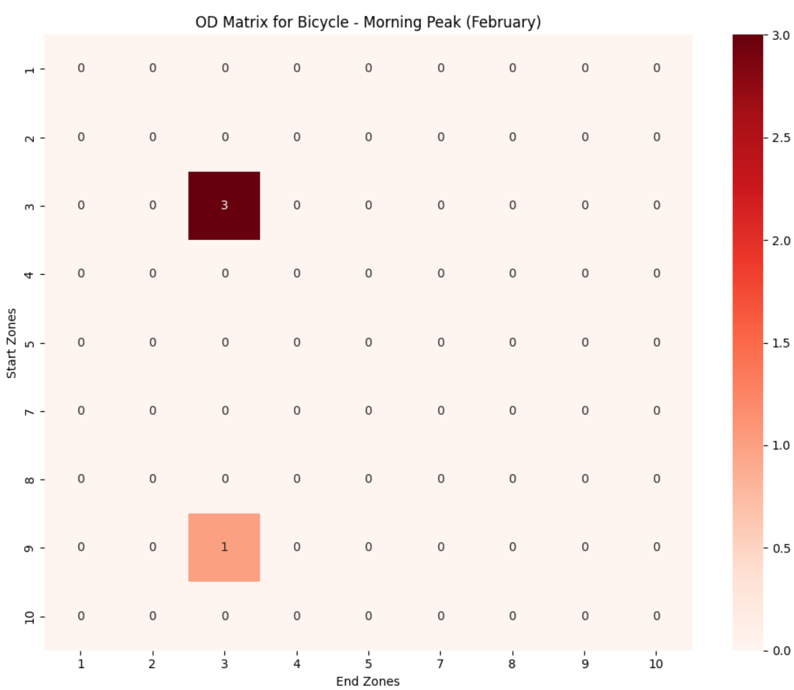


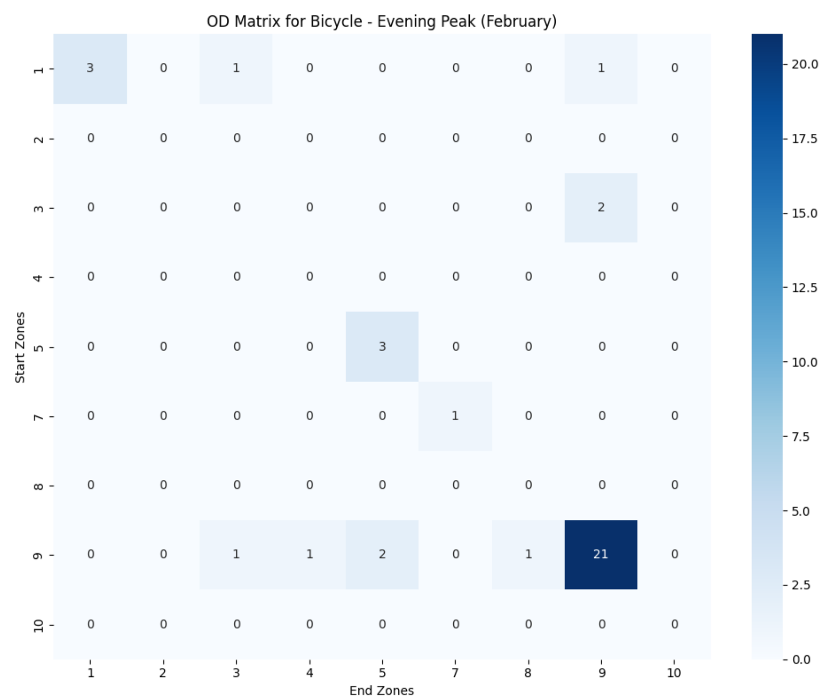
Scooter- February





Bicycle- February





Key Observations by Mode of Transportation from previous matrices

Scooter Travel Patterns

- Morning Peak:
  - Highest Usage: Council District 9 consistently sees the highest activity in both departures and arrivals, indicating it is a central hub during morning hours.
  - Lowest Usage: Council Districts 7, 8, and 10 exhibit negligible or no activity during the morning peak.
  - October vs. February: Scooter usage significantly drops from October to February, likely due to weather or seasonal factors.
- Evening Peak:
  - October Peak: Council Districts 1, 3, and 9 have the highest evening activity, with District 9 dominating arrivals and departures.
  - Decline in Winter: A noticeable reduction in usage during February evenings across most districts, but District 9 maintains its position as a key hub.
  - Directional Flow: The highest trip flows are concentrated between Districts 9 and 3, especially in October and December evenings.

Bicycle Travel Patterns

- Morning Peak:
  - Low Activity: Bicycle activity is minimal during the morning peak, with only District 9 showing slight movement in October and December.
  - Winter Decline: February sees the lowest bicycle activity overall, with many districts showing zero activity.
- Evening Peak:
  - October as a Peak Month: October evenings have relatively higher bicycle activity compared to December and February, with Districts 3, 5, and 9 contributing the most trips.
  - Directional Flow: Key flows include trips within District 9 and between Districts 3 and 9 in October.

Seasonal Impact on Travel Patterns

- October (Fall):
  - Both scooters and bicycles see the highest usage, indicating favorable weather and higher demand for shared micromobility options.

    - Evening peaks (5–7 PM) have significantly more trips compared to morning peaks (7–9 AM), suggesting a preference for travel after work hours.
- December (Winter):
    - Scooter usage sees a moderate decline in most districts, but District 9 remains a hub.
    - Bicycle activity decreases further, with minimal trips observed.
- February (Winter):
    - Scooter and bicycle trips reach their lowest levels, highlighting the impact of colder weather on micromobility usage.

Peak Hour Insights

- Morning Peak (7–9 AM):
    - Travel is highly centralized around District 9 for scooters.
    - Bicycle usage during this time is sparse and almost negligible.
- Evening Peak (5–7 PM):
    - Both scooters and bicycles experience higher activity during evening hours.
    - District 9 emerges as a central hub, with Districts 3, 1, and 5 also showing significant contributions.

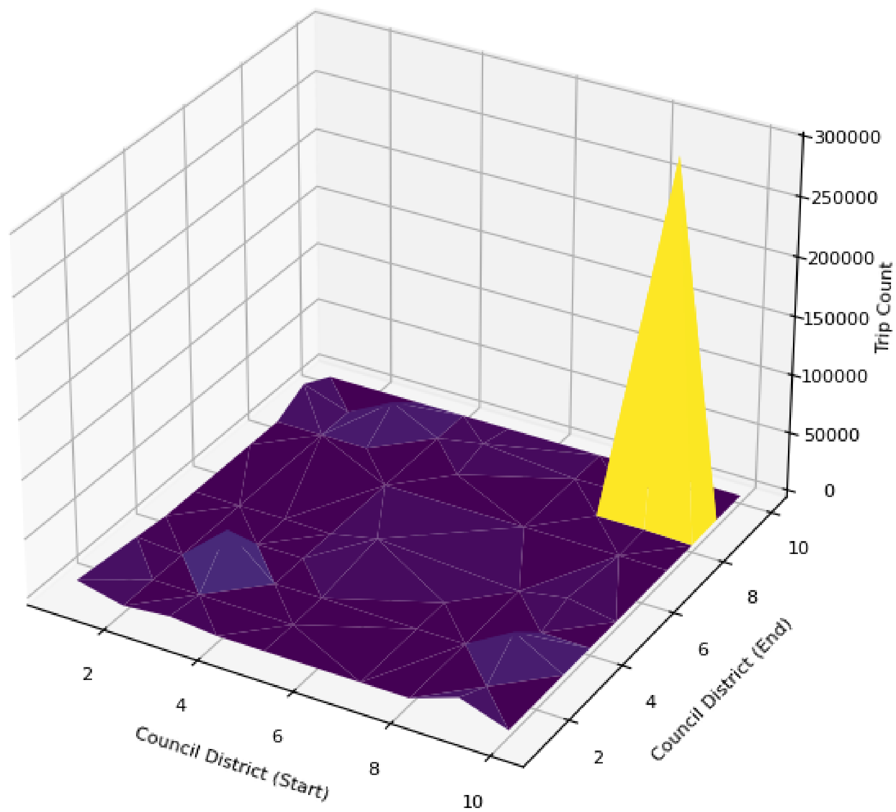
3- Revised Analysis of Micromobility Patterns: Addressing Outlier Behavior

Identifying and Removing Outliers

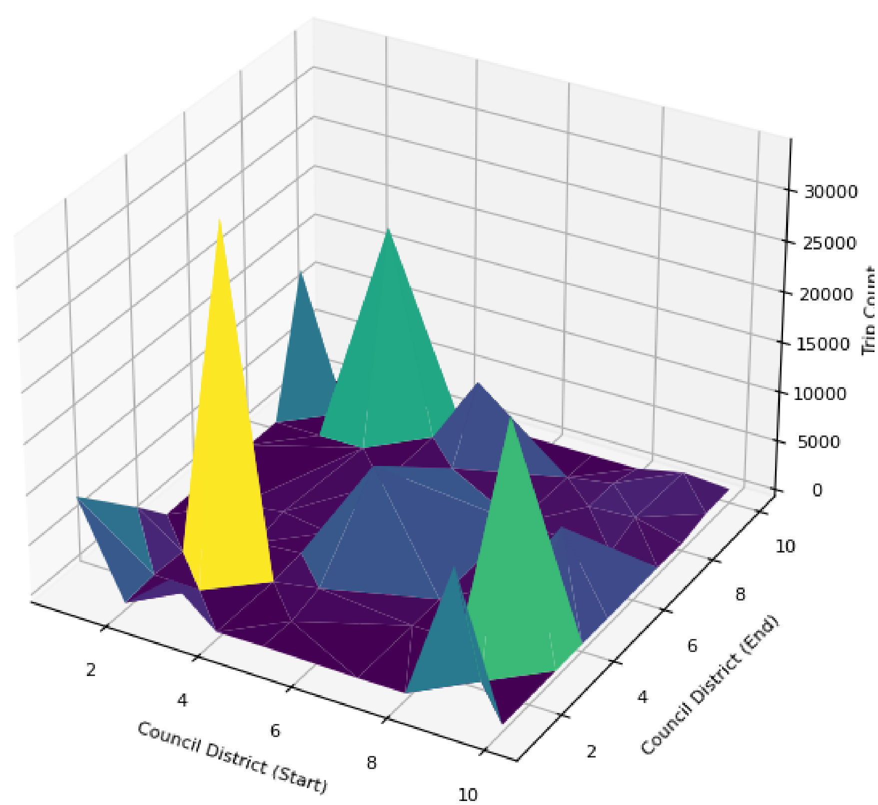
In the initial analysis, trips starting and ending within District 9 (referred to as "9-to-9" trips) emerged as a significant outlier, with a disproportionately high number of recorded trips compared to other district-to-district flows. While it is possible that this data reflects genuine usage trends due to unique characteristics of District 9 (e.g., high population density, key attractions, or better micromobility infrastructure), such extreme values can skew the overall interpretation of inter-district travel patterns.

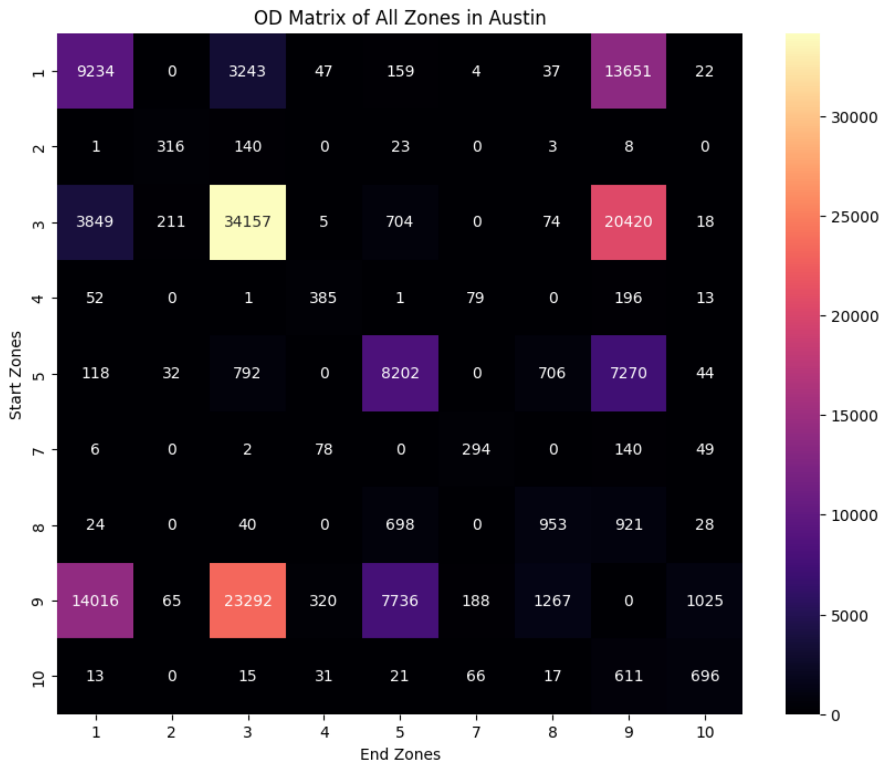
To ensure a more balanced analysis and gain insights into broader micromobility trends, the "9-to-9" trips were removed from the dataset. This adjustment provides a clearer understanding of inter-district travel patterns and highlights the dynamics of trips between other districts without the overwhelming influence of one specific data point.

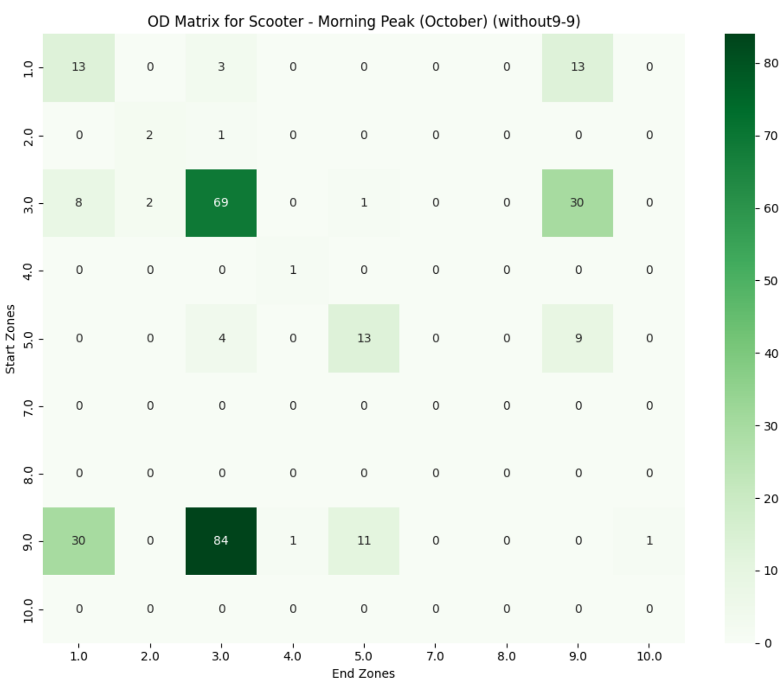
Micromobility Trips Between Council Districts

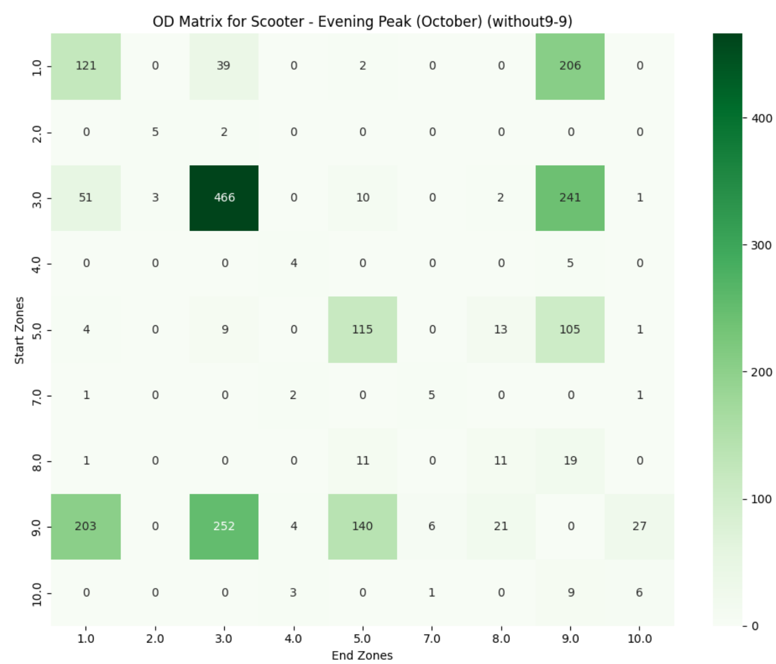


Micromobility Trips Between Council Districts (without 9-9)









- Note: to avoid overloading with extensive matrix data, only this three OD matrices are samples. These matrices are illustrative examples representing the updated analyses performed without the outlier trips (9-to-9 trips). On the following pages, the results and insights derived from these refined OD matrices are explained in detail.

Dominant Districts

- **District 9**: Continues to be the primary hub for micromobility trips. However, with the exclusion of 9-to-9 trips, its dominance is more proportionate to other districts.
- **District 3**: Gains prominence as a significant origin and destination, especially in interactions with District 9.
- **District 1**: Maintains a notable role in flows directed toward Districts 9 and 3.

Underutilized Districts

- Districts 7, 8, and 10 exhibit consistently low activity, underscoring their underutilization across all periods and seasons. These districts represent areas with potential for service expansion or targeted interventions.

Peak Hour Trends

- **Morning Peak (7–9 AM)**:
  Districts 1 and 3 dominate as origins, with District 9 being the primary destination. Other inter-district flows gain importance due to the exclusion of internal (9-to-9) trips.
- **Evening Peak (5–7 PM)**:
  District 9 remains a key destination, while District 3 stands out as a significant hub, particularly in trips involving District 5.

Seasonal Patterns

- **October**: Exhibits the highest micromobility activity, driven by strong evening peaks and significant contributions from Districts 1, 3, and 5.
- **December & February**: Reflect seasonal declines in activity, with minimal trips recorded in Districts 7, 8, and 10. However, Districts 9 and 3 consistently maintain high activity levels.

Comparative Impact of Removing Outliers

- Excluding 9-to-9 trips has clarified inter-district flow patterns and highlighted the importance of Districts 1 and 3. This adjustment ensures a more balanced and actionable understanding of micromobility usage trends.

Concluding Remarks

This analysis emphasizes the need to balance infrastructure support for high-demand districts while addressing underutilized areas. Seasonal variations further suggest the importance of tailored strategies to sustain micromobility adoption year-round. By refining the dataset to exclude outlier trips, the results offer a clearer and more representative understanding of micromobility patterns.

Exercise 3 :

Part 1 - Interaction Between Micromobility and Public Transport in Chicago

Introduction

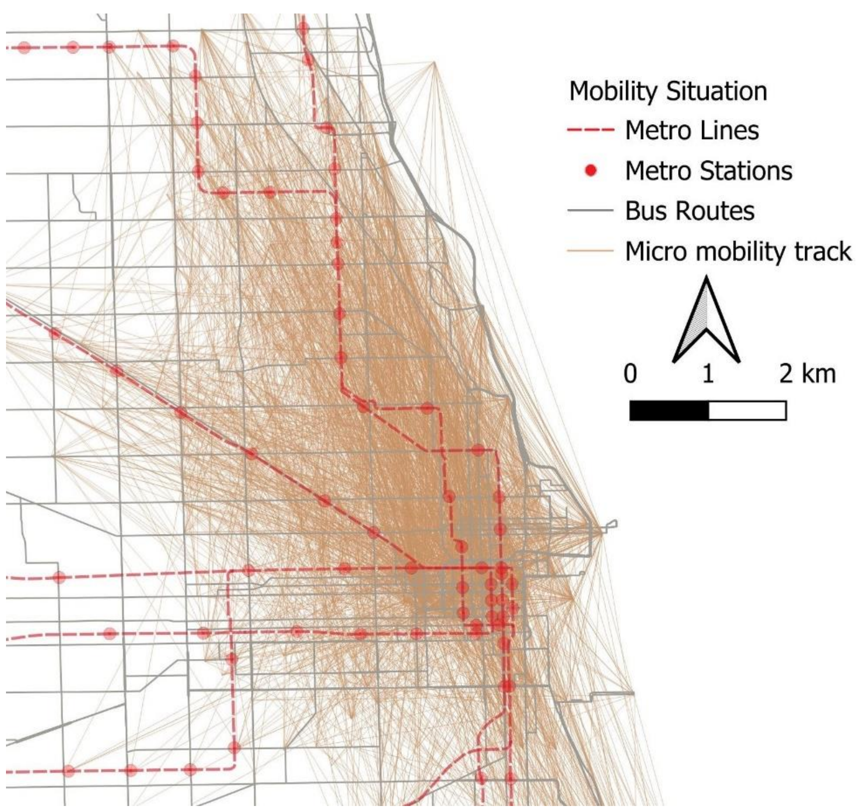
The interaction between micromobility and public transport is crucial for understanding their roles in urban mobility. This analysis uses **Chicago micromobility data** for one month and overlays it with **public transport lines** (KML data) in QGIS/ArcGIS to explore patterns of interaction. The goal is to identify whether micromobility complements or competes with public transport and to document spatial and temporal trends.

Data Preparation:

- Filtered Chicago micromobility data to include one month of records (July 2014) and peak time stamp (7am to 9am , 5pm to 7pm).
- Imported public transport routes (e.g., bus and train lines) as a **KML layer** and micromobility trip data as a **CSV layer** into QGIS.

Visualization:

- Overlaid micromobility trip origins and destinations on the public transport layer.



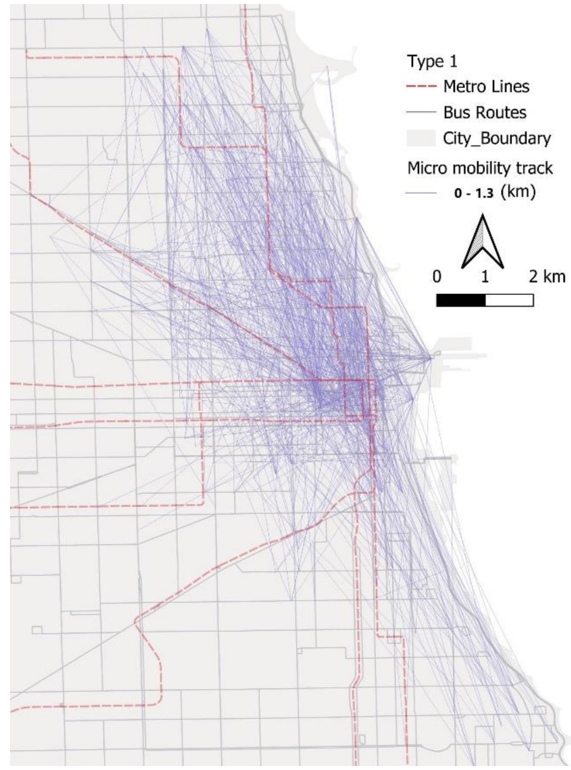
Key Observations

1. Complementary Relationship Between Metro and Micromobility:
    - The proximity of orange micromobility tracks to red metro lines and stations indicates their role as effective last-mile solutions.
    - High-density micromobility tracks surrounding metro stations emphasize their importance in enhancing connectivity from these transit hubs to nearby destinations.
2. Overlap with Bus Routes:
    - Several micromobility tracks and bus routes follow similar paths, suggesting potential competition in some areas. This raises questions about the efficiency of resource allocation and the need for integrated planning to minimize redundancies.
3. Urban Connectivity Patterns:
    - Micromobility tracks are more prominent in regions with multiple metro stations and bus routes, signifying a well-integrated transport network.
    - Peripheral areas with fewer micromobility tracks and limited metro or bus coverage could benefit from expanded micromobility infrastructure to bridge mobility gaps.
4. Optimization Opportunities:
    - Regions where micromobility tracks are sparse but metro and bus networks are dense present an opportunity for infrastructure investment to enhance multi-modal transportation options.
    - Conversely, areas with overlapping bus routes and micromobility tracks might benefit from redesigning service coverage to avoid inefficiencies.

Comparison of Trips by Distance Categories
we want to analysis of trips taken in July 2014, categorized by travel distances. The intervals for the five categories, determined using natural breaks, are as follows:

- **Type 1:** Up to 1.3 km
- **Type 2:** 1.3 – 2.4 km
- **Type 3:** 2.4 – 3.8 km
- **Type 4:** 3.8 – 5.8 km
- **Type 5:** 5.8–10 km

Type 1: Micro-Mobility Tracks (0 – 1.3 km)



Interaction:

High density of tracks concentrated near metro stations and bus stops, indicating short-distance trips complementing public transit hubs.

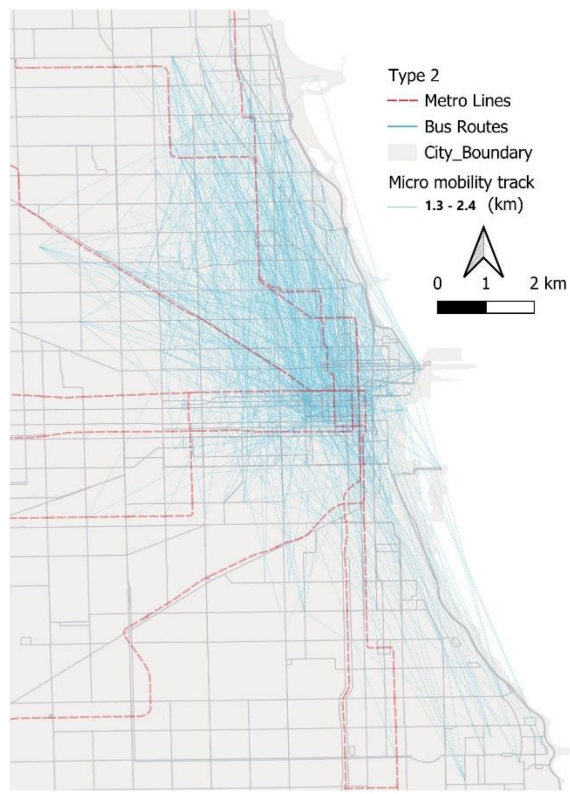
Tracks are clustered around the city center, with limited peripheral coverage.

Observations:

Serves as a feeder to metro and bus networks.

High potential for last-mile connectivity.

Type 2: Micro-Mobility Tracks (1.3 – 2.4 km)



Interaction:

Similar clustering near metro and bus routes but with slightly extended range compared to Type 1.

Tracks begin to reach areas beyond the immediate vicinity of transit hubs.

Observations:

Effective in medium-distance connectivity but still centered around urban areas.

Type 3: Micro-Mobility Tracks (2.4 – 3.8 km)

Interaction:

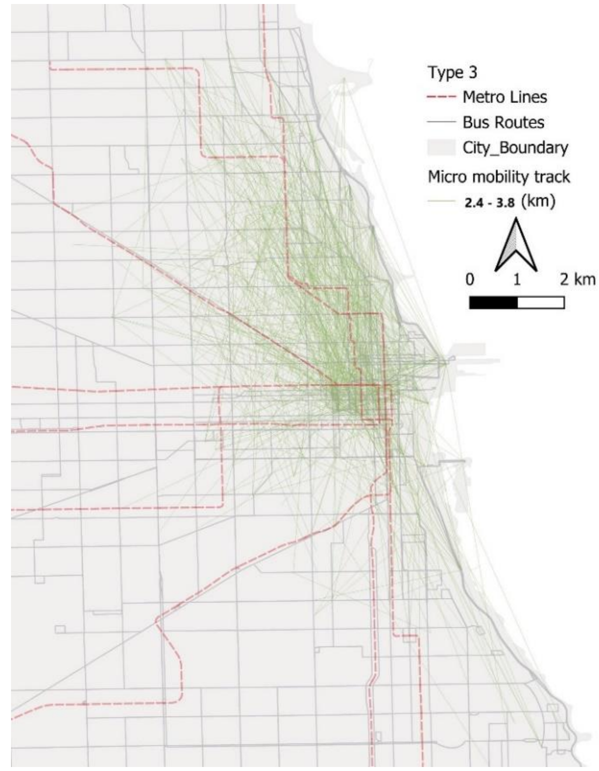
Tracks spread further, providing better inter-district connectivity.

Greater alignment with metro lines, particularly on major corridors.

Observations:

Tracks begin to complement public transit for trips spanning multiple neighborhoods.

Reduced clustering compared to shorter tracks.



Type 4: Micro-Mobility Tracks (3.8 – 5.8 km)

Interaction:

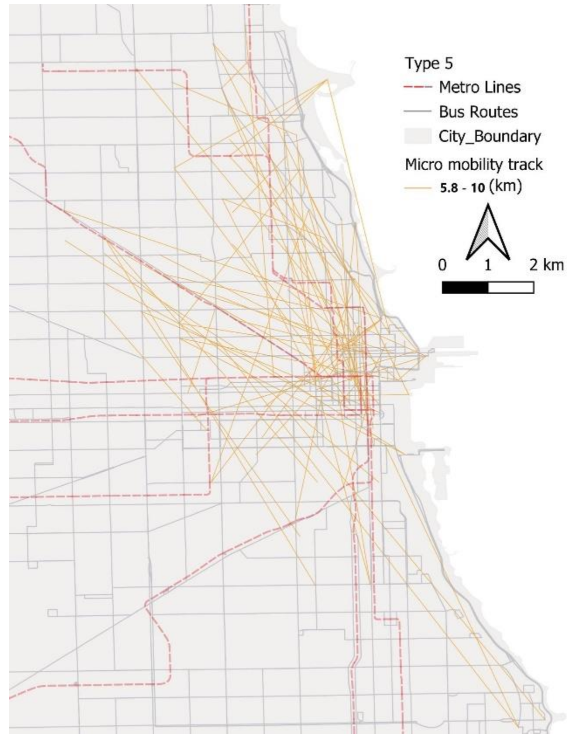
Tracks extend deeper into the suburbs, bridging gaps in public transit coverage.

Slight reduction in alignment with metro lines but continued interaction with bus routes.

Observations:

Supports medium to long-range urban trips but may face reduced usage for such distances.

Type 5: Micro-Mobility Tracks (5.8 – 10 km)



Interaction:

Tracks provide significant inter-regional connectivity, often serving as standalone routes rather than feeders.

Limited alignment with public transit, indicating independent usage patterns.

Observations:

Likely used for recreational purposes or by specialized commuters.

Coverage extends well into suburban areas, addressing accessibility gaps.

Trends and Key Findings

- **Clustering and Range:** Short-distance tracks (Types 1 and 2) are concentrated near metro and bus hubs, while longer tracks (Types 3 to 5) provide inter-regional connectivity.
- **Transit Integration:** Shorter tracks strongly complement metro and bus routes. Longer tracks are less dependent on public transit.
- **Coverage:** Peripheral areas benefit significantly from tracks of Types 4 and 5, filling gaps in transit accessibility.
- **Potential Challenges:** Safety concerns, track maintenance, and demand alignment for longer-distance micro-mobility usage.

Recommendations

1. **Enhance Peripheral Connectivity:** Focus on expanding the network of shorter tracks to underserved suburban areas.
2. **Promote Multimodal Integration:** Develop incentives for combining micro-mobility with metro and bus routes, especially for medium-distance tracks (Types 3 and 4).
3. **Improve Infrastructure:** Prioritize safety measures and maintenance for longer tracks to encourage consistent usage.

Conclusion

The analysis reveals a strong potential for micro-mobility to complement public transit, particularly for last-mile connectivity and medium-distance trips. Strategic network expansion and integration with metro and bus services can maximize the utility of micro-mobility tracks. Longer tracks, while less integrated, play a vital role in regional accessibility and should be supported with targeted infrastructure investments.

Exercise 4: Analysis of Parking Duration, OD Matrix, and Business Model in Chicago

1. Introduction

This exercise focuses on analyzing micromobility data in Chicago to determine:

- The average parking duration of vehicles across different wards.
- Overlapping visualizations of OD (Origin-Destination) matrices and average parking durations for different wards of the city.
- A preliminary financial analysis of the micromobility business model by calculating revenues and costs.

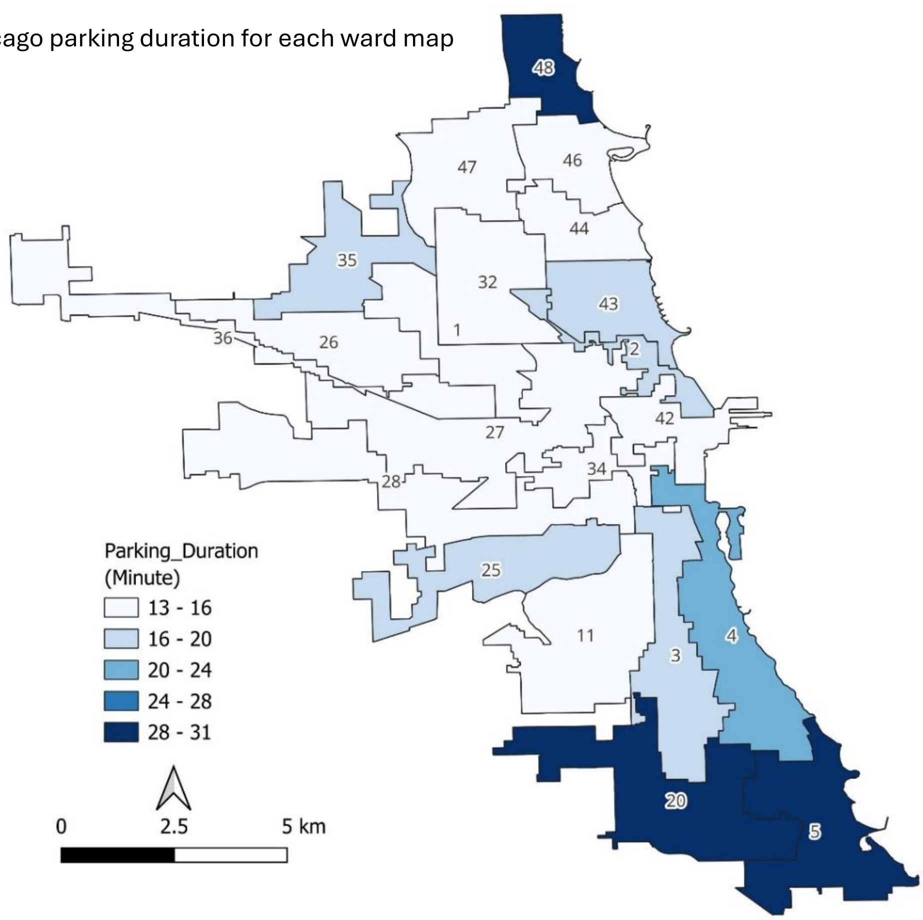
2. Analysis of Average Parking Duration Across Wards

The average parking duration for vehicles was computed for each ward using the Chicago dataset. The following insights were derived:

- Ward 5,20 and 48 exhibit higher average parking durations, with Ward 20 having the maximum average parking duration of 31.87 minutes.
- Wards 27, 28, and 34 have the shortest parking durations, with Ward 28 recording the lowest duration at 13.06 minutes.

ward	Parking duration
28	13.06
34	13.31
27	13.78
47	14.08
1	15.09
32	15.25
44	15.78
42	16.02
11	16.16
26	16.31
36	16.41
46	16.44
25	16.92
43	18.25
2	19.23
3	19.26
35	19.88
4	22.15
48	28.66
5	30.62
20	31.87

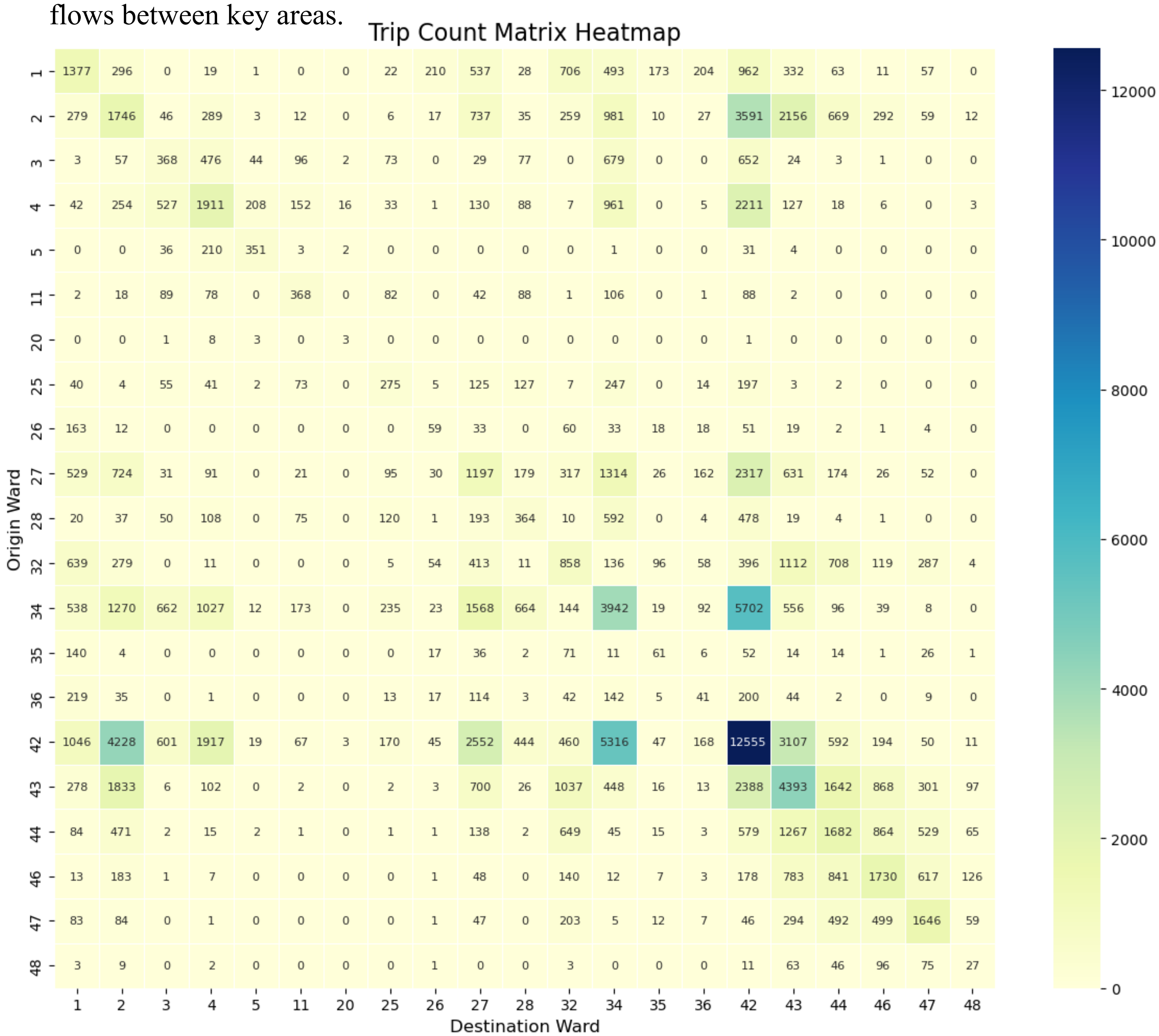
Chicago parking duration for each ward map



3. OD Matrix and Overlapping Visualizations

An OD matrix was computed to represent the number of trips originating and ending in different wards. The results are represented in the following:

- **Heatmap**: A detailed representation of the trips between wards, highlighting high-density flows between key areas.



Insights from the OD Matrix

Major Hubs:

  - Ward 42 is the busiest hub, with high trip exchanges, likely due to its central location or business activity.

Key Corridors:

- Significant travel occurs between central wards like 42, 43, and 34, indicating strong intra-city travel patterns.

Peripheral Trends:

- Peripheral wards like 20 and 48 have minimal connectivity, reflecting residential or low-demand areas.

Imbalances:

- Wards like 20 show more outbound trips than inbound, suggesting commuter-heavy areas.

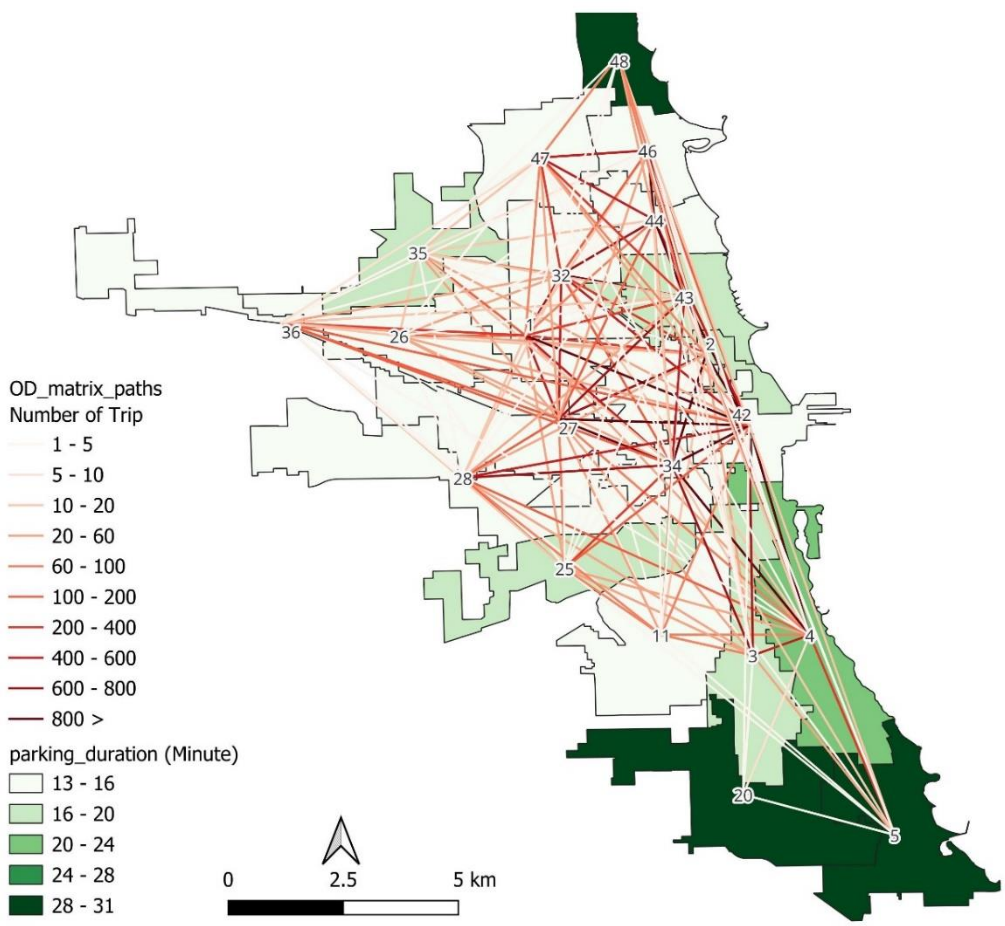
Optimization Potential:

- High-demand corridors need more resources, while low-activity areas may benefit from promotional efforts.

Overlap Map:

This map visualizes the interplay between trip flows and average parking durations:

- Red lines represent the number of trips, with darker reds indicating higher trip counts.
- Green shades overlay wards to depict parking duration.



Relationship Between Number of Trips and Parking Duration

High Trip Volume, Shorter Parking Duration:

- Central wards like 42, 43, and 46 have high trip activity and shorter parking durations (16–18 minutes), reflecting efficient vehicle turnover and heavy demand.

Low Trip Volume, Longer Parking Duration:

- Peripheral wards (e.g., 20, 5, and 48) show low trip volumes and long parking durations (28–32 minutes), indicating underutilized vehicles and lower demand.

Geographic Patterns:

- Central wards act as transit hubs with high connectivity and faster turnover.
- Peripheral areas experience longer idle times, requiring redistribution of vehicles.

Optimization Strategies:

- Relocate vehicles from low-demand areas to high-demand hubs.
- Offer promotions in peripheral wards to boost usage.
- Enhance parking infrastructure in central wards to accommodate higher activity.

4. Business Model Analysis

The financial analysis of the micromobility system included revenue and cost estimation:

1. Total Revenue from Customers and Subscribers

- **Formula:**

$$\text{Total Revenue} = (\text{Number of Customers} \times \text{Average Revenue per Customer}) + (\text{Number of Subscribers} \times \text{Subscription Fee})$$

Inputs:

Data on the number of customers, their average spending, and subscription fees would be derived from usage records.

This total includes usage fees (e.g., per-minute or per-trip charges) and subscription revenues.

2. Extra Revenue from Subscribers Exceeding Free Usage

- **Formula:**

$$\text{Extra Revenue} = \text{Total Overage Minutes (Subscribers)} \times \text{Overage Fee per Minute}$$

- **Inputs:**

Total Overage Minutes: The number of minutes subscribers used beyond their free allowance.

Overage Fee per Minute: Fee charged for exceeding the free usage limit.

3. Total Fixed Costs

- **Formula:**

$$\text{Fixed Costs} = \text{Depreciation of Assets} + \text{Maintenance Costs} + \text{Administrative Costs}$$

- **Inputs:**

Depreciation of Assets: Cost of vehicles and infrastructure, spread over their useful life.

Maintenance Costs: Regular service and repair expenses for vehicles.

Administrative Costs: Salaries, office rent, and other overheads.

4. Total Variable Costs

- **Formula:**

$$\text{Variable Costs} = \text{Energy Costs} + \text{Labor Costs for Operations} + \text{Other Operational Costs}$$

- **Inputs:**

Energy Costs: Charging costs for electric micromobility vehicles, derived from usage patterns and electricity rates.

Labor Costs: Wages for operational staff involved in vehicle redistribution, customer service, etc.

Other Operational Costs: Insurance, marketing, or other incidental costs linked to vehicle usage.

5. Profitability (Revenue Surplus)

- **Formula:**

$$\text{Profit/Loss} = \text{Total Revenue} - (\text{Fixed Costs} + \text{Variable Costs})$$

- **Revenue**:

Total revenue from customers and subscribers amounted to **$16,447,169**.

Additional revenue from subscribers exceeding free usage contributed a marginal **$1,379.79**.

- **Costs**:
  - Fixed costs were estimated at **$1,799,350**, while variable costs totaled **$2,159,873**.

The profitability analysis reveals that the system operates with a significant revenue surplus over costs, demonstrating financial viability. Profit = **$2,097,846**

Metric	Value $
Total Revenue from Customers and Subscribers	6055689.70
Extra Revenue from Subscribers (above free usage)	1379.79
Total Fixed Costs	1799350.00
Total Variable Costs	2159873.21
Profit/Losss	2097846.28

5.Conclusions

1. **Parking Duration Insights**:
    - Longer parking durations are predominantly observed in peripheral wards, suggesting lower vehicle turnover rates in these areas.
    - Central wards, such as 27, 28, and 34, exhibit shorter parking durations, indicative of high demand and faster turnover.
2. **Trip Flow Analysis**:
    - The OD matrix and overlap map reveal high trip densities between central wards, aligning with public transport hubs and business districts.
    - Peripheral areas exhibit fewer trips but longer parking durations, indicating less frequent usage of micromobility services.
3. **Business Viability**:
    - The system demonstrates strong financial performance, with revenues significantly exceeding operational and capital costs.
    - Additional strategies, such as increasing subscriber usage or optimizing parking durations, could further enhance profitability.

Exercise of Calculation of the generalised cost of the trip “Home-Politecnico”

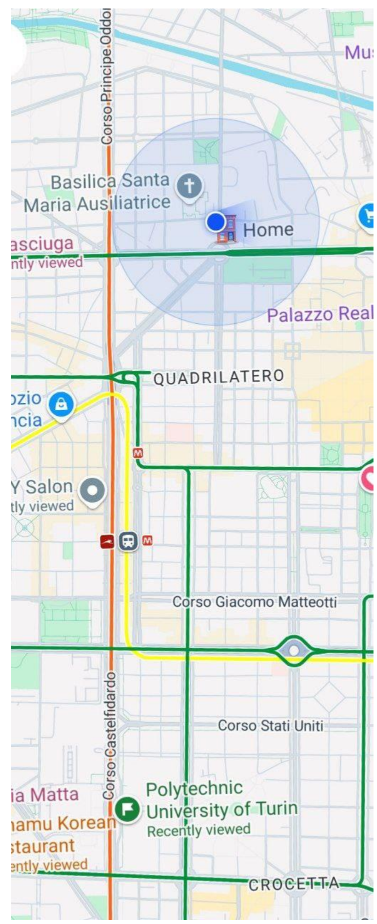
Introduction

This report aims to assess the generalized cost of a typical daily journey from "Home" to "Politecnico," utilizing a variety of transportation modes, including private car, car sharing, bike sharing, micro-mobility options, and public transport. The analysis will take into account both the financial costs and the time value (Value Of Time - VOT) associated with each mode of transport. The primary objective is to evaluate the total cost of commuting by considering factors such as travel time, monetary expenditure, and the subjective perception of time spent during the journey.

My home address: Via Francesco Cigna

"All the data , information and calculation related to this section is provided in the Excel file sent to the portal and via email along with this report. This table serves as a summary of all the transportation modes cost used for traveling from home to Polito (for round trip)

Way of transportation from home to polito	Cost per round trip
Private E-scooter (Xiaomi Mi Electric Scooter Pro 2)	€ 6.73
Private Bike (Airbici)	€ 7.95
Sharing Bike (Lime)	€ 12.75
Sharing Scooter (Lime)	€ 14.99
Public Transport (GTT)	€ 15.61
Sharing Car (SHARE NOW)	€ 17.45
Taxi (FREE NOW)	€ 17.60
Private car (Fiat Panda)	€ 27.48



Exercise on Maas

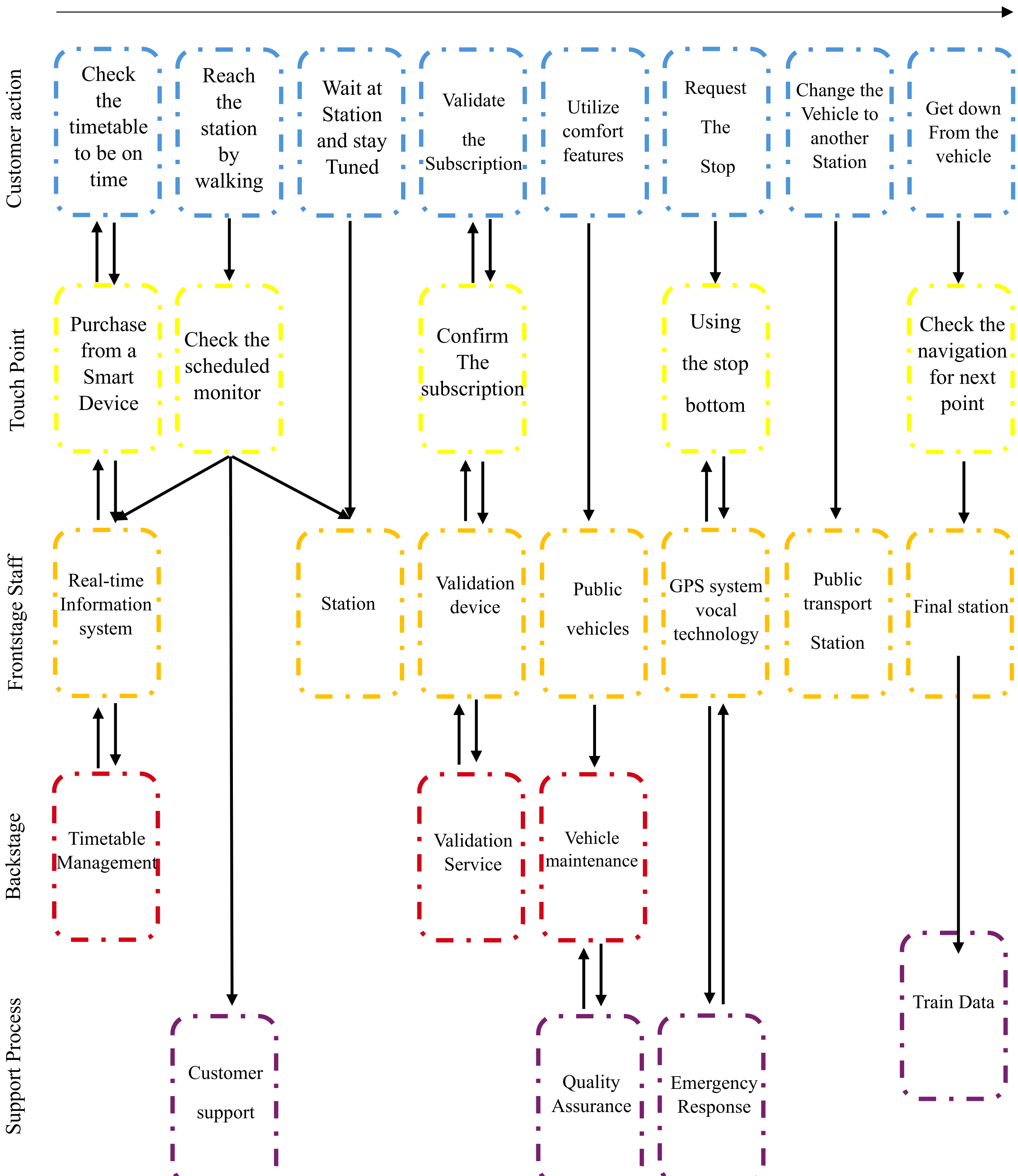
User Persona

Carlo, a 67-year-old retired man from Grugliasco, uses public transport three times a week for leisure trips to San Mauro Torinese, shopping, and errands. Although he finds public transport safe and eco-friendly, he feels it is too slow, rigid, uncomfortable, and not very enjoyable. His longest journey, which takes about 60 minutes, makes him want a faster, more comfortable, and flexible travel option.

Carlo spends about €18 per month on public transport, and with a monthly income of €1501-2000, he can afford other options. A good solution for Carlo would focus on being eco-friendly, saving time, offering comfort, and being flexible. This would help people like Carlo easily switch from traditional public transport to modern, better travel options

Current Situation Blueprint

Journey



Description about the solution

To enhance Carlo's commuting experience, a car-sharing service called "Share Now" is recommended. This service allows users to find, reserve, and use a car nearby through a mobile app, without the need for car ownership. The costs are calculated based on the duration and distance of the trip.

For example, if Carlo plans to travel from Grugliasco to San Mauro Torinese, a distance of approximately 29 kilometres, the costs would be as follows: SHARE NOW info

Model: Peugeot 208

Minute rate: €0.19

Duration: 27 minutes

Cost: 27 minutes × €0.19 = €5.13

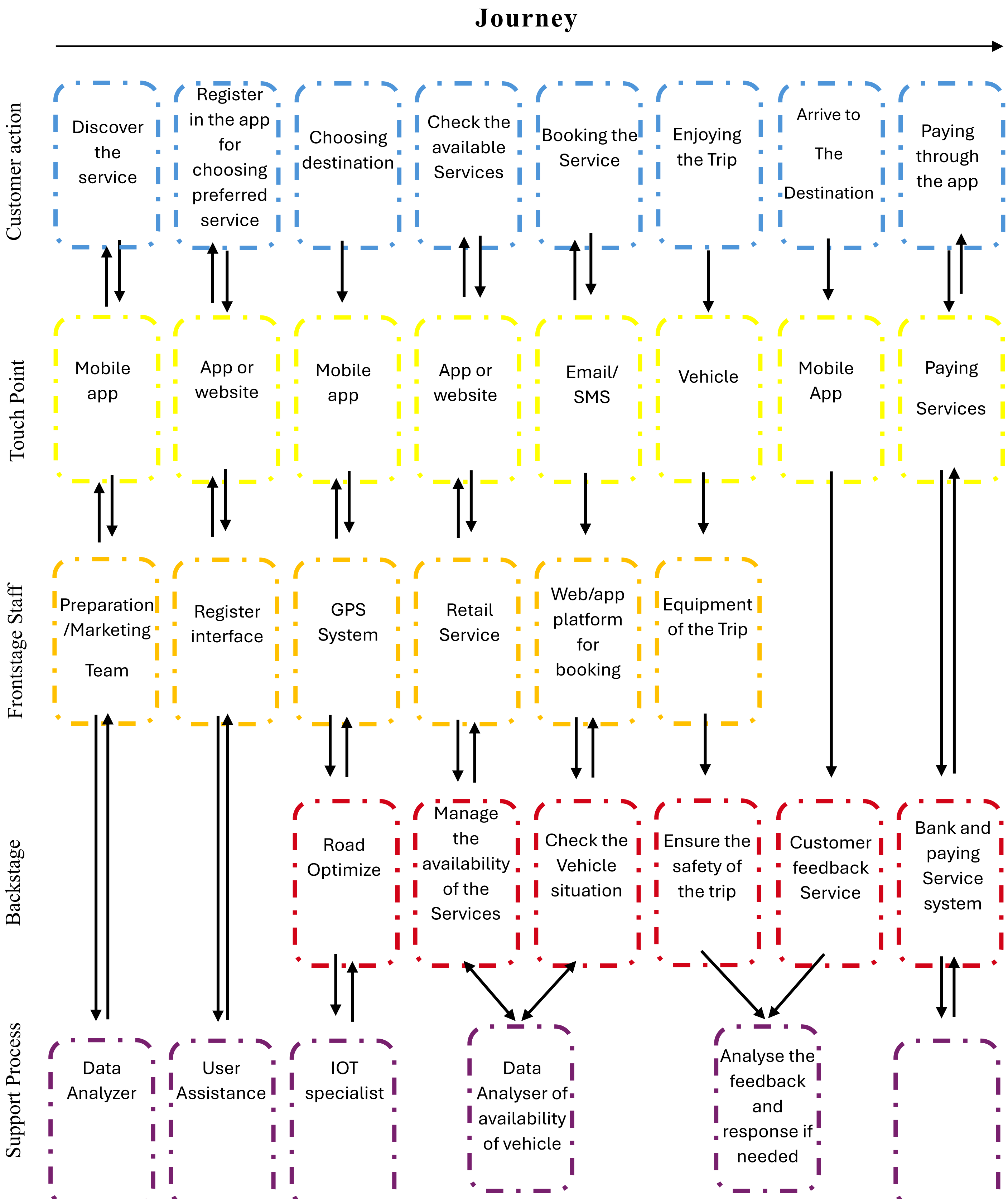
This amount includes fuel, insurance, and parking in the designated area.

Carlo becomes aware of this service through advertisements, recommendations from friends, or online searches. He then downloads the user-friendly app and completes the registration process, granting him access to the platform. Using the app, Carlo enters his destination, and the app provides him with the best options. The app serves as the main point of contact, allowing users to register, find available cars, and book them seamlessly. After reaching his destination, Carlo ends the trip, and payment is processed automatically through the app. Additionally, in-car interfaces and customer support services enhance Carlo's experience by providing security during his commute.

The development team focuses on creating a user-friendly registration interface while offering personalized recommendations based on Carlo's travel patterns. They also ensure that the fleet consists of well-maintained and comfortable vehicles. Information about sustainability efforts aligns with Carlo's values, providing an engaging user experience. This car-sharing solution not only caters to commuters like Carlo but also presents an opportunity to create a community-centric mobility service, especially for those heading in the same direction.

After Carlo learns about the service, the entire process through the app takes about 7 minutes, and his trip lasts approximately 27 minutes, totaling around 34 minutes. It's important to note that this timeframe is an estimate for the overall process. By using this platform, individuals can optimize their commuting experience by sharing rides, promoting resource efficiency, and reducing environmental impact. This sense of community aligns with Carlo's commitment to sustainability, as it supports efforts to reduce the impact caused by personal transportation

Future Blueprint



Conclusion

Based on the analysis and recommendations provided in this exercise, it is evident that modernizing Carlo's travel experience through a car-sharing solution like "Share Now" offers significant improvements in terms of time, cost efficiency, and comfort. For instance, Carlo's typical 60-minute public transport journey can be reduced to approximately 34 minutes with a cost of €5.13 for a one-way trip, covering fuel, insurance, and parking. This approach aligns with his priorities, such as flexibility, sustainability, and an eco-friendly commute.

By leveraging technology, including a user-friendly mobile app, real-time vehicle availability, and efficient route planning, the proposed solution not only meets Carlo's needs but also promotes resource optimization and environmental benefits. As urban mobility evolves, this model represents a sustainable and user-centric alternative to traditional public transport.