Smart Rideshare Matching: Feasibility of Utilizing Personalized Preferences

Shaguna Gupta[1,2][a], Shi Feng[3] and B. Brian Park[4][b]

[1]*Link Lab, University of Virginia, Charlottesville, Virginia, U.S.A.*
[2]*School of Computer Science and Statistics, Trinity College Dublin, College Green, Dublin, Ireland*
[3]*Link Lab, Department of Civil and Environmental Engineering, University of Virginia, Charlottesville, Virginia, U.S.A.*
[4]*Link Lab, Departments of Civil & Environmental Engineering and Systems & Information Engineering,*
Uni .S.A.
guptas2@tcd.ie, {sf5jh, bp6v}@virginia.edu

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Abstract: We investigated the feasibility of utilizing vehicular telematics data for ride-sharing matching. The main focus was to use personalized preferences including home and workplace departure and arrival times. A case study was conducted using the vehicular telematics commuting data between their home to the University of Virginia (UVA) campus. Using data from April 2022, which captures vehicle trips, arrival times, and departure times at UVA, this research analyzed vehicle trips over two weeks to identify individuals with similar commuting schedule preferences. By clustering vehicles based on proximity and timing, we proposed a framework for matching individuals who share similar arrival and departure schedule preferences and live in nearby locations, thereby facilitating coordinated ride-sharing opportunities. The findings are presented through visualizations illustrating ride-matching potential, particularly during peak commuting hours. The matching would offer a convenient ride-sharing solution for UVA commuters while maintaining their commuting flexibility. This approach could also offer a sustainable transportation solution that enhances travel efficiency, lowers environmental impact, and supports the broader adoption of ride-sharing within academic and urban settings. The proposed framework provides a scalable model for systematic ride-sharing implementation and could guide future research and policy development for sustainable campus mobility solutions.

1 INTRODUCTION

Current transport-share systems or carpooling typically rely on users to actively request or offer a ride and to coordinate the time and pickup location. Services such as Lyft and Uber have addressed this problem by using location to provide ride services that are convenient and on-demand. The on-demand and convenience aspects of transportation might also be the main reason behind using personal cars as they allow to combine commutes with other activities (e.g., picking up kids to and from school, running errands, going to off-campus meetings, etc.). This convenience, however, comes at a great personal and societal cost, including traffic congestion and parking demand. Despite various agencies' incentives and discounts for ride-sharing, this kind of service has not been widely used in daily commuting for obvious reasons mentioned above as well as hassled coordination, scheduling requirements, commitment, and having to actively request or offer rides.

In this research, we conducted a case study using a university community to increase engagement in ride-sharing by analyzing vehicular telematics data made available by Wejo. The analyses mainly focused on drivers' commutes to the University of Virginia (UVA) and the potential of matching based on their arrival times to the University and departure times to their work-to-home trips. The UVA is centralized around the Charlottesville area and faces challenges in managing traffic flow due to its limited parking spots. As campus activities fully resumed in 2022, making a return to normalcy after the disruptions caused by the COVID-19 pandemic, the flow of traffic to and from the campus noticeably increased. Because of the ever-increasing parking demands on the campus, there is an opportunity to optimize traffic

[a] https://orcid.org/0000-0002-9361-3097
[b] https://orcid.org/0000-0003-4597-6368

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flow using ride-sharing initiatives.

Ride-sharing can be an efficient mode of sustainable transport for work colleagues or people who live in close proximity, especially in areas with limited public transport, walking, or cycling options. Ride-sharing or car-pooling can be beneficial for organizations and individuals in terms of reduced travel costs, improved parking efficiency, decreased traffic congestion, and positive environmental impacts. Besides, it can be a productive, greener, and more sustainable choice for individuals and the wider community. This research presents an analysis of vehicle trips to and from UVA over a two-week period in April 2022, with the goal of identifying potential ride-sharing opportunities based on personalized commuting arrival/departure time preferences.

The key objectives of this analysis are to mainly recommend ride-sharing suggestions based on timing and proximity. By identifying individuals who arrive at UVA at similar times and leave UVA at similar departure times, the aim is to enable coordinated ride-sharing opportunities that align with their schedules. Furthermore, the study suggests ride-sharing options for individuals commuting from and to nearby locations relative to each other to enhance convenience. These criteria are used to group vehicles based on their arrival and departure locations, both at UVA and at their home locations before and after the UVA trips.

This research details the methodology used to identify these ride-sharing opportunities, evaluates the results obtained from the analysis, and presents visualizations to support the findings. The insights gained from this study could be instrumental in developing a systematic ride-sharing program that enhances the commuting experience for UVA students, faculty, and staff. We expect that the approach used in this research is applicable to many similarly situated communities and institutions, where optimizing transportation systems can significantly lower environmental impact, and improve overall travel efficiency. This framework tailored to different settings can serve as a versatile solution for fostering sustainable and convenient commuting practices in urban and academic environments alike. The remainder of this paper is organized as follows. Section 2 summarized the status of existing literature related to car sharing, followed by section 3 with data and approaches used to analyze the vehicular data. Section 4 presents feasibility evaluation and results, followed by section 5 discussion, section 6 conclusions and section 7 future work.

2 LITERATURE REVIEW

Interest in ride-sharing to address traffic, parking, and energy issues in cities, companies, and college campuses has driven extensive research on optimizing models and understanding influencing factors. Our study reviews current research on carpooling models, preferences, and system improvements.

Studies have proposed models and algorithms aimed to enhance car-sharing systems to benefit both users and car-sharing companies. Focusing on the user perspective, Narman et al. presented a model that employs a two-layer matching system (Narman et al., 2021), and Hussain et al. proposed a system specifically designed to optimize car sharing framework for employees in large organizations (Hussain et al., 2022), while Masoud and Jayakrishnan introduced a real-time algorithm to address the ride-matching problem within a flexible ride-sharing system (Masoud and Jayakrishnan, 2017). In the two-layer model that Narman et al. developed, the first layer matches riders based on personal characteristics, such as safety, punctuality, and comfort. The second layer limits wait times with personalized thresholds. A machine learning-based recommendation system achieved 90 percent accuracy in predicting rider preferences, providing successful matches and trip completions. Considering car sharing in large companies, Hussain et al. developed a framework that considers factors like home location, target destination, time windows, and personal behavior to optimize carpooling groups. The system updates schedules in real time, offering flexible carpooling solutions. The proposed framework efficiently manages recurrent travel demand, especially for company employees. The flexible system that Masoud et al. proposed allows for dynamic, real-time matching and multi-hop rides, considering users' preferences and minimizing waiting times. Their algorithm can also solve large-scale ride-matching problems quickly, providing comfort to riders through optimal routing and reducing the number of transfers. These studies developed innovative models using algorithmic approaches to enhance user experiences in car-sharing systems, fostering greater participation and efficiency in car-sharing systems.

Some researchers have also concentrated on optimizing road networks, particularly in relation to road congestion and capacity. De Palma et al. focused on the impact of dynamic congestion on carpooling matching in their paper (de Palma et al., 2022). The study considered scheduling preferences and dynamic congestion in its ride-sharing framework. Results showed optimal matching occurs when drivers and passengers are sequenced by location, but differing arrival times complicate matching and may introduce tardiness penalties. Considering users' choice of ride-sharing, destination, and path, Xingyuan Li et al. presented a ride-sharing trip-assignment model using a bi-level programming approach for optimizing the reserve capacity of road networks. The programming was then formatted into a single-layer optimization problem (Li et al., 2024). They concluded that subsidizing ride-sharing drivers can enhance road capacity, rivaling the effects of road expansion without ride-sharing. Incorporating dynamic congestion and user preferences, these studies show that effective ride-sharing strategies can significantly improve road networks and reduce congestion.

Other researchers have examined the social aspects of carpooling. Limited participation in carpooling can be attributed to specific strategies employed by ride-hailing companies, as well as concerns expressed by passengers. Naumov and Keith focused on the economic and environmental impacts of ride-hailing (Naumov and Keith, 2023). The study found most ride-hailing trips, especially pooled rides, are unprofitable due to subsidies. Adjusting pricing by widening the gap between individual and pooled ride costs could increase revenue, reduce vehicle miles traveled, and benefit both companies and the urban environment. Linchao Li et al. explored what influences college students' views on carpooling by implementing a multinomial logit model based on survey-based data (Li et al., 2023). They concluded that concerns about safety and cost are key reasons carpooling is not popular among students. Safety and cost are primary concerns, a reliable carpooling information platform for students could therefore increase support for carpooling. These studies provided various insights into how ride-sharing systems can be modeled, optimized, and influenced by users' preferences.

Despite the valuable findings provided by the reviewed studies, there exists a notable gap in the research: few studies have utilized real-world vehicle trajectory data that specifically capture drivers' departure and arrival time preferences in their daily commuting trips. Most existing ride-sharing models rely on simulations or survey data, which may not fully reflect the dynamic nature of actual commuting patterns. In addition, the integration of vehicle telematics data has been under-explored in the context of optimizing ride-sharing on university campuses commuting patterns. To address this gap, our study proposes an innovative approach that leverages real-world vehicular telematics data to analyze commuting patterns at the University of Virginia (UVA), and the potential for matching based on their arrival and departure times at UVA, which generates private route options for users. This research allows for more accurate identification of potential ride-sharing opportunities based on the timing and availability of potential vehicle trips on campus, which aims to reduce traffic, improve efficiency, and create a more sustainable transportation system in the city of Charlottesville.

3 MATERIALS AND METHODS

As noted, our research focuses on identifying patterns where individual commuters arriving at and departing from a university campus at similar times or from similar locations could benefit from shared transportation. Leveraging trip data, including Trip_IDs, Vehicle_IDs, ignition status, and geographical coordinates, we can cluster vehicles based on their arrival and departure times and locations. This allows us to propose ride-sharing opportunities that could reduce traffic congestion, lower transportation costs, and contribute to a more sustainable campus environment.

3.1 Vehicular Telematics Data

This research used vehicular telematics data made available to the research team by the Virginia Department of Transportation (VDOT). It is noted that VDOT purchased the data from Wejo company. Out of 26 weeks of data, this research utilized vehicle trips for ten working days in April 2022, focusing on Trip_IDs, Vehicle_IDs, ignition status, and geographical coordinates (latitude and longitude) to identify potential ride-sharing clusters. These ten consecutive weekdays were selected as other months were affected by COVID-19 (some still teleworking during Fall 2021) and many University academic activities (e.g., Spring recess in March, graduation in May).

3.2 UVA Boundary

To accurately determine which trips were associated with UVA, a boundary polygon was created to represent the UVA campus, including its parking lots (University of Virginia, 2023). This polygon was used to filter trips that either started or ended within the UVA boundary. Only trips that had their ignition turned off (KEY_OFF) within this boundary were considered as arriving at UVA, while trips that had their ignition turned on (KEY_ON) within the boundary were considered as departures. Figure 1 shows the UVA campus boundary on OpenStreetMap (OpenStreetMap contributors, 2017) used to filter relevant trips and this is being utilized to understand the arrivals and departures in the subsequent sections.

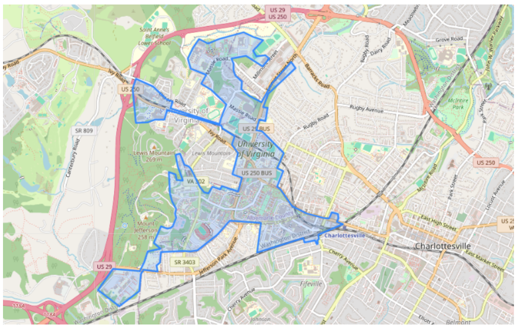

Figure 1: UVA Polygon Boundary.

3.3 Vehicle Operational Schedule Understanding

The initial phase in the methodology involved loading and transforming the data. Timestamps recorded in Coordinated Universal Time (UTC) were converted to Eastern Time (EDT) to align with the local time zone at UVA. The data was then filtered to include only relevant trips, specifically those between 5 AM and 8 PM on weekdays, and within a predefined set of valid postal codes within the 25-mile radius of UVA.

3.3.1 Arrival and Departure Schedule

Based on the UVA polygon boundary, the filtered data was further processed to identify arrivals and departures at UVA. The study specifically analyzed trips that ended or started within the UVA polygon area, considering these as the first trip of the day to UVA and the last trip of the day from UVA. Based on this, we finalized the trips that arrived or departed.

- Arrivals Extraction Algorithm

  This algorithm is designed to find the first trip each vehicle makes to UVA on any given day. A trip is classified as an arrival at UVA when the vehicle's ignition is turned off, represented by the KEY_OFF ignition status. The algorithm processes data related to vehicle trips and extracts the earliest instance of a vehicle arriving at UVA on each day within the dataset. This approach filters the dataset to include only trips where the vehicle's ignition was turned off (i.e., arrival events) and then sorts the data by vehicle and timestamp.

- Departures Extraction Algorithm

  This algorithm identifies the last trip for each vehicle that departs from UVA on a given day. The trip is considered a departure if the vehicle's ignition is turned on, represented by the KEY_ON ignition status. The algorithm identifies the last trip departing from UVA for each vehicle on that day. This is designed to primarily extract the first row of the last recorded trip for vehicle departures from a defined location based on its timestamp.

  Both algorithms identify the first trip and last trip of each vehicle arriving at and departing from UVA on a given day. The key steps involve filtering for relevant trips (ignition off/on), sorting, grouping by vehicle and date, extracting the first trip, and cleaning the dataset to remove unnecessary information. The algorithms also utilize Pandas and Polars for data manipulation and transformation.

Algorithm 1: First Trip Arrival Extraction Algorithm.

1: **Input:** DataFrame df, Polygon $uva\_polygon$
2: **Output:** DataFrame $first\_rows\_of\_first\_trip$
3: Convert $Timestamp\_est$ to $Trip\_Date$ (date only).
4: Filter rows where $Ignition\_Status$ is KEY_OFF.
5: Sort DataFrame by $Vehicle\_ID$ and $Timestamp\_est$.
6: Group by $Vehicle\_ID$ and $Trip\_Date$ to get the first $Trip\_ID$ of the day.
7: Join the dataset with the first $Trip\_ID$ to get the full details of the first trip.
8: Convert df to Pandas format for spatial filtering.
9: Convert back to Polars DataFrame.
10: Group by $Vehicle\_ID$ and $Trip\_Date$ to keep only the first rows of the first trip.
11: Drop unnecessary columns.
12: Return the cleaned DataFrame.

Algorithm 2: Last Trip Departure Extraction Algorithm.

1: **Input:** DataFrame df, Polygon $uva\_polygon$
2: **Output:** DataFrame $first\_rows\_of\_last\_trip$
3: Create a new column $Trip\_Date$ by extracting the date from $Timestamp\_est$.
4: Filter df where $Ignition\_Status$ is KEY_ON.
5: Sort df by $Vehicle\_ID$ and $Timestamp\_est$.
6: Group df by $Vehicle\_ID$ and $Trip\_Date$.
7: For each group, select the last $Trip\_ID$.
8: Join df with $last\_trip\_ids\_df$ to get the last trip's rows.
9: Convert df to Pandas for spatial filtering.
10: Convert the filtered DataFrame back to Polars.
11: Extract the last trip's first row for each vehicle and day.
12: Drop unnecessary columns.
13: Return the resulting DataFrame.

3.3.2 Start and end Trip Schedule

- Start and End Point Extraction Algorithm

  This code processes vehicle trip data by identifying start and end points based on key events (key-on and key-off) before and after vehicle arrivals and departures at UVA. The process focuses on merging, filtering, and ranking key-on and key-off events to capture home locations by calculating distances between start and end trip locations.

Algorithm 3: Start-End Trip Points Extraction Algorithm.

1: **Input:** Arrival, Departure, Key-on, Key-off data, UVA parking boundary.
2: **Output:** Excel with start/end trip points, arrival and departure times, and distances.
3: Load data from Parquet files into Pandas DataFrames.
4: Convert $Timestamp\_est$ to timezone-naive datetime.
5: Select $Vehicle\_ID$, $Timestamp\_est$, $Date$, $Latitude$, $Longitude$ and remove duplicate records.
6: Merge $arrival\_df$ with key-on events on $Vehicle\_ID$ and $Date$.
7: Keep the first three key-on events before each arrival.
8: Merge $departure\_df$ with key-off events on $Vehicle\_ID$ and $Date$.
9: Keep the first three key-off events after each departure.
10: Remove trip points within the UVA parking boundary.
11: Use Haversine formula to compute distances between start to end trip points and arrival to departure points.
12: Merge cleaned arrivals and departures into a $final\_df$ with vehicle IDs, dates, trip times, and distances.
13: Export final DataFrame as Excel.

3.4 Clustering Approach

The filtered data was further processed to identify potential ride-sharing opportunities. The analysis involved visualizing and clustering vehicles based on spatial and temporal proximity at various stages of their trips (Jain and Dubes, 1988). Three distinct clusters were defined to gain insights into the ride-sharing potential. The clustering logic grouped vehicles by:

- Arrival Points: Vehicles arriving at UVA over the duration of 10 days composes our arrival points. This will lead to the potential for detecting vehicles that arrive around the same time. The arrivals spread across UVA boundary over 10 days can be visualized to show the density of the vehicles around UVA parking lots (Figure 2).
- Departure Points: The location of vehicles leaving UVA over 10 days captures the departure points. Again, departure points will help identify the vehicles departing around the same time, offering a chance to cluster and optimize ride-sharing for return trips. The departures spread across the UVA boundary can be visualized as shown in Figure 3.
- Home-to-UVA Points: These points compose our Home-to-UVA start locations highlighting where vehicles begin their trips, which is crucial for identifying potential ride-sharing clusters based on spatial proximity referring to the vehicles departing for UVA.
- UVA-to-Home Points: Vehicles departing from UVA to return to home locations will compose the UVA-to-Home end locations. This will enable identifying vehicles returning to similar home locations at similar times, which will be key for optimizing ride-sharing on the return trip, reducing the number of independent return trips.

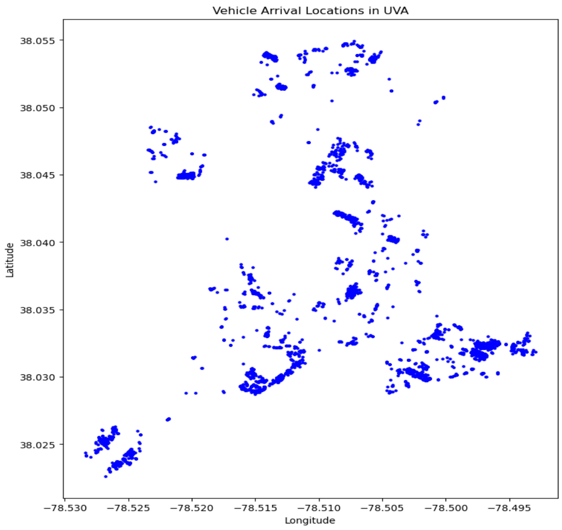

Figure 2: Arrivals spread at UVA boundary.

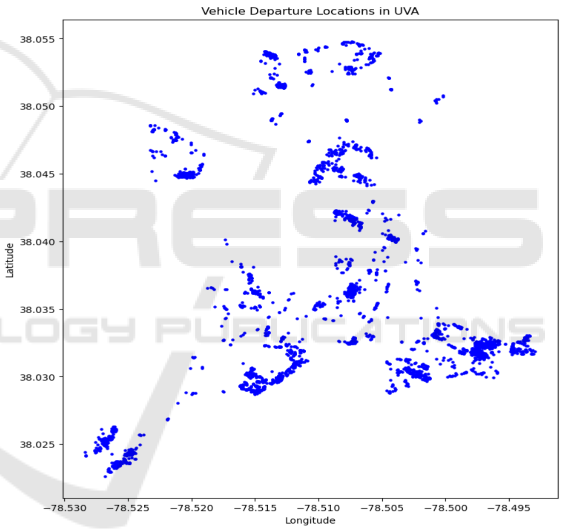

Figure 3: Departures spread at UVA boundary.

3.4.1 Defining Clusters

1. Arrival Time Clustering: Vehicles arriving at UVA within a similar time window (e.g., 15-30 minute intervals) could be grouped together. This temporal clustering will help identify vehicles that could potentially share rides to reduce the number of trips to UVA.
2. Departure Time Clustering: Similarly, vehicles departing from UVA within the same time windows can be grouped to suggest ride-sharing for

the return journey. This clustering will help identify those vehicles that leave UVA at similar times, enabling ride-sharing for the trip home.

3. Home Location Clustering: This clustering involved identification of start and final location of the vehicles. Vehicles that started their trips from nearby locations (e.g., within 2 miles of each other) could be identified as potential ride-sharing candidates. This was done for both the trip to UVA and the return trip home. Therefore, vehicles that begin their trips from nearby locations heading toward UVA or leaving UVA for nearby locations could be grouped together, suggesting ride-sharing routes for both legs of the journey.

This analysis allowed us to group vehicles that start and end their trips from and to nearby locations respectively within a predefined radius (e.g., 2 miles) or using a clustering algorithm such as K-means and arrive at UVA and depart from UVA within the same time window (Li and Chung, 2020).

4 EVALUATION AND RESULTS

The evaluation of the clustering process was conducted by analyzing the number of vehicles that were successfully grouped based on the defined criteria. The results indicate several significant clusters of vehicles that could benefit from ride-sharing, especially during peak arrival and departure times. The analysis identified several clusters of vehicles that could potentially benefit from ride-sharing.

4.1 Evaluation Metric 1: Number of Vehicles in Each Day Within 10 Days Bracket

The provided graphs show the daily number of unique vehicle arrivals and departures at UVA over a 10-day period in April 2022. In Figure 4, vehicle arrivals ranged from a low of 297 on April 15 to a high of 372 on April 22, with some fluctuation observed throughout the period. In Figure 5, vehicle departures ranged from a minimum of 285 on April 15 to a maximum of 365 on April 13, indicating a similar level of day-to-day variability. Overall, both arrivals and departures exhibit peaks and troughs, but both the distribution of the unique vehicle arrivals and departures follow a similar pattern in the researched period.

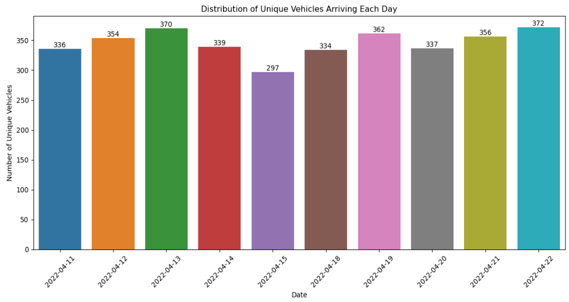

Figure 4: UVA Unique Arrivals Each Day.

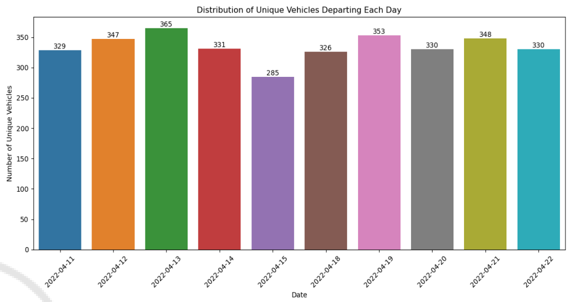

Figure 5: UVA Unique Departures Each Day.

4.2 Evaluation Metric 2: Number of Vehicles in Each Hour for 10 Days

The following figures illustrate the hourly distribution of vehicle arrivals and departures at UVA over the researched 10-day period.

In Figure 6, arrivals have a peak during the morning hours, particularly between 7 AM and 9 AM, with the highest number of unique vehicles observed around 9 AM. After this peak, the number of arrivals gradually decreases throughout the day until the evening. Figure 7 shows departures, which exhibit a different pattern with peaks occurring in the late afternoon, particularly between 3 PM and 5 PM, with a peak at around 4 PM. Departures steadily increase from late morning until reaching their maximum, after which they decline towards the evening hours. The data indicates that arrivals are concentrated in the morning while departures peak in the late afternoon, suggesting typical commuting behavior.

4.3 Evaluation Metric 3: Number of Vehicles in Every 30-Minute Window for 10 Days

The following figures contain the number of unique vehicle IDs arriving and departing at UVA in 30-minute intervals across the researched 10-day period.

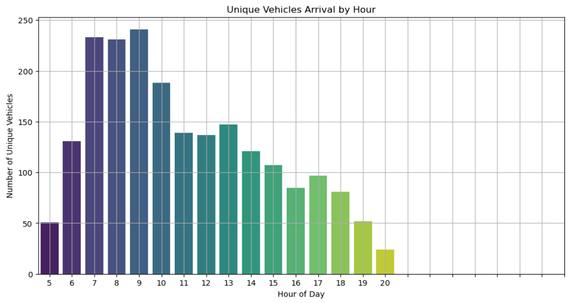

Figure 6: UVA Unique Arrivals per hour for 10 Days.

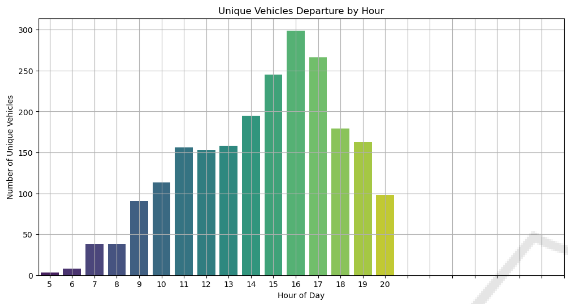

Figure 7: UVA Unique Departures per hour for 10 Days.

In Figure 8, the arrivals show a clear peak during the morning hours, especially between 7:30 AM and 9:30 AM, with the highest number reaching 164 around 7:30 AM. After this peak, the number of arrivals steadily declines throughout the day, indicating that most arrivals happen in the early part of the day. In Figure 9, the departure reveals a different trend. Departures increase gradually throughout the day, peaking between 4:00 PM and 5:30 PM, with the highest number reaching 182 unique vehicle IDs at 4:30 PM. After this peak, the number of departures decreases toward the evening hours. This pattern suggests a typical commuting behavior where vehicles arrive in the morning and depart in the late afternoon.

Arrival and Departure Clusters: Significant clustering was observed for vehicles arriving and departing within 30-minute windows, indicating potential for coordinated ride-sharing as shown in the figures.

4.4 Evaluation Metric 4: Vehicles Distribution in Total 10 Days

Table 1 shows the distribution of vehicle counts for the different number of days starting from 10 days to 9 days and so on, with each number of day's absolute count and corresponding percentage of the total. Row with number of vehicles coming only 1 day out of a total 10 days has the highest count at 375, making up 38.38% of the total. This may be due to the reason of having travelers to the hospital or daily visitors to the University for other purposes. As the total number of days increases, their respective counts and percentages generally decrease, with total days 10 showing the lowest count at 76, which accounts for 7.78% of the total percentage of vehicles. The Grand Total is confirmed to be comprising 977 total unique vehicle entries to UVA in 10 days. Similar pattern is seen for vehicles exiting UVA in these days.

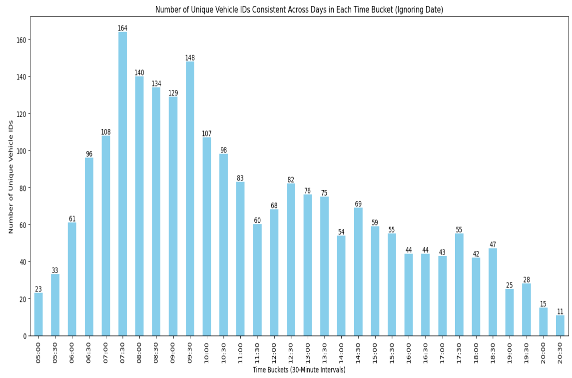

Figure 8: UVA Unique Arrivals for 10 Days.

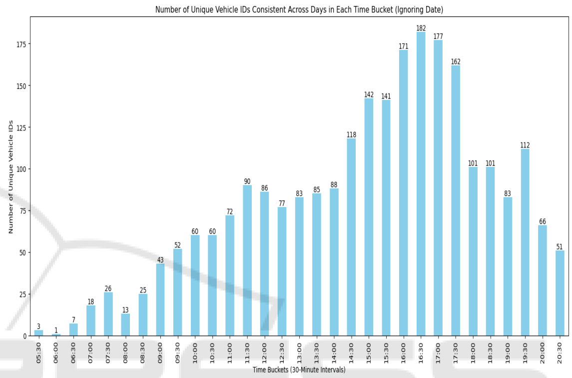

Figure 9: UVA Unique Departures for 10 Days.

Table 1: Arrival Count Distribution by Vehicle ID and Days.

Total Days	Count	Percentage
10	76	7.78%
9	46	4.71%
8	35	3.58%
7	36	3.68%
6	46	4.71%
5	46	4.71%
4	72	7.37%
3	92	9.42%
2	153	15.66%
1	375	38.38%
Grand Total	**977**	**100.00%**

5 DISCUSSION

While each day has around 300 vehicles arriving to and departing from the UVA campus, it is noted that UVA currently employs about 16,000 faculty and staff and 7,000 UVA health employees. Given the Wejo data is only available from newer vehicles made after 2015 and selected automakers, the study only matched a small number of vehicles. As this study focuses on the feasibility of ride-sharing using vehicular telematics data, it is feasible to show ride-sharing can be matched from these 300 vehicles. It is possible that 300 vehicles matched daily could have been over 20,000 vehicles, assuming around 90% of around 23,000 employees commute by their personal vehicle. Actual matching would be accomplished via new sources of data, including ride-sharing App that UVA plans to adopt in the near future.

6 CONCLUSIONS

This research highlighted the potential to match commuters for ride-sharing by leveraging vehicular telematics data. Using the case study of the UVA campus, we showcased the ride-sharing matching could reduce traffic and improve transportation efficiency for individuals commuting to and from UVA. Leveraging both individual preferences in commuting times and their proximity criteria (i.e., home location and parking lot), this study identified opportunities for ride-sharing that could be implemented through a coordinated system, thereby enhancing the overall commuting experience while contributing to sustainability goals. The results suggested that a significant number of trips to and from UVA could be consolidated through ride-sharing, leading to a more efficient and sustainable transportation system on campus.

7 FUTURE WORK

Following the analysis of home location clusters, we will focus on presenting the results of home location clusters to explore their implications for optimizing ride-sharing routes to and from UVA. After filtering and clustering trips that start or end at UVA and preparing groups of vehicles, route overlap analysis could provide a deeper probability of providing ride-sharing opportunities. Evaluating the overlap of routes for vehicles within the same cluster to suggest potential ride-sharing pairs or groups.

In addition, future work should also focus on evaluating a larger, recent dataset to enhance ride-sharing analysis. Incorporating an expanded dataset, researchers could capture more travel patterns to find temporal changes in commuting behavior and identify emerging trends in ride-sharing demand. This would allow a more comprehensive understanding of current UVA commuting behaviors and facilitate the design of more effective ride-sharing initiatives and policies.

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REFERENCES

de Palma, A., Stokkink, P., and Geroliminis, N. (2022). Influence of dynamic congestion with scheduling preferences on carpooling matching with heterogeneous users. *Trans. Res. Part B: Methodol.*, 155:479–498.

Hussain, I., Knapen, L., Bellemans, T., Janssens, D., and Wets, G. (2022). A matching framework for employees to support carpooling in the context of large companies. *IEEE Trans. Intell. Transp. Syst.*, 23(2):1159–1170.

Jain, A. K. and Dubes, R. C. (1988). *Algorithms for clustering data*. Prentice-Hall, Inc., USA.

Li, L., Zhang, H., and Gan, Z. (2023). Factors affecting college students' attitudes toward carpooling. *Transportation Safety and Environment*.

Li, X., Cheng, Y., Peng, H., and Dai, X. (2024). Can ridesharing improve the reserve capacity of transportation network? *IEEE Access*, 12:73196–73209.

Li, Y. and Chung, S. H. (2020). Ride-sharing under travel time uncertainty: Robust optimization and clustering approaches. *Computers & Industrial Engineering*, 149:106601.

Masoud, N. and Jayakrishnan, R. (2017). A real-time algorithm to solve the peer-to-peer ride-matching problem in a flexible ridesharing system. *Trans. Res. Part B: Methodol.*, 106:218–236.

Narman, H. S., Malik, H., and Yatnalkar, G. (2021). An enhanced ride sharing model based on human characteristics, machine learning recommender system, and user threshold time. *J. Ambient Intell. Humaniz. Comput.*, 12(1):13–26.

Naumov, S. and Keith, D. (2023). Optimizing the economic and environmental benefits of ride-hailing and pooling. *Prod. Oper. Manag.*, 32(3):904–929.

OpenStreetMap contributors (2017). Planet dump retrieved from https://planet.osm.org . https://www.openstreetmap.org.

University of Virginia (2023). Updated parkingmastermap. [Online; accessed October 15, 2024].