TRANSCOM 2025: 16th International Scientific Conference on Sustainable, Modern and Safe Transport

Data-Driven Analysis of Rideshare Spatial Travel Patterns and Ride Metrics

Hao Wang[1], Deema Almaskati[1], Sharareh Kermanshachi[2] , Jay Michael Rosenberger[1], Apurva Pamidimukkula[1], Chen Kan[1], Ann Foss[3]

[1]*University University of Texas at Arlington, Arlington, Texas, U.S.A.*
[2]*Penn State University, Middletown, Pennsylvania, U.S.A.*
[3]*City of Arlington, 101 W. Abram St, Arlington, Texas, U.S.A.*

INTRODUCTION

- Ridesharing has the **potential to bridge transit gaps**, enhancing coverage beyond fixed routes and providing flexible transportation options (Patel et al., 2022).
- As these services become more common globally, **studies increasingly seek ridership data to understand the demand and patterns in user behavior**.
- This study examines ridesharing's role in meeting transit needs within a car-dependent community without fixed route public transportation (PT).
- Prior research has evaluated rideshare demand in urban areas like Chicago and New York (Brown, 2020; Ghaffar et al., 2020; Marquet, 2020), but **suburban regions like Arlington, Texas, lack attention**.
- Thus, this study seeks to **provide insight into rideshare patterns in a smaller suburban area without PT**.
- **Rideshare providers, city planners, and residents can leverage findings to enhance transit equity and service design.**
- This research study aims to contribute to the existing literature on rideshare and spatial demand by **investigating the correlation between spatial demand analysis and various ride characteristics for a city in Texas without a fixed-route system**.
- Rideshare data from **Via, an operator in Arlington, Texas**, was utilized to analyze rideshare spatial demand and ride metrics.
- The findings will facilitate a more **informed decision-making** process for stakeholders.

MATERIALS, METHODS & IMPLEMENTATION

- This study analyzes Via's rideshare data Texas over a two-year period (2021-2022), focusing on 5,961 unique origin-destination routes and aiming to evaluate differences across routes to **uncover route-specific transit patterns**.
- Data was cleaned by removing invalid entries (zero/negative distances or durations) and standardized with datetime formatting.
- The data was examined for frequency, distance, duration, time-of-day, day-of-week trends, and wheelchair-accessible vehicle (WAV) requests, using sorting, binning, and visualization techniques.
- **Temporal variations** in demand based on time of day and day of the week were explored, along with **WAV request patterns** across routes. Finally, **ride distances** were categorized into bins to compare typical trip lengths, uncovering additional patterns.
- Table 1 provides a clear overview of the top 10 used routes within the transportation network, serving as the foundation for deeper insights into ride characteristics and demand patterns, where the census identifiers represent areas within Arlington.

Table 1. Origin destination routes with the greatest frequencies

No.	Origin-Destination Route	Frequency	No.	Origin-Destination Route	Frequency
1	122300 – 121702	17,979	6	111525 – 122400	10,627
2	122300 – 111525	16,804	7	122400 – 121702	10,615
3	121702 – 122300	15,283	8	122400 – 122300	10,367
4	122400 – 111525	14,507	9	122300 – 122300	10,332
5	111525 – 122300	12,121	10	121702 – 122400	9,912

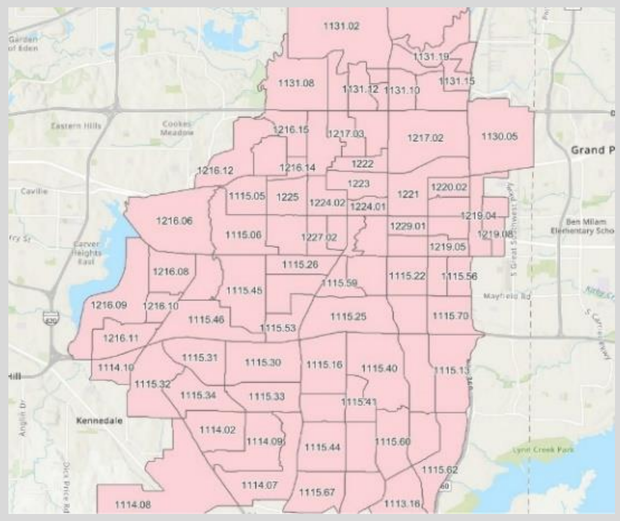

Figure 1. GIS map of the service with census tract identifiers

RESULTS

- Figure 2 shows weekly ride counts for top origin-destination routes, revealing distinct trends—some routes aligned, while others fluctuated uniquely, reflecting **diverse passenger demands**. **Ridership rose gradually in Fall 2021, surging in Fall 2022** as Via gained traction and COVID-19 restrictions eased, driving student campus returns.
- Figure 3 displays ride counts for the top 10 routes by time of day (6 AM–9PM, in 3-hour blocks), showing varied patterns. Some routes peak during morning (e.g., 9–11:59 AM, tracts 122300/122400 to 111525) or evening commutes (e.g., 6–8:59 PM, 111525 to 122400/122300), suggesting **roundtrip behavior**, while others show broader daily demand.
- Figure 4 shows ride frequencies for the top ten origin-destination routes by day of the week. Rides remain stable from Monday to Thursday but increase significantly on Friday and Saturday for certain routes, suggesting **shifts in travel behavior toward the weekend**. As the service does not operate on Sundays, it was excluded from the analysis.
- Figure 5 shows ride counts by WAV requests across the top 10 routes, revealing consistently low and similar numbers, indicating **minimal route-specific variation in accessibility demand**.
- Figure 6 displays ride distances for each top route, divided into intervals, revealing variability within origin-destination pairs despite the expectation of fixed distances. This suggests that **while distance helps describe trips, its unpredictability limits its usefulness in predictive models**.
- In summary, this study reveals that **origin-destination routes exhibit distinct characteristics**, with variations in ride frequency that are based on factors such as time of day, day of week, and specific route combinations.

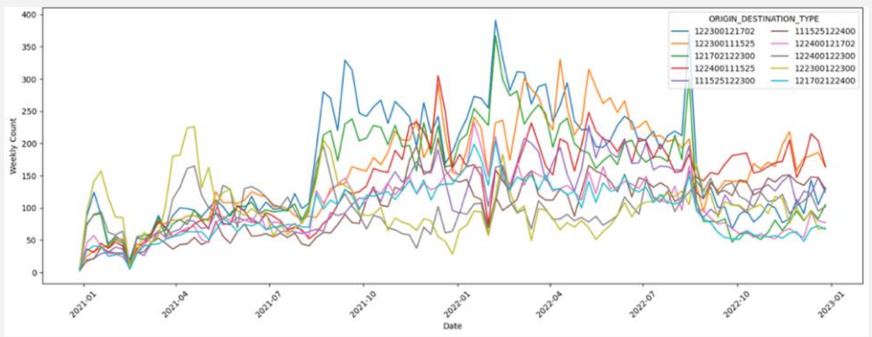

Figure 2. Weekly number of rides of frequent origin-destination routes

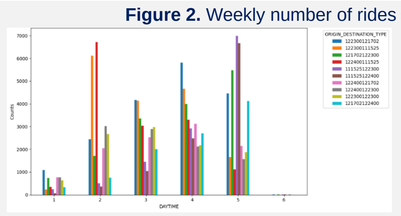

Figure 3. Number of rides by time of day

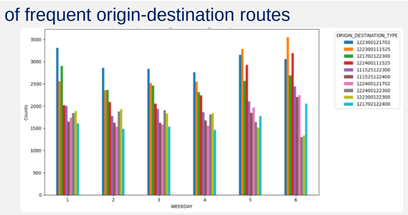

Figure 4. Number of rides by day of week

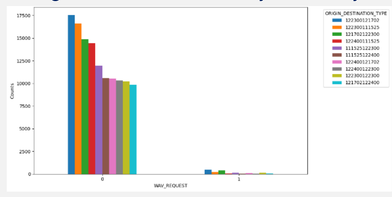

Figure 5. Number of rides by WAV requests

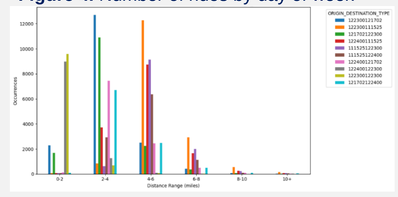

Figure 6. Number of rides by distance

CONCLUSION & IMPLEMENTATION PATH

- Ride demand varies across routes, influenced by time of day and day of the week, with peak-hour commuter patterns and increased activity toward the week's end. These variations help predict demand under different conditions.
- WAV requests remain consistently low across routes, limiting their usefulness for route-based analyses. Ride distances, despite expected consistency within origin-destination pairs, show notable variability, affecting predictability.
- **Understanding these patterns enables service optimization through strategic scheduling, resource allocation, and route planning**. Policymakers can adjust service availability to match demand, enhancing efficiency, reducing wait times, and informing **data-driven transportation policies**.

ACKNOWLEDGEMENTS

We gratefully acknowledge the support and generosity of the City of Arlington and Via, without which the present study could not have been completed.

REFERENCES

- Brown, A.E., 2020. Who and where rideshares? Rideshare travel and use in Los Angeles. Transportation Research Part A: Policy and Practice, 136, pp.120-134.
- Ghaffar, A., Mitra, S. and Hyland, M., 2020. Modeling determinants of ridesourcing usage: A census tract-level analysis of Chicago. Transportation Research Part C: Emerging Technologies, 119.
- Marquet, O., 2020. Spatial distribution of ride-hailing trip demand and its association with walkability and neighborhood characteristics. Cities, 106.
- Patel, R.K., Etminani-Ghasrodashti, R., Kermanshachi, S., Rosenberger, J.M. and Foss, A., 2022. Mobility-on-demand (MOD) Projects: A study of the best practices adopted in United States. Transportation Research Interdisciplinary Perspectives, 14.