Evaluating Usage, Acceptance, Integration, and Safety Impacts of Demand Responsive Transportation (DRT) Services

by

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Dedication

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ABSTRACT:

Evaluating Usage, Acceptance, Integration, and Safety Impacts of Demand Responsive Transportation (DRT) Services

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Transportation systems are vital in providing accessibility and mobility to city residents. Auto-oriented transportation systems have faced several challenges, including traffic congestion, crashes, and environmental pollution. Proponents of mass transit systems present them as a sustainable alternative to private automobiles. Although mass transit offers several benefits, these benefits are not very significant in rural, midsized, and low-density cities due to low public transit ridership. New modes of public transit, such as demand-responsive transport (DRT), also called on-demand public transport, have recently gained popularity across the United States. DRT systems are used in several mid-sized cities, either as an alternative to fixed route transit systems or in support of them by providing first and last-mile connections.

This dissertation explores three questions about the DRT systems, including their usage, acceptance, integration, and safety impacts, using a wide range of data and methodologies.

The first chapter introduces the topic, the broad research background, and the research questions. An outline of the dissertation is also presented.

The second chapter investigates the usage and adoption of Shared Autonomous Vehicles (SAVs) – a demand-responsive transport system using an SAV pilot project in Arlington, TX, as a case study. The project is named RAPID (Rideshare, Automation, and Payment Integration Demonstration), which started operations in March 2021. This study used real-time trip-level

ridership data from the RAPID project, surveyed the SAV riders, and developed a study based on ordered logistic regression to estimate the determinants of ridership frequency. The data analysis of real-time ridership data revealed that the spatial distribution of activities and service accessibility are important factors in forming current users' travel patterns. The findings from the Order Logistic Regression showed that users from higher-income households are less likely to be frequent riders of the RAPID service. The impact of the usual mode of transportation on RAPID usage showed that those who usually walk, bike, or utilize the on-demand ridesharing services are likely to use SAVs more frequently than private vehicle users. The users with higher levels of safety perception are also more likely to be frequent users of the service. The findings of this study could provide planners with a better understanding of the SAV ridership patterns and guide decision-makers in establishing and adopting the appropriate policies for future SAV implementation projects.

The third and fourth chapters of this dissertation aim to analyze the impacts of ridesharing services on the number of traffic crashes and injuries using two DRT services, RideAustin in Austin, TX, and Via Arlington in Arlington, TX, as the case studies. We used an Interrupted Time Series Analysis (ITSA) and the Difference-in-Difference (diff-in-diff) analysis approach to investigate how these services were related to the number of traffic crashes and injuries in Austin and Arlington, respectively. The findings from both studies showed that the DRT systems were related to fewer traffic crashes and severe injuries. In the case of Austin, TX, these impacts would be more significant if the number of trips per block group was relatively higher. Via Arlington's availability was associated with fewer weekly traffic crashes and injuries in Arlington.

The fifth chapter investigates the potential benefits of integrated DRT services by examining the three DRT services in Arlington, TX. We first identified the spatial patterns of the ridership on a

localized scale by adopting the geographically weighted regression (GWR) for existing paratransit service, i.e., Handitran. Then, assuming that the existing ridership will be combined in the future with the shared autonomous vehicles, we looked at integration options based on the spatial patterns of supply and demand and payment options for the riders. The analysis results of the trip data suggest that the paratransit service, Handitran, is currently used by a small proportion of the eligible population, whose travel patterns vary in terms of age. The results of the GWR model indicate that the significant determinants of Handitran usage are the percentage of older adults, racial distribution, and household vehicle ownership; the coefficients of these factors vary across the city. The results of hot-spot analyses reveal that the integration of the services will improve the efficiency of the existing transportation system by responding to the excess rider demand, particularly in the downtown area. Finally, the study describes the policy implications of AV integration for government agencies, service providers, and other stakeholders. It also suggests future research topics.

The final chapter summarizes the policy implications based on the research findings in this study and discusses some future research opportunities.

Keywords: Shared Autonomous Vehicles; On-demand ridesharing; Demand Responsive Transport Services; Mobility on Demand; Traffic Safety; Time Series Analysis; Ordered Logistic Regression

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Chapter 1: INTRODUCTION

Transportation advancements, such as the advent of automobiles, entirely changed how humans live and cities function. Although automobiles play a key role in economic development, improvement of accessibility, and urban mobility, they have created several challenges, including traffic crashes, congestion, and environmental pollution (Bao et al., 2021; Jamal et al., 2021; Sohail et al., 2021; Umar et al., 2021; Wang & Debbage, 2021; Yang et al., 2022). For example, according to the National Highway Traffic Safety Authority (NHTSA, 2022), on average, 90 people die due to traffic crashes every day in the United States, and only in the first six months of 2021, there were more than 20,000 traffic-related deaths in the country. Texas, as one of the states with the highest crash rates, had its last fatality-free day in November 2000. According to the CDC, traffic fatalities have been the leading cause of death in American's lives in the first three decades.

Meanwhile, there has been a significant increase in vehicle ownership. From 1960 to 2017, households without cars decreased from 22% to 9%, and multivehicle households increased from 22% to 58%. This resulted in an increase in traffic congestion. According to the traffic data analytical service, i.e. INRIX, Americans lose 97 hours to congestion every year, which is equivalent to a total cost of approx. $87 billion. Texas also follows the national trends in traffic congestion. A study by Texas Transportation Institute (TTI) revealed that the number of registered vehicles in Texas increased by 172% in the past four decades. However, there has been a meager increase of only 19% in the road capacity.

Public transit is expected to alleviate these challenges and make transportation systems more efficient, equitable, and sustainable (Etminani-Ghasrodashti et al., 2021). However, public transportation has also faced several challenges in recent years. Public transit ridership decreased by 3.8% from 2010 to 2018, even before the COVID-19 pandemic had any impact on transit ridership. It got even worse during the pandemic (Olayode et al., 2022). Transit ridership decreased by 79% from 2019 to 2020, and the numbers stayed significantly low. Due to the highly dynamic environment during the pandemic, operating costs of transit systems have increased manifolds. The public transit sector faces a shortage of $39.3 billion, which is expected to last until 2023.

The era of digital advancement is called the 'fourth' industrial revolution. The rapid development of digital technologies and their widespread availability are enabling new ways of delivery, utility, and access to transportation services. It has resulted in the emergence of new and innovative modes, such as ride-hailing ridesharing services, also known as Transportation Network Companies (TNCs), reshaping the urban mobility landscape (Diao et al., 2021). Technological advancements have paved the way for implementing Shared Autonomous Vehicles (SAVs) as an alternative mode in many cities around the world (Ohnemus & Perl, 2016). Demand Responsive Transport (DRT), historically provided transportation services to elderly and disabled populations, also evolved and expanded their scope to supplement other public transit services in low-density rural areas and places with lower travel demand. Several transit systems adopt the DRT services for first- and last-mile connections to improve transit accessibility.

Digital technologies like smartphones, the internet of things, and big data analytics, coupled with demographic change, are leading transportation to a new future by satisfying the new service expectations of commuters and opening a variety of ramifications for stakeholders, especially the operators and the regulators of the transportation system. This transformation has enabled, as a pre-condition, the evolution of ridesharing or DRT services and facilitated the demands for deeper research about how to gain maximum benefits from these services.

In terms of transport policy, DRT systems are likely to play a vital role in future collaborative and connected mobility in the presence of both driver-operated and driverless vehicles, Shared

Autonomous Vehicles (SAVs). They are expected to reduce car ownership and other negative externalities by enabling commuters to satisfy their mobility needs without owning the assets such as private automobiles. DRT services within the context of the evolving transportation ecosystem have not received much attention in the past due to their limited scope.

Therefore, this dissertation is a combination of three related topics, each tackling a different but related research question using different types of DRT services and exploring the impacts of DRT services using several existing DRT systems as empirical studies. First, this study focuses on the SAVs, particularly exploring the patterns and the determinants of ridership using an SAV project in Arlington, TX, as an empirical case. Second, the impacts of DRT services on traffic safety are explored in terms of traffic crashes and injuries, using two DRT services as case studies. Third, the possibility of integrating multiple DRT services is explored by employing a DRT service for transportation-dependent populations (older adults or people with disabilities) in a case study.

DISSERTATION OUTLINE

As described above, this dissertation consists of three related but independent essays. Each essay is a stand-alone research paper with an independent structure, but all focus on different aspects of Demand Responsive Transport (DRT) systems. For each research paper, the introduction, literature review, data, methodology, and results sections are included relevant to the research questions addressed by the individual paper.

The dissertation begins with chapter 2, which is a ridership evaluation analysis that explores the characteristics of Shared Autonomous vehicle riders and the contributing factors for the ridership frequency of the service. The findings from the logistic regression demonstrated that those with higher household incomes are less likely to be frequent riders of RAPID, while those usually walking, biking, or utilizing the on-demand ridesharing services are likely to use SAVs more often.

Commuters with higher levels of safety perception are also more likely to be frequent users of the service. The findings of this study will provide planners with a better understanding of the SAV' ridership patterns and will guide the decision-makers nationwide to establish and adopt the policies appropriate for future SAV implementations.

Chapters 3 and 4 explore the impact of demand-responsive transport services on traffic safety in terms of traffic crashes and fatalities. Based on the crash data from Arlington, TX, I adopt the time series analysis to study the trends of traffic crashes. A similar study is completed based on the crash data from Austin, TX using a difference-in-difference analysis approach. The results show that the DRT services have statistically significant relationship with the reduced number of traffic crashes in their service areas.

Chapter 4 explores the potential of integrating shared autonomous vehicles in urban public transit systems by employing Arlington, TX as an empirical case. It analyzes the ridership of several services, the intersection of their services areas, and the likely shift of riders from one service to another. The analysis is conducted using Geographically Weighted Regression (GWR) models followed by hotspot analysis of the ridership frequency. The results from spatial analysis show that there is a great potential of integrating the shared autonomous vehicles with existing public transit services to enhance the overall mobility of commuters. This study evaluates the integration of Handitran (a service for disabled and senior citizens), Via-Arlington (an on-demand rideshare service) and RAPID (a shared ride service that uses a fleet of Autonomous Vans) in an empirical study.

Chapter 5 marks the end of the dissertation, which discusses several policy implications on the base of research findings and makes some suggestions on future research directions.

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Chapter 2: A Ridership Evaluation Study of Shared Autonomous Vehicles

ABSTRACT

Cities around the world are piloting projects to evaluate the feasibility and benefits of shared autonomous vehicles (SAVs), as their large-scale implementation and integration into public transit systems have the potential to improve individuals' accessibility and transportation equity. To understand the full potential of SAVs and their likely adoption, it is important to identify how the services can be utilized most effectively and what determines the composition of the ridership. This research aims to explore the usage and adoption of SAVs, focusing on a project called RAPID (Rideshare, Automation, and Payment Integration Demonstration) that was launched in Arlington, TX. We used real-time trip-level ridership data from the SAV platform, conducted a survey of SAV riders and developed a study based on ordered logistic regression to estimate the determinants of ridership frequency. Data analysis of real-time ridership data revealed that spatial distribution of activities and service accessibility have crucial roles in forming the current users' travel patterns. The findings from the logistic regression demonstrated that those with higher household incomes are less likely to be frequent riders of RAPID, while those who usually walk, bike, or utilize on-demand ridesharing services are likely to use SAVs often. Users with higher levels of safety perception are also more likely to be frequent users of the service. The findings of this study will provide planners with a better understanding of SAV ridership patterns and will guide decision-makers nationwide in establishing and adopting policies that will be appropriate for future SAV implementation projects.

Keywords: Shared Autonomous Vehicles; On-demand ridesharing; Transportation

INTRODUCTION

Autonomous vehicles (AVs) or self-driving cars are an emerging technology that uses a combination of sensors, computer processors, and repositories to take over tasks or responsibilities otherwise assumed by human operators. The technology promises to alter the fundamentals of human travel behavior and lead to significant social and infrastructural changes (Zhang et al., 2019).

The evolution of autonomous vehicle technologies will also develop some new ridesharing modes like shared autonomous vehicles, and will provide low-cost mobility to underserved and disadvantaged populations (Krueger et al., 2016). SAVs are self-driving shuttles that potential riders can request via a mobile application (Bansal et al., 2016; Fagnant & Kockelman, 2014). They could become an attractive mobility option for elderly adults, people with disabilities, and low-income people who have limited access to private vehicles and reside in suburban areas with few public transit options (Krueger et al., 2016). They could also provide first- and last-mile solutions for commuting to work by offering riders on lower-demand bus and rail-transit routes and complementing the existing public transit services. One of the benefits for riders is that they are free to relax or work while being taken to their destination (Krueger et al., 2016). The potential SAV's user attributes and travel-related behavior need to be identified to predict the short-term adoption of AV technology and promote the acceptance of SAVs in the long term (Bansal et al., 2016). Accordingly, understanding the public's acceptance and potential adoption of SAVs is fundamental. Several studies have explored the potential users and riders of AVs by modeling their willingness to use and pay for this technology (Acheampong & Cugurullo, 2019; Etzioni et al., 2021; Nazari et al., 2019; Shabanpour et al., 2018; Wang & Akar, 2019; Yuen et al., 2020); however, the extent to which the research findings will coincide with reality when self-driving vehicles are on the road is still unclear. This study employs a non-simulated, real-world environment based on an SAV pilot project called RAPID (Rideshare, Automation, and Payment Integration Demonstration) in the city of Arlington, Texas, which is a unique case study, as it is one of the largest cities in the United States without access to a fixed-route mass transit service (Harrington, 2018). It does, however, have access to app-based, on-demand ridesharing services and SAV technologies that are available throughout the city and provide connections to the Dallas/Fort Worth (DFW) region. Our research focuses on the SAV ridership dataset and identifies the trip trends and patterns of actual SAV users. To better understand ridership, we used data collected from the SAV customer's survey and explored the main factors affecting the self-driving shuttles as a new mobility mode by considering two data sources: an SAV riders' survey and an actual trip dataset. The SAV ridership platform data provides objective data, and the results of the rider's survey provides data and information regarding self-driving usage.

This study aims to (1) assess SAV ridership patterns, (2) identify the most frequent users of SAV services, and (3) evaluate the determinant factors of the SAV ridership frequency. The findings from this study will provide guidance to transportation planners as they strategize and make decisions relative to implementing a similar service in their cities.

LITERATURE REVIEW

Several studies have been conducted to identify the public's willingness to use and pay for SAVs (Acheampong & Cugurullo, 2019; Etzioni et al., 2021; Nazari et al., 2019; Shabanpour et al., 2018; Wang & Akar, 2019; Yuen et al., 2020), and sociodemographic characteristics have been suggested as one of the main factors that shapes individuals' views and inclinations to avail themselves of self-driving technology. For example, females and older people are less likely to use driverless buses with onboard assistance operators than well-educated males between the ages of

18 and 34 years old who earn above-average incomes and live in dense urban areas (Bansal et al., 2016; Lavieri et al., 2017; Lu et al., 2017; Wang & Akar, 2019).

Individuals' attitudes, preferences, concerns, and perceptions towards automated technology are constantly explored through AV and SAV literature, which has revealed that technically savvy people are more likely to have a positive attitude towards using an AV service that has been integrated into an existing public transit system (Song & Noyce, 2019). On the other hand, AV safety concerns can negatively influence its adoption (Nazari et al., 2019), as people who feel unsafe and uncomfortable riding transit are less likely to choose automated transit. Organized people who enjoy multi-tasking are more likely to choose automated transit over private vehicles (Etzioni et al., 2021), as are risk-takers, who are more likely to utilize them than older individuals with risk-averse attitudes (Hulse et al., 2018).

Travel behavior and daily trip patterns also can predict the extent to which an individual will accept and use SAVs. Considering the current driving habits of an individual is important in choosing the type of self-driving vehicle (Haboucha et al., 2017). Research shows that regular public transit users are more likely to use an autonomous bus service, while those who ride public transit infrequently are less interested in using an AV transit service (Kassens-Noor et al., 2020). Public transit users are more inclined to share a ride in an SAV than non-users, and those who use ridesharing services are more likely to accept riding in SAVs (Wang & Akar, 2019). Individuals with multimodal travel patterns are reported to be more interested in experiencing novel transportation modes (Krueger et al., 2016).

Although the literature on individuals’ decision-making regarding self-driving technology helps predict the potential determinants of SAV acceptance, some dimensions require deeper investigation. First, the results of the past studies indicate some general similarities concerning the acceptance and usage of AVs and SAVs; however, the detailed findings are not consistent due to the different sample sizes, variety of socioeconomic attributes, and variations in geographical locations (Asgari & Jin, 2019). Second, the literature concentrates on potential riders who have no actual ridership experience and provides no insight into the actual riders' evaluation and perception towards SAV fleet attributes and SAV trip features that affect the acceptance of self-driving shuttles after experiencing the technology. Third, although the literature explores public interest, perception, willingness, adoption, and acceptance of AV and SAV technology (Acheampong & Cugurullo, 2019; Bansal et al., 2016; Etzioni et al., 2021; Haboucha et al., 2017; Krueger et al., 2016; Nazari et al., 2019; Shabanpour et al., 2018; Wang & Akar, 2019; Yuen et al., 2020), the majority of the studies are based on surveys and agent-based simulation methods of hypothetical scenarios rather than real-time ridership data. There is no empirical evidence indicating the characteristics of early adopters of self-driving shuttles.

METHODOLOGY

We used the ridership and survey data to perform descriptive statistics and ordered logistic regression to analyze the patterns and determinants of ridership. First, we explain the RAPID SAV service and its characteristics, then describe in detail the ridership and survey data, including the variables used for the analysis. The results, based on each source of data, are presented in the following paragraphs.

RAPID SAV Service

This study focuses on a rideshare, automation, and payment integration (RAPID) pilot project that began deploying self-driving shuttles in the city of Arlington, Texas in March 2021. The Federal Transit Administration (FTA) of the U.S. Department of Transportation (DOT) awarded the project funds, as part of an Integrated Mobility Innovation (IMI) grant, to integrate an existing on-demand rideshare service (Via) with AV technology (Khan et al., 2022). RAPID, as a mobility on demand (MOD) project, employs advanced technologies to improve the efficiency and equity of trips, particularly for the low-income people without access to a private vehicle, and people with disabilities (Patel et al., 2022). Prior to the pilot project, Arlington had an app-based on-demand rideshare service that provided the entire city with rides in six-passenger vans anywhere within the service boundary (City of Arlington, 2020). The RAPID SAV pilot project is a partnership among Via Transportation, May Mobility, UTA, and the City of Arlington. It offers self-driving shuttles in downtown Arlington and on the University of Texas at Arlington (UTA) campus that integrate the rides using the Via platform. The service is fully on-demand and provides rides from 7:00 a.m. to 7:00 p.m., Monday through Friday. To achieve the equity goals of the pilot project, RAPID provides university students free rides and includes a wheelchair-accessible vehicle (City of Arlington, 2019). The City's RAPID fleet has four hybrid-electric Lexus vehicles and one fully electric Polaris GEM vehicle that is equipped to carry wheelchairs. All RAPID vehicles are autonomous, meaning that the vehicle can sense its environment and operate without human involvement, but fleet attendants continuously monitor them to ensure a safe and enjoyable passenger experience. The May Mobility, partnering with the city, Via, and UTA for the one-year pilot, owns and operates the fleet of autonomous vehicles. The City of Arlington is piloting RAPID to recognize the potential uses of autonomous transportation technology as a part of its existing public transportation strategy. This pilot program started in March 2021 and continued to operate to date (April 2022). The service area for RAPID and Via (2020 service area) and boundaries of city of Arlington are shown in Figure 1. Via service area boundaries were obtained from the City of Arlington's open data portal (City of Arlington, 2020) and the city boundaries data was collected from the Nahtion Historic GIS (NHGIS) database (Manson et al., 2022). The map was created using Maptitude[1], a mapping software by Caliper corporation. Google Map's (Google, n.d.) basemap was utilized as the background map using the imagery feature of the Maptitude software. RAPID service area mainly includes the University of Texas at Arlington (UT Arlington) campus and the downtown area of Arlington, TX.

Anyone with access to the Via-Arlington app can request a RAPID ride regardless of their student status; however, UTA students are eligible for free rides through RAPID. The data indicates that the RAPID service usage is mostly by UTA students, who account for 98.49% of all RAPID trips, while less than 2% of the total trips are taken by non-UTA students . This could be attributed to the service area of RAPID and the free rides available to the UTA students. Via does not collect information about the trip purposes but based on the land uses in the service area, it is likely that most of the trips are related to the commuting of student to UTA campus and professionals to downtown Arlington's business/offices.

Monthly ridership for RAPID has been progressively increasing since the start of the service. Figure 2 shows the number of total monthly trips since March 2021. The total number of rides per month ranges from 769 in April 2021 to 3547 in November 2021, over the course of March 2021 to February 2022. Since the service is only available in the UTA and downtown area, the impact of university classes scheduling is evident in the ridership. The ridership numbers are higher during the fall and spring semesters than in other months. For example, the ridership in August 2021 is almost double compared to July 2021, more likely due to the start of the Fall semester in August.

Data and Variables

[1] https://www.caliper.com/maptovu.htm

The real time ridership data for the RAPID service was provided by Via-on demand, the service with which RAPID has been integrated. .

SAV Ridership Data

The RAPID SAV ridership data describes the users' travel behavior and the service's performance. The dataset encompasses 10,379 rides that were requested from March to September 2021. The variables are defined below.

- *Number of passengers:* Number of seats booked in a single ride request
- *Average Trip Distance:* Average distance of all trips requested in miles
- *Average Trip Duration:* Average duration in minutes for all rides requested
- *Pickup Date and Day:* Date and day a rider was picked up from the requested location
- *Pickup Time:* Via does not share exact pickup times for privacy reasons, but the data is aggregated in timeslots given below:
  - Early morning: 7 am to 8:59 am   Morning: 9 am to 11:59 pm
  - Early afternoon: 12 pm to 2:59 pm   Late afternoon: 3 pm to 5:59 pm
  - Evening: 6 pm to 6:59 pm   Out-of-Operation Hours: 7 pm to 6:59 am

SAV Survey Data

In addition to the data from the SAV platforms, two surveys (one short and one long) were administrated to collect data from actual and potential users during the deployment of the RAPID pilot project for the purpose of measuring their perceptions of the service's flexibility, reliability, and efficiency. The short survey used for this study explores the SAV users' perceptions and experiences of different features of the service.

The questionnaire was designed to collect data from those who had experienced at least one SAV ride and targeted all the individuals who reside, work, and/or study in Arlington, TX. Most of the questions were asked at an ordinal scale ranging from 1 to 7, based on the question. It was reviewed and approved by the UTA Institutional Review Board (IRB), then was put online, using the QuestionPro platform to create a link. A flyer containing the link was designed and sent to the targeted population, and the survey was distributed through various outlets, including Questionnaire URLs; emails to university students, faculty, staff; and the community. To increase the participation rate, the City of Arlington and Via assisted in distributing the survey link and recruited potential RAPID riders from the public via email and on social media. The survey had several parts, including SAV ridership characteristics, attitudes towards SAVs, individuals' travel behavior, residential attributes, and sociodemographic information. It was conducted based on the real-time SAV platform data and a self-reported survey of RAPID SAV users. A total of 402 individuals began the survey, and 261 actually completed it by answering at least all the questions that were marked as mandatory. Most respondents also answered the questions that were marked as optional.

The present study is developed based on the following data derived from the survey:

- *Sociodemographic characteristics of the respondents:* To identify the demographics of riders, the survey asked the respondent's age, gender, and household income. Responses were provided based on categorical options.

- *SAV trip purpose:* Respondents were asked to provide the purpose of most of their trips on RAPID SAVs. Options include work, school, shopping, medical, social, and home destinations.

- *SAV ridership frequency:* To understand the trip patterns of the SAV riders, the survey asked respondents how frequently they have used the service since its implementation. The responses were provided by a six-point Likert-type scale from 1 to 6 (“this is my first trip” to “more than two times per week”).
- *Usual transportation mode:* Respondents were also asked about their usual transportation mode. The answers were given through categorical options that reflected the available transportation modes in Arlington, TX, including private vehicles; private app-based ride services, such as Uber or Lyft; Via, Handitran (a paratransit service provided by the city of Arlington), UTA transportation, walking/biking, and RAPID service.
- *Safety perception:* Users were asked if they felt safe sharing a ride in an SAV that they had to respond at a scale of strongly disagree to strongly agree based on their perception of safety during a shared ride in SAVs.
- *Ethnicity:* This variable represents the ethnicity with which a respondent is identified. The survey respondents were asked about the ethnicity with which they are identified, and they were to choose from two options, Hispanic or Non-Hispanic.

DATA ANALYSIS & RESULTS

This section analyzes the data collected from the SAV ridership platform and riders’ survey. It identifies the trends of the RAPID ridership and the key features of the SAV ridership data, based on the trip time, day, distance, and duration. The determinant factors of SAV ridership frequency were investigated through ordinal regression analysis.

SAV Ridership Features: Platform Data

The RAPID SAV platform provides detailed trip information for each requested and completed trip. Table 1 indicates the descriptive statistics of numeric variables in this dataset.

Ridership Day and Time

The SAV pilot project provides rides Monday through Friday. Although the dataset displays a moderate distribution of rides during the week, more rides are requested on Wednesdays and Thursdays (see Fig. 3a). The comparison of ridership during different times of the day indicates that the demand for SAV services is at the lowest point in the early morning and rises throughout the day, with the number of riders being the highest in the early and late afternoons (see Fig.3b).

Ridership Duration and Distance

Figures 4a and 4b show the average duration and the distance of trips in minutes by the time of day. Ridership duration is at its peak in the late afternoons and is comparatively low in the early mornings and evenings. Average trip distance is longer in the morning and is the lowest in the early morning and the evening. These patterns could be attributed to class schedules and the amount of traffic on the streets that could impact the speed of the SAVs.

Figures 5a and 5b show the distribution of trip durations in minutes and trip distances in miles. The data suggests that majority of trips (68.47%) are between 3 and 8 minutes long, and most of them (74.43%) are between 0.5 to 1.5 miles long. The short trip distance can be attributed to the SAV's small service area, as it covers only 18 miles of city streets (City of Arlington in Texas).

Determinants of SAV Ridership Frequency

To evaluate the determinant factors of the SAV ridership frequency, we discuss the results from the analysis of the service users' survey in this section. SAV ridership frequency was defined as an ordinal variable in six categories. Table 2 depicts the descriptive statistics of the ridership frequency for 261 survey respondents. Around 45% of the respondents reported that they only had used the service once to twice since its deployment. Nevertheless, around 43% of the users frequently used the RAPID service and had at least one SAV trip per week.

Ordered Logistics Regression Model

In this section, we analyze how the key variables affect SAV ridership frequency. Due to the ordinal nature of the variables, the authors employed an ordered logistic regression (OLR) model to identify the probability that a respondent would belong to one of the six user groups. Ordered logistic regression is a type of binary logistic regression model, where the dependent variable is an ordered scale variable (Fullerton, 2009) and the model can be expressed as an mathematical equation (Greene & Hensher, 2009):

$$logit[Prob(y_i \leq \mathrm{j})] = \log \frac{Prob(y_i \leq j \mid x_{i)}}{1 - Prob(y_i \leq j \mid x_{i)}} \qquad (1)$$

Where,

y = outcome variable

x = the independent variables

j = the number of possible categories (six in this study)

In the equation for this analysis, the probability of the outcome is the probability of a respondent being part of one of the six SAV user groups, based on usage frequency. Independent variables include the respondent's household income, gender, usual mode of transportation to work, trip purpose, and perception of safety.

Results of the Ordered Logistics Regression Model

Table 3 shows a summary of the ordered logistics. We used Stata, Version 15 (StataCorp-https://www.stata.com/) to develop the ordered logistic regression. The results indicated that the overall model was statistically significant at 0.05 levels, with a probability (Chi2) of 0.0000. The Pseudo R2 of the model was 0.083. (See Table 3).

Table 4 shows the results of the ordered logistic regression model with SAV ridership frequency as the outcome variable. Threshold parameters or cut points for each category are given at the end of the table. Household income is negatively associated with SAV ridership frequency but is not statistically significant (p-value = 0.793). Males are less likely to be frequent riders than females, but this is also statistically insignificant (p-value = 0.290). The association of usual mode of transportation with SAV usage frequency is different for each mode. Compared to those who drive private vehicles, those who ride Uber or Lyft, Via on-demand ridesharing service, or UTA transportation, walk or bike as their usual mode of transit are more likely to be frequent users of SAV; the results are statistically significant at 0.05 levels.

Feeling safe while sharing a ride on SAV is positively and significantly associated with frequent ridership (p value= 0.000). This shows that riders with a higher level of safety perception are more likely to be frequent users. Ethnicity is also related to being a frequent rider and is found to be statistically significant. Non-Hispanic users are more likely to be frequent users than the Hispanic users.

Different from the traditional linear regression, the coefficient of the output of a logistic regression does not give an intuitive estimate of the coefficient's value. Therefore, this study calculated the marginal effects of each variable, using the "margins" command in STATA. Margins values for the dependent variables are shown in percentage points in relation to the outcome variables. Results for each variable are explained in Tables 5 - 10 below.

The first column shows the six categories of usage frequency of RAPID SAV, where the first category represents a first-time rider, the second category represents a second-time rider, the third represents the users that ride at least once a month, the fourth represents users that use the service at least a twice a month, the fifth represents the users who make at least one trip a week, and the sixth represents the riders who use the service more than twice a week. The second column (dy/dx) shows the marginal effects in percentage points. Positive signs indicate that a user is more likely to be in a category with a one-unit increase in a respective variable, while negative signs indicate less likelihood.

Table 5 shows the relationship between household income and ridership frequency. Those at the lowest income level are 0.4% more likely to be in the least frequent category, and as the income increases, the likelihood to be in the most frequent group decreases because higher income respondents are less likely to be in the most frequent category. A user from the highest income group is 0.4% less likely to be in the most frequent category. This indicates that an increase in household income is negatively associated with the frequency of SAV ridership.

Feeling safe in an autonomous vehicle may be a decisive factor for users to demand such a service. The results shown in Table 6 indicate that the users who feel safer sharing a ride in an SAV are more likely to use the service. The users with the lowest perception of safety are 4.5% less likely to be frequent users, while users with the highest perception of safety are 4.7% more likely to be frequent riders.

The marginal coefficient values of the categorical variables are given with respect to the reference category. For example, in gender, female is taken as the reference category, and the results in Table 7 show that males are 5.3% more likely than females to be in the least frequent group and 5.8% less likely to be in the most frequent group. These results indicate that females are more likely to be frequent users of the RAPID service as compared to males.

The usual mode of transportation before the implementation of this service is also an important factor in determining whether a person will be a frequent user of the SAV service. Users of certain transportation modes are more likely to be frequent users as compared to others. The results in Table 8 show that the users of Via, Uber, or Lyft, and University transportation services, and those who walk and bike as their usual mode of transportation show a statistically significant positive association with RAPID usage frequency. The coefficient values are given against the reference level of “private vehicle” as the usual mode of transportation. For example, regular users of private app-based ride services such as Uber or Lyft are 15.7% more likely to be frequent users of RAPID. Users of Via on-demand ridesharing service, UTA transportation, or RAPID SAV, or those who walk or bike as their usual mode of transportation are 25.3%, 25.9%, 23.1%, and 20.9% more likely to be more frequent users of SAV service than those who use private vehicles as their usual mode of transportation. Coefficients for Uber and Lyft, Via on-demand ridesharing service, and walking/biking are statistically significant at 0.05 levels. This shows the tendency of users who do not own private vehicles to use such services more frequently than private vehicle owners.

The results of trip purposes by SAV users in Table 9 indicate that commuters are most likely to use the service for work-related trips. In comparison to work-related trips, users are 9.4%, 20.5%, 7.3%, 23.4%, 21.9% less likely to use SAVs for trips for going to school, shopping, medical, social activities, and returning home, respectively as compared to using SAV for work trips.

Table 10 shows the marginal coefficients for ethnicity of the respondents. Out of the two available options, Hispanic is used as the reference value and the results show non-Hispanic users are 19.8% more likely to be frequent users of SAVs as compared to non-Hispanic users.

DISCUSSION & CONCLUSION

This paper introduces an SAV project that provides rideshares to people in Arlington, Texas. It identifies the users' travel patterns and the ridership trends of the new mobility service, the frequency with which the service is used, and the determinant factors affecting the service usage. Users' ridership datasets extracted from the RAPID SAV platform and the SAV users' survey were the basis of the study. The research questions were answered through descriptive statistics of data and an ordinal logistic regression model.

The analysis of the SAV real-time data revealed that Wednesdays and Thursdays are the busiest days of the week, while early and late afternoons are the busiest times of day. This temporal pattern can be the result of users' going to school and returning home. These results indicate that temporal and spatial distribution of activities have crucial roles in forming the SAV travel patterns of its current users. This finding confirms the pre-evaluation of the SAV service that identifies geographic area and accessibility as the primary concerns of potential service users (Etminani-Ghasrodashti et al., 2021). We used ordinal logistic regression analysis to understand the factors that differentiate frequent users from non-frequent users of the service. The results suggest that an individual's routine transportation mode plays a significant role in whether or not they are a frequent user. Users who ride with Via on-demand ridesharing service, app-based private on-demand services such as Uber or Lyft, walk/bike, or ride UTA transportation services are more likely to ride shared self-driving shuttles frequently. This result supports findings from past studies that suggest that the current commute mode can significantly influence the adoption and usage of commuting by SAVs (Wang & Akar, 2019). Accordingly, the integration of the SAV technology into the existing transportation services can be more efficient and successful in the areas with higher ridership in transit and on-demand ridesharing services. This is particularly true if the new

SAV service operates as frequently as the shared mobility services (Chee et al., 2020). Another explanation for this result can be adjusted by a recent empirical study. The study indicates that approximately 80% of individuals are not likely to use SAVs if they cost more than the available carsharing option (Kontar et al., 2021). Since the cost of riding RAPID SAV in this study is very close to that of Via on-demand ridesharing, the frequent users of Via potentially use the new SAV more frequently. Furthermore, this finding confirms that SAV can complement on-demand ridesharing services on the short and low demand routes.

Our results also show that respondents are more likely to use the SAV services frequently if they have a higher perception of safety toward sharing rides through the SAV services. This result is supported by a study that explored Americans' willingness to pay (WTP) to ride with a stranger in a shared AV fleet vehicle on various types of trips. This finding is in agreement with the literature that the perception of safety is positively related to the usage of public transit (van Lierop & El-Geneidy, 2017).

Although the literature suggests that men are more likely to have a positive attitude toward automated vehicles than females (Liljamo et al., 2018), the actual evidence from our study seems to be the reverse: males are less likely to be the frequent users of the SAV. This could be attributed to the demographics of the users' population in the service area, the majority of them are students. Our regression results show that income has a negative association with being an SAV frequent user, which is also in contrast with the literature that the higher-income individuals living in metropolitan areas are more likely to adopt AVs (Shabanpour et al., 2018). The low-income individuals with less access to a private vehicle can also be the early adopters of new shared AVs, however (Krueger et al., 2016).

CONCLUSION

This study uses real-time data in a survey to understand the patterns of usage and determinants of frequency of usage of an SAV service in Arlington, Texas. Although multiple studies have been conducted to predict the early users of AV and SAV in the near future, the actual adoption of this technology can be determined only after the introduction of SAVs in the market and the operation of the vehicles on the roads. Accordingly, SAV pilot projects can be an excellent opportunity for decision-makers to comprehend the demand for SAVs and learn what factors will shape SAV ridership. Moreover, understanding the ridership trends of pilot SAVs can help planners and policymakers to accommodate related policies before the widespread demonstration of this new mobility option. While the data analysis of this study is specific to Arlington, Texas, several key results, and policy recommendations can be made. First, the temporal distribution of the platform dataset indicated that the SAV usage is predicted to show a difference in ridership during weekdays and daytime. This temporal pattern is shown due to the concentration of SAV demand at specific times and the trip features such as trip purpose and trip waiting time (Etminani-Ghasrodashti et al., 2022). However, the temporal demand over time contributes to an additional increase in trip waiting time and frustrates users from riding the service in the long term. (Sanaullah et al., 2021). Consequently, SAV projects should be able to improve and adjust their performance features such as fleet size and the service schedule to address the actual real-time spatiotemporal demand, particularly at the early demonstration of the technology. This strategy will help improve the service reliability and accessibility, help attract users, and stimulate the SAV occasional users into becoming frequent users. Second, improving the safety perception of self-driving vehicles is an important factor in the acceptance and adoption of the technology by people. Therefore, policymakers should pay enough attention to the safety concerns of the riders in pilot demonstrations, use pilots as an opportunity, and improve public trust through the real-life experience of the technology. Users stated preference surveys and focus group interviews with riders during the SAV pilots can be a reliable data source for service operators to know more about the actual preferences and concerns of SAV riders.

Third, our results indicate that individual's usual mode of transport as their current travel pattern is associated with the SAV usage. Accordingly, policies and strategies that motivate people to integrate their on-demand ridesharing, public transit, and walking/cycling modes into the SAV service usage are suggested as the most beneficial approach for engaging automated technology in transportation systems. This can happen through trip planning and fare integration in order to combine travel choices into a single user interface and therefore decrease the travel barriers multimodal travelers typically face. In addition, at the early stage of the SAV demonstration, users are more interested in adopting the service to experience the technology for its own sake, rather than a derived demand to arrive at a destination (work/school/home).

As we move forward to public demonstrations of SAVs, there will be an increasing need to apply effective policies to improve the performance of the service while considering the population that is more likely to use it and the patterns in which people travel.

Since this study's primary goal is to understand the SAV travel pattern and the ridership trends, we only modeled the data analysis of individuals who have taken the SAV service. Consequently, the study results do not include the potential users who did not have any SAV ridership experience. Further studies are needed to identify the factors affecting the ridership of the potential users of SAVs. In addition, students took over 98% of the rides, and as part of the pilot project, UTA students were offered free rides. Therefore, this study could not include a cost variable in our analysis. However, the free rides offer expired in March 2022, so further studies are needed to evaluate the impacts of trip cost on SAV ridership trends in future analysis when cost-related data are available.

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TABLES

Table 1. Descriptive Statistics of SAV

Trip Characteristics	Mean
Average number of passengers per requested ride	1.013
Average travel distance (mile)	1.19
Average travel time (minute)	6.91

Table 2. SAV RAPID ridership frequency (n = 261)

Dependent variable (SAV ridership frequency)	Frequency	Percent
This is my first time	84	32.2
This is my second time	34	13.0
About once per month	11	4.2
About twice per month	21	8.0
About once per week	25	9.6
More than two times per week	86	33

Table 3. Summary of Ordered Logistics Regression Model

Number of observations (n)	Prob > chi2	Log likelihood	Pseudo R2
234	0.0000	-332.621	0.083

Table 4. Summary of Results for Ordered Logistics Regression Model

SAV Ridership Frequency (Outcome Variable)	Coef	Std. Err.	z	P>|z|	[95% Conf. Interval]	
Household income	-0.024	0.091	-0.260	0.793	-0.201	0.154
Gender						
Female			(Base value)			
Male	-0.308	0.291	-1.060	0.290	-0.879	0.263

Usual transportation mode						
Private vehicle	(Base value)					
Uber/ Lyft	0.963	0.434	2.220	0.026	0.113	1.814
Via on-demand ride service	1.461	0.370	3.940	0.000	0.735	2.186
Handitran service	1.327	1.316	1.010	0.314	-1.253	3.906
UTA transportation	1.201	0.485	2.480	0.013	0.252	2.151
Walking/biking	1.128	0.387	2.910	0.004	0.369	1.888
RAPID SAV service	2.912	1.199	2.430	0.015	0.562	5.262
Others	1.766	0.900	1.960	0.050	0.003	3.530
Trip Purpose						
Work	(Base value)					
School	-0.447	0.383	-1.170	0.243	-1.197	0.304
Shopping	-1.021	0.546	-1.870	0.061	-2.091	0.048
Medical	-0.349	0.857	-0.410	0.684	-2.028	1.331
Social/recreational activity	-1.189	0.602	-1.970	0.048	-2.369	-0.008
Returning home	-1.099	0.419	-2.630	0.009	-1.920	-0.279
Others	-2.287	0.555	-4.120	0.000	-3.376	-1.199
Safety Perception	0.254	0.070	3.610	0.000	0.116	0.392
Ethnicity						
Hispanic	(Base value)					
Non-Hispanic	1.225	0.396	3.090	0.002	0.448	2.001
/cut1	1.155	0.685			-0.188	2.498
/cut2	1.803	0.690			0.450	3.156
/cut3	2.016	0.693			0.657	3.374
/cut4	2.443	0.698			1.074	3.812
/cut5	2.906	0.705			1.524	4.289

Table 5. Marginal Effects of Household Income Level

Ride Frequency	dy/dx	Std. Err.	Z	P>|z|	95% CI (Lower)	95% CI (Upper)
First ride	0.004	0.016	0.260	0.792	-0.027	0.036
Second ride	0.001	0.002	0.260	0.794	-0.003	0.005
Once a month	0.000	0.000	0.250	0.799	0.000	0.001
Twice a month	0.000	0.000	-0.250	0.803	0.000	0.000
Once a week	0.000	0.001	-0.260	0.793	-0.003	0.002
More than twice a week	-0.004	0.017	-0.260	0.793	-0.037	0.029

Table 6. Marginal Effects for Safety Perception

Ride Frequency	dy/dx	Std. Err.	z	P>|z|	95% CI (Lower)	95% CI (Upper)
First ride	-0.045	0.012	-3.770	0.000	-0.068	-0.022
Second ride	-0.006	0.002	-2.890	0.004	-0.010	-0.002
Once a month	-0.001	0.001	-1.360	0.172	-0.002	0.000
Twice a month	0.001	0.001	0.610	0.544	-0.001	0.002
Once a week	0.004	0.001	2.420	0.016	0.001	0.006
More than twice a week	0.047	0.012	3.850	0.000	0.023	0.071

Table 7. Marginal Effects for Gender

Ride Frequency	dy/dx	Std. Err.	Z	P>|z|	95% CI (Lower)	95% CI (Upper)
Male						
First ride	0.053	0.049	1.080	0.278	-0.043	0.150
Second ride	0.007	0.008	0.970	0.330	-0.007	0.022
Once a month	0.001	0.001	0.790	0.429	-0.002	0.004
Twice a month	0.000	0.001	-0.170	0.864	-0.002	0.002
Once a week	-0.004	0.003	-1.120	0.265	-0.010	0.003
More than twice a week	-0.058	0.055	-1.050	0.292	-0.166	0.050

Note: Gender (Female) is used as the base category

Table 8. Marginal Effects for Usual Transportation Mode

Ride Frequency	dy/dx	Std. Err.	Z	P>|z|	95% CI (Lower)	95% CI (Upper)
Uber or Lyft						
First ride	-0.201	0.088	-2.280	0.022	-0.373	-0.028
Second ride	-0.006	0.010	-0.540	0.588	-0.026	0.015
Once a month	0.004	0.004	1.220	0.222	-0.003	0.012
Twice a month	0.017	0.009	1.860	0.062	-0.001	0.035
Once a week	0.028	0.014	2.060	0.040	0.001	0.054
More than twice a week	0.157	0.074	2.120	0.034	0.012	0.302
Via On-demand Ride Service						

First tide	-0.300	0.084	-3.580	0.000	-0.464	-0.136
Second ride	-0.018	0.014	-1.260	0.208	-0.046	0.010
Once a month	0.003	0.005	0.680	0.495	-0.006	0.013
Twice a month	0.026	0.014	1.790	0.073	-0.002	0.053
Once a week	0.036	0.015	2.390	0.017	0.006	0.065
More than twice a week	0.253	0.069	3.690	0.000	0.119	0.388
Handitran						
First ride	-0.286	0.071	-4.050	0.000	-0.425	-0.148
Second ride	-0.023	0.012	-1.860	0.063	-0.047	0.001
Once a month	0.001	0.004	0.290	0.774	-0.007	0.009
Twice a month	0.016	0.009	1.640	0.100	-0.003	0.034
Once a week	0.034	0.013	2.640	0.008	0.009	0.058
More than twice a week	0.259	0.063	4.110	0.000	0.136	0.383
UTA Transportation						
First ride	-0.265	0.221	-1.200	0.231	-0.698	0.169
Second ride	-0.018	0.050	-0.350	0.723	-0.115	0.080
Once a month	0.002	0.011	0.220	0.826	-0.019	0.024
Twice a month	0.017	0.013	1.330	0.185	-0.008	0.042
Once a week	0.033	0.016	2.030	0.042	0.001	0.064
More than twice a week	0.231	0.273	0.840	0.399	-0.305	0.766
Walking/Biking						
First ride	-0.244	0.091	-2.680	0.007	-0.422	-0.066
Second ride	-0.013	0.015	-0.860	0.388	-0.043	0.017
Once a month	0.003	0.004	0.770	0.442	-0.005	0.012
Twice a month	0.017	0.009	1.880	0.060	-0.001	0.036
Once a week	0.032	0.013	2.430	0.015	0.006	0.057
More than twice a week	0.205	0.089	2.290	0.022	0.030	0.379

Note: Mode (Private vehicle) is used as the base category

Table 9. Marginal Effects Trip Purposes

Ride Frequency	dy/dx	Std. Err.	Z	P>|z|	95% CI (Lower)	95% CI (Upper)
Going to school						
First ride	0.067	0.055	1.210	0.227	-0.042	0.175
Second ride	0.017	0.016	1.100	0.272	-0.013	0.048
Once a month	0.004	0.004	1.000	0.316	-0.004	0.013

Twice a month	0.005	0.006	0.920	0.357	-0.006	0.017
Once a week	0.000	0.003	0.030	0.977	-0.005	0.006
More than twice a week	-0.094	0.081	-1.160	0.244	-0.252	0.064
Going shopping						
First ride	0.170	0.096	1.780	0.074	-0.017	0.358
Second ride	0.032	0.017	1.940	0.052	0.000	0.065
Once a month	0.006	0.004	1.470	0.143	-0.002	0.015
Twice a month	0.004	0.007	0.620	0.532	-0.010	0.018
Once a week	-0.009	0.010	-0.840	0.403	-0.029	0.011
More than twice a week	-0.205	0.104	-1.970	0.048	-0.409	-0.001
Going to a medical facility						
First ride	0.051	0.133	0.380	0.701	-0.209	0.311
Second ride	0.014	0.032	0.430	0.669	-0.049	0.077
Once a month	0.004	0.008	0.460	0.649	-0.012	0.019
Twice a month	0.005	0.009	0.510	0.611	-0.013	0.023
Once a week	0.001	0.004	0.160	0.876	-0.007	0.008
More than twice a week	-0.073	0.179	-0.410	0.681	-0.424	0.277
Going to social and/or recreational activities						
First ride	0.204	0.111	1.830	0.067	-0.014	0.421
Second ride	0.034	0.016	2.170	0.030	0.003	0.066
Once a month	0.006	0.005	1.330	0.185	-0.003	0.015
Twice a month	0.002	0.009	0.260	0.798	-0.016	0.021
Once a week	-0.013	0.014	-0.900	0.369	-0.040	0.015
More than twice a week	-0.234	0.108	-2.160	0.031	-0.446	-0.022
Returning home						
First ride	0.186	0.068	2.740	0.006	0.053	0.319
Second ride	0.033	0.016	2.140	0.033	0.003	0.064
Once a month	0.006	0.004	1.440	0.149	-0.002	0.015
Twice a month	0.004	0.007	0.550	0.586	-0.009	0.017
Once a week	-0.010	0.008	-1.360	0.174	-0.025	0.005
More than twice a week	-0.219	0.082	-2.660	0.008	-0.380	-0.058

Note: Trip purpose (Going to work) is used as the base category

Table 10. Marginal Effects for Ethnicity

Ride Frequency	dy/dx	Std. Err.	Z	P>|z|	95% CI (Lower)	95% CI (Upper)
Non-Hispanic						
First ride	-0.236	0.077	-3.070	0.002	-0.387	-0.086
Second ride	-0.009	0.008	-1.150	0.250	-0.024	0.006
Once a month	0.003	0.004	0.880	0.377	-0.004	0.011
Twice a month	0.016	0.010	1.640	0.101	-0.003	0.034
Once a week	0.028	0.013	2.200	0.028	0.003	0.052
More than twice a week	0.198	0.052	3.790	0.000	0.096	0.301

Note: Ethnicity (Hispanic) is used as the base outcome

Chapter 3: Do Ridesharing Transportation Services Alleviate Traffic Crashes? A Time Series Analysis

ABSTRACT

On-demand ridesharing services are considered to provide several benefits, such as improving accessibility and mobility and reducing drive-alone trips and greenhouse gas emissions. However, the impacts of these services on traffic crashes are not completely clear. This paper investigates the availability of Via- an on-demand ridesharing service in Arlington, TX, to identify the effects of this service on traffic crashes. We hypothesize that the launch of Via would result in more shared rides, fewer drive-alone trips, and fewer traffic crashes.

We implement an Interrupted Time Series Analysis (ITSA) approach to study the impact of Via service availability on traffic crashes using weekly counts of all traffic crashes, the number of injuries, and serious injuries that occurred in Arlington from 2014 to 2021.

The results show a statistically significant reduction in the weekly number of total crashes and total injuries but do not show any significant impact on the number of serious injuries. Shared Autonomous Vehicles have the potential to reduce traffic crashes caused by driver's fault.

This study reveals the potential impacts ridesharing services can have on traffic crashes and injuries in a mid-sized city. The results of this study can help decision and policymakers to understand the full potential of ridesharing services that can contribute to making relevant decisions toward the creation of sustainable and safer transportation systems in cities.

Key Words: On-demand ridesharing; Vehicle Crashes; Shared Autonomous Vehicles; Time Series Analysis; Traffic Safety

INTRODUCTION

The emergence of on-demand ridesharing services has considerably overcome conventional travel barriers and improved personal mobility options [3]. On-demand ridesharing services can impact mobility efficiency, equity, and sustainability [14]. These services enable users to share a ride to the same destinations and improve trip reliability by reducing point-to-point travel time. Advocates of on-demand ridesharing services argue that flexible transit can contribute to the sustainability of public transport networks by improving the performance of conventional fixed-route services in the cities [24]. While ridesharing services are described as a mobility mode complementing the operation of public transit in low-demand periods in metropolitan areas, it may also be a substitute for fixed-route transit in small cities and rural areas [22].

Controversial views exist regarding the ultimate advantages of on-demand ride services on urban traffic congestion and motor vehicle crashes. Some studies debate that the introduction of Transportation Network Companies (TNCs) (e.g., Uber and Lyft) into the urban mobility market in the U.S., has intensified road congestion in large cities [4].On-demand ride services that provide real-time shared rides to users can be game-changers, decreasing traffic congestion by increasing the level of vehicle occupancy [16]. In addition, some studies suggest the positive effects of ridesharing services on crash reduction in motor vehicle crashes. On-demand ridesharing services are perceived as a more convenient, accessible, and cheaper travel mode than taxies and thus a preferred mode of travelling for individuals after alcohol consumption. Consequently, and therefore they can reduce the probability of alcohol-involved crashes [18]. Comparing crash incidences in 155 US cities with Uber operations reveals fewer overall fatalities and arrests for driving under the influence of alcohol over time [5]. UberX is suggested as a factor that has reduced the number of alcohol-involved crash fatalities by 3.6%–5.6% in California (Greenwood and

Wattal 2015). In some studies, Ubers' demonstration has been reported as the factor that can lower the driving rate under the influence (DUI), fatal accidents, arrests for assault, and disorderly conduct [5].

However, the results from different geographical areas are mixed; while some studies show no association, others even observe an increase in fatalities. Evidence from 100 heavily populated U.S. counties reveals no difference in fatal crashes due to the availability of Uber operations [2]. A recent study explores the injury crash data for New York City (NYC) from 2017 and 2018 and proposes that ridesharing can raise any motor vehicle injury crash [19]. Examining the relationship between Uber availability and traffic fatalities in the 100 most populated metropolitan areas in the United States indicates no association between Uber availability and changes in total, alcohol-involved, and weekend and holiday-specific traffic fatalities. However, Uber availability can increase traffic fatalities in dense areas [1]. Some studies found that since Uber can be substituted with public transit, cities with higher demand for Uber encounter more significant traffic congestion and risk of accidents [12]. Since the results of different geographical contexts are inconsistent and controversial, there is a vital need to explore the relationships between the presence of on-demand ridesharing services and the changes in traffic crashes.

Most of the previous studies were done in big cities with multiple transit systems. Contrary to these previous studies, we focus on Arlington, TX, a mid-size city, with no fixed route transit, to contribute to the knowledge by testing the changes in crashes over time. E*valuating the performance of the Via on-demand ridesharing service in Arlington and assessing its safety impacts can provide city planners with valuable insights into implementing similar projects.*

We hypothesize that the implementation of Via on-demand ridesharing in Arlington would be associated with lower crash incidents. To test this assumption, we answer the following question,

Does the deployment of an on-demand ridesharing service impact the number of crashes and injuries in its service area?

In addition to answering this research question we also discuss how the relationships between on-demand services and traffic crashes provide an opportunity to implement alternative transit services such as shared autonomous vehicles in a city and the potential of an SAV service to reduce crashes caused by driver's faults.

DATA AND METHODOLOGY

This study aims to evaluate the impact of on-demand ridesharing services and shared autonomous vehicles (SAVs) on traffic crashes of different severity levels in Arlington, TX. First, an Interrupted Time Series Analysis (ITSA) is conducted on the weekly number of crashes, the total number of injuries, and the number of serious injuries to analyze the crash patterns before and after deploying the on-demand ridesharing service, Via. Second, a descriptive statistical analysis using spatial mapping and frequency of crashes in downtown Arlington is developed to hypothesize the likely impacts of Shared Autonomous Vehicles on traffic crashes caused by human errors.

Study Area and existing transportation services

This study is conducted in the City of Arlington, TX - a mid-sized city located in the Dallas-Fort Worth metroplex with a population of 395,477 (American Community Survey, 2019). The City is highly dependent upon private cars as 82% of workers use private cars as the primary mode of transportation. Car ownership rates are also high, only 4% of households do not have any vehicle, while 33% of households have at least one vehicle, 40% own at least two vehicles, and 22% have three or more vehicles (American Community Survey, 2019). The city does not have traditional fixed-route public transit and is the largest City in the U.S. without a mass transit system (Khan et al., 2022). Still, it provides multiple, flexible, on-demand transportation options such as Via, Handitran (a dial-a-ride service for senior citizens and people with disabilities), and RAPID (an on-demand ridesharing service that uses a dynamically routed Level 4 AV fleet within an existing public rideshare transit system).

Via is a flexible on-demand ridesharing service that has been providing rides to Arlington residents since December 11, 2017, to the present (City of Arlington website). According to the 2019 data, Via offered 160,914 trips running 968,281 revenue miles, and more than one passenger was shared in 69.76% of all rides offered during 2019 (City of Arlington). With so many shared rides, Via likely replaced several drive-alone trips. Thus, this study hypothesize that it could also reduce traffic crashes in the city, which was tested in this analysis.

Data

The data for this study were collected from two primary sources: the City of Arlington and the Texas Department of Transportation (TxDOT). Data for traffic crashes were extracted from the Crash Record Information System (CRIS) database by the TxDOT. The dataset contains details of all traffic crashes reported to the police [23]. The information included in the database is the time and date of a crash, casualties such as number of deaths, number of total, and severe injuries. For this study, we extracted data from January 1, 2014, to June 25, 2021, for all crashes in the City of Arlington, TX. Figure 1 shows the spatial distribution of crashes that occurred in Arlington. We only included the crashes that took place within the Via service area.

Analytical Approach

Interrupted Time Series Analysis (ITSA)

Considering Via services as a natural experiment, we used an interrupted time-series analysis (ITSA) design by comparing the patterns of traffic crashes before and after Via on-demand ridesharing deployment to see if there was a statistically significant change in the weekly frequency of traffic crashes. In an ITSA model, an outcome variable is tested over multiple equal time periods before and after an intervention. The trend over time for the outcome variable is likely to be impacted by the intervention [17]. An ITSA model compares the predictions of intervention vs. no-interventions scenarios. Compared to simple before and after tests, the ITSA model provides (1) trends over time and (2) simple and intuitive visualizations to interpret the changes happening over time.

Interrupted time-series analysis (ITSA) is a study method broadly employed in public health and policy to recognize the longitudinal variations in a process and evaluate the performance and effectiveness. However, only a few studies have applied this technique in traffic safety studies [6,10,21].

In this analysis, the crash dataset contains observations for three years before and three years after the intervention, i.e., the launching of Via services in the Arlington, TX. Since crashes are rare incidents, we aggregated the frequency of crashes on weekly basis to avoid multiple zero observations and have enough data points to run a time series analysis. Then a single-group ITSA was carried out to measure the impacts of the Via service on traffic crashes measured in three different variables: the total number of crashes per week, the number of total injuries per week, and the number of serious injuries per week. The analysis of the number of deaths was impossible due to very small number of observations. In this study, we used autoregressive time series interventions models for ITSA.

The model form used for the ITSA regression is shown in eq. 1,

$$\boldsymbol{Y = b_0 + b_1 Time + b_2 ViaAvailability + b_3 TimeSinceViaAvailability + \epsilon} \quad \textbf{(1)}$$

Where;

Y = Number of crashes/injuries per week

Time = time (week) since the start of the analysis period (first week of 2014)

ViaAvailability = Dummy variable showing if the period was before or after Via (0 or 1)

TimeSinceViaAvailability = time since the launching of Via service in the city

ϵ = Error term

Coefficients associated with each variable to measure the impact of Via availability on crashes are:

$\boldsymbol{b_0}$ = intercept

$\boldsymbol{b_1}$ = slope of the dependent variable since the start of the study period

$\boldsymbol{b_2}$ = change observed immediately after the intervention

$\boldsymbol{b_3}$ = effect of the treatment over time

We used three time-series models to analyze the impact of various aspects of the Via ridesharing services on traffic crashes. Details of the dependent and independent variables for each of the three models are given below.

Dependent Variables for the ITSA Model

In the first model, the dependent variable is the weekly number *of traffic crashes*. This includes all crashes reported to the police and those included in the CRIS database. The dataset comprises data for 396 weeks, where 214 weeks are before and 182 weeks after the deployment of via services in

Arlington. On average, there were 40.24 crashes recorded per week ranging from a minimum of 3 to a maximum of 68 crashes in a single week.

The dependent variable for the second model is *the total number of injuries per week* with a mean value of 24.96 and ranges from 2 to a maximum of 60 injuries per week. Total injuries include all types of injuries- minor, major, serious, and possible injuries.

For the third model, the dependent variable is the *total number of serious injuries per week*. The average number of weekly serious injuries is 1.14 and ranges from 0 to a maximum of 7 in a single week.

Independent Variables for the ITSA Model

Via Availability The availability of Via service is used as a dummy variable showing the availability of via services for a specific period. The variable has a value of 0 before the launching of Via service and a value of 1 after the launch. The coefficient values for this variable indicate the impacts of the intervention immediately after its implementation.

Time This variable shows the time for the entire study period with a value of 0 at the start of the study (first week) and the study period and 396 for the last week of the study duration.

Time Since Via Availability This variable accounts for the time since the deployment of via services. The values are 0 before deployment and get an increment of 1 every week after Via's deployment.

Descriptive statistics for all variables (dependent and independent) are given in table 1.

Hotspot and Frequency Analysis (Alcohol Related Crashes)

To hypothesize the potential effects of alternative ridesharing transportation services on reducing traffic crashes in the case study, this study focuses on the implementation of an SAV services. A self-driving shuttle service called RAPID (Rideshare, Automation, and Payment Integration Demonstration) started in downtown and the campus of the University of Texas at Arlington in March 2021. SAVs are a relatively new mobility service and have only been launched in a few cities in the world, therefore, there is little research on the safety impacts of these services. This study was conducted in a short time after the implementation of the of RAPID service, hence, we did not analyze the impacts of RAPID on traffic crashes. Since the environmental impacts of a transportation project are typically long-term in nature, evaluating the measures of effectiveness (MOEs) for the SAV project, such as the safety impacts, can be performed in the long run. Instead, this study evaluated the hotspots of crashes caused by human error that could potentially be avoided if enough SAVs operate in those areas in the future. Therefore, we analyzed the hotspots and frequency of crashes caused by a driver's physical condition within the RAPID service area, to evaluate the likely impacts of SAVs on crashes, assuming those crashes could be avoided by self-driving vehicles.

RESULTS

ITSA Model Results

The visual representation of the results for total crashes and the likely impacts of the intervention are shown in figure 2. On the x-axis are the week numbers for the entire study period (1-393), and on the y-axis are the number of total weekly crashes. The dotted red vertical lines show the intervention point (week 214) when Via service was launched. The solid blue line shows the predicted trend line from the data, while the dotted orange line depicts the counterfactual trend.

The counterfactual trend assumes that there was no change in the trend line before or after the intervention.

Table 2 shows the results of the time series model for the weekly frequency of traffic crashes in Arlington. The positive coefficient (0.077) of the time variable indicates a statistically significant increase in the frequency of traffic crashes for the entire study period. Availability of Via (trend soon after launching the service shows a negative trend (-3.12) on the frequency of crashes but is not statistically significant. This result reveals that since the deployment of Via service, there was a statistically significant negative trend in traffic crashes (-0.10).

Table 3 shows the results of the time series model for weekly number of total injuries due to traffic crashes. The results for injuries show a similar trend to that of the frequency of total crashes. There has been a significant increase in total injuries over the study period (0.04). Availability of Via has a statistically significant negative effect on the total number of injuries (-3.33). Conversely, there is a statistically significant decrease in total traffic injuries after deployment of Via services (0.05).

Table 4 shows the results of the time series model for the weekly number of serious injuries and associated independent variables. Overall, during the study period, there was a slight decrease in the number of total serious injuries, but it is not statistically significant. The results also show that the availability of Via has a negative but insignificant association with the number of serious injuries. After deployment of Via services, there is a minimal increase in the number of serious injuries, but that is also statistically insignificant.

Likely Impacts on the future Shared Autonomous Vehicles

To identify the crashes that are resulted from drivers' physical condition/fault, we focused on driving under the influence (DUI) that is one of the main causes of traffic crashes. Every day, about

28 people die in the United States due to drunk driving crashes ("Drunk Driving | NHTSA" 2019). According to the Center of Disease Control (CDC) 10,497 people died (28% of all deaths) in crashes caused by alcohol-impairments in 2016. Other factors of traffic crashes caused by driver fault include driving while using a phone, being fatigued, or falling asleep while driving.

To see the hotspots of crashes caused by drivers' fault, we mapped and created a heat/density map of all such crashes where the primary contributing factor is defined as either "fatigued or asleep", "had been drinking", "using cell/mobile phone", "under the influence – alcohol", or "under the influence – drug". There were 2,194 such crashes in Arlington, out of which 66 crashes were within the RAPID service area. The spatial distribution of crashes is shown in figure 3. Approximately 3% of all traffic crashes caused by driver's fault in Arlington occurred within the RAPID service area which is only 1.01% of the city's total area.

This study conducted the density analysis of actual crash locations using the mapping software called Maptitude[2] by Caliper Corporation. The areas with dark spots indicate higher density of crashes at the location. As shown in figure 4, most of the hotspots are on the Interstate Highways (I-20, I-30 & SH-360) that pass through the city. There are two major hotspots other than highways, and one of them is within the RAPID service area. Since the downtown/university area is already a hotspot for crashes caused by drivers' fault, there is a great potential to prevent such crashes if self-driving cars provide these rides. **Figure 4**. Density map of crashes caused by drivers' fault showing the hotspots of crash sites.

However, the impact of SAVs on crashes can only be materialized if SAVs take enough trips and the number of trips by private cars is reduced significantly. Since safety is reported as the primary

[2] https://www.caliper.com/maptitude/mappingsoftware.htm

concern of SAV's potential users [8], the quantification of the impacts of SAVs on traffic crashes could be a research question in future research.

DISCUSSION

This study conducts a time-series analysis to identify the effects of the availability of the on-demand ridesharing service on the frequency of traffic crashes. Since the Via on-demand ridesharing service is one of the main transit options that provides shared rides to people in Arlington, we proposed that the demonstration of this service can influence on the number of crashes.

We modeled the total number of traffic crashes, the number of injuries, and the number of serious injuries per week and to identify the crash trends. The availability of Via on-demand ridesharing service was treated as an independent variable of the study. The findings, to some extent, support our assumptions.

Our results from exploring the effects of on-demand ridesharing service in a mid-size city are in contrast with the previous studies that show either no effect or negative influence of Uber on traffic crash outcomes [1,2]. Our findings indicate the availability of Via on-demand ridesharing service coincides with a decline in the frequency of traffic crashes and support the earlier findings that reported a reduction in traffic crashes after the emergence of Uber [18]. It suggests that the increased comfort and convenience, and the decreased cost of traveling with on-demand ridesharing services compared to riding in private vehicles can encourage people to use fewer private vehicles and alleviate traffic crashes [13].

We found that the total traffic injuries have significantly decreased after Via's service deployment though there has been a significant increase in the total injuries over time. This result is in contrast with an earlier study's findings that suggested an increase in crash fatalities in urban, densely populated areas by Ubers' deployment [1]. A possible interpretation for this result is that the Via service shares rides between passengers, reducing the dependency on private vehicles, decreasing the single trips by vehicle, and subsequently having the potential to decrease traffic injuries resulting from traffic congestion.

The results also demonstrate a negative but not statistically significant relationship between the number of serious injuries and the availability of Via in the city over time. To some extent, the reduction of traffic crashes and injuries can be derived from the spatial structure of Arlington, TX, and the sociodemographic of the city population. Arlington is a mid-sized city with a sprawling land use pattern, so the availability of Via on-demand ridesharing would not exacerbate the traffic congestion. In addition, unlike the previous studies that suggest the availability of app-based on-demand services such as Uber in metropolitan areas with high population density is associated with additional vehicle trips, traffic congestion, and consequently traffic incidents [1], deployment of on-demand ridesharing services such as Via in suburban areas can substitute personal car trips and decrease traffic congestion.

Figures 3 and 4 mapped the hotspot crashes resulting from drivers' faults and indicated the potential for self-driving vehicles to reduce traffic crashes and fatalities in the service area. This result is supported by the past studies that revealed the integration of the SAVs in the downtown area can improve the efficiency and mobility of the current transportation services by feeding the excess ridership demand [9,15]. Accordingly, SAVs will likely reduce fatality and mortality from traffic crashes if they are regulated and designed appropriately [20].

Study Limitations

Although this study attempted to investigate the impact of on-demand ridesharing services on traffic crashes, it has some limitations mostly originated from data availability restrictions. First, the crash data received from TxDOT is only based on crashes that were reported to the police department and included in the "Crash Record Information System" (CRIS). Not all crashes that happen on Texas roads are reported to the police and this reporting could potentially create a measurement bias in this study.

Second, the database does not contain complete information for all crashes. Many incidents included in the raw dataset did not have latitude and longitude values reported and consequently were dropped from the dataset in the study.

Third, the data used to analyze the trends in traffic crashes this analysis ranges from 2014 to 2021. During this analysis period, the COVID-19 Pandemic impacted mobility patterns all over the world, including in Arlington. The ITSA analysis provides coefficients for the intervention impacts in terms of immediate impact after the intervention and impacts since the intervention represented as "Via Availability" and "Time Since Via Availability" variables in the ITSA model respectively. Although the results show a negative impact of Via availability on traffic crashes, both immediately after the intervention and for the entire period after the intervention, the impacts of the Pandemic on traffic crashes could not be ignored. The COVID-19 impacts on traffic congestions could be a confounding factor in this analysis, which at the same time provide possible avenues for further research.

Eventually, because this study was conducted a short time after implementation of RAPID SAVs and due to the lack of access to crash data related to SAVs, this study did not analyze the impacts of RAPID on traffic crashes. This limitation can be addressed through future research on traffic congestion and crashes trends in the case study area in the more extended period after implementing the service.

CONCLUSION

The demonstration of a reliable on-demand ridesharing service can affect individuals' tendency to shift from private cars to ridesharing, reduce individuals' need to own a private vehicle over time, and lower the overall vehicular traffic congestion and crashes in urban areas. Increasing the possible benefits of on-demand ridesharing and enhancing the efficiency and equity of ridesharing can be realized by conforming such services with urban form. Land use and built environment characteristics such as population density, employment density, street network design, land use diversity, and destination accessibility can moderate the efficiency of on-demand ridesharing services. Accordingly, considering the impacts of built environment attributes on traffic and the safety of on-demand ridesharing services can assist policymakers and transit agencies to adjust and specify the DRT services to the characteristics of the service area. The identification and the evaluation of disparities in different urban areas and built environments should be performed before demonstrating on-demand ridesharing service platforms.

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FIGURES

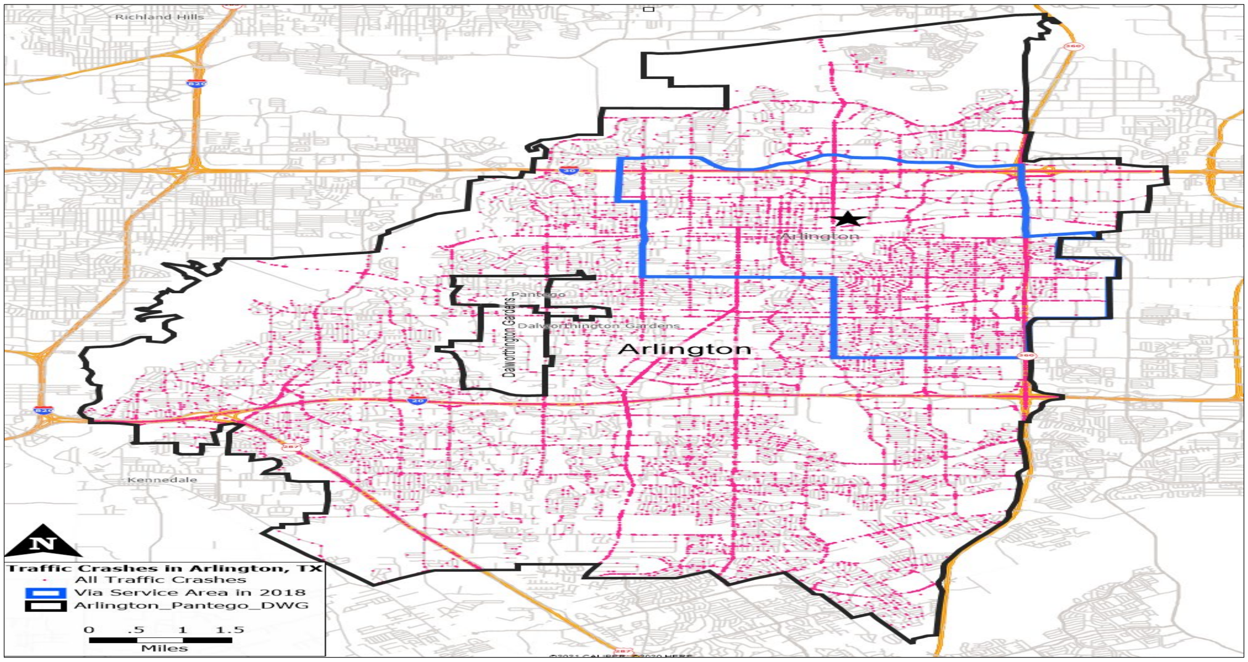

Figure 1. Spatial Distribution of Traffic crashes in Arlington, TX from 2014-2021. Black lines show city boundaries, blue color shows Via services are boundary

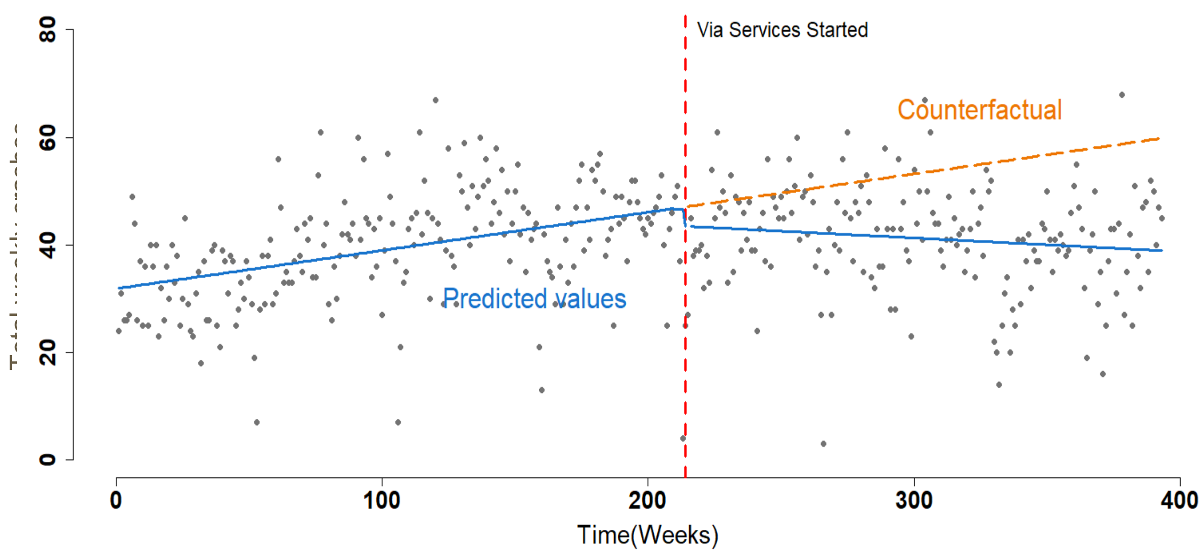

Figure 2. Graphical representation of the of ITSA Model.

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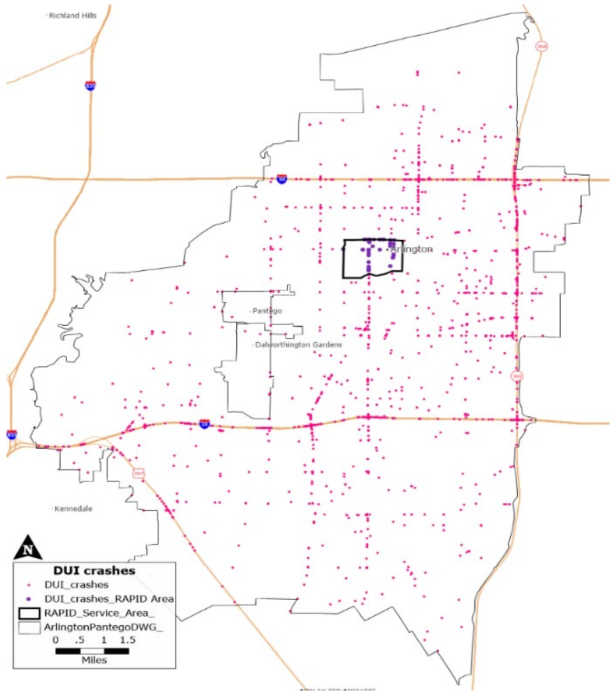

Figure 3. Spatial distribution of crashes caused by drivers' faults. The small purple box shows the service area of RAPID

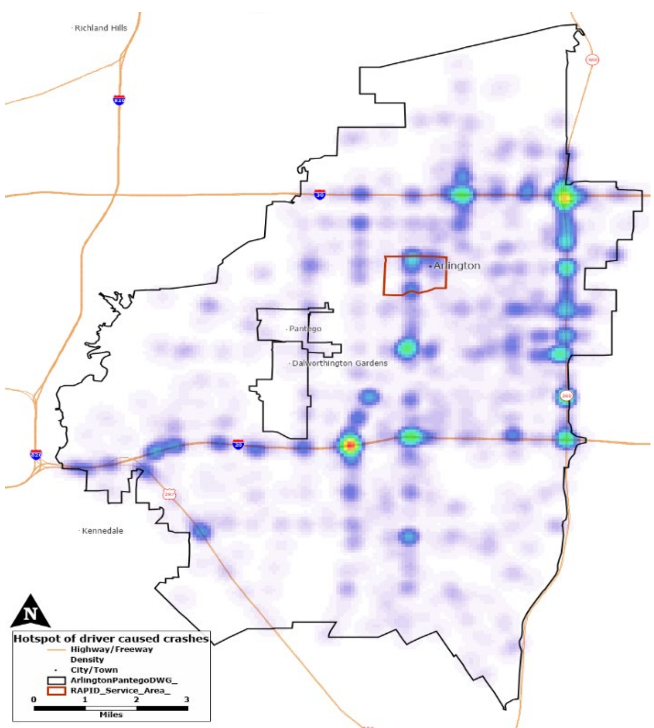

Figure 4. Hotspots of the crashes caused by a driver's fault

TABLES

Table 1. Descriptive statistics of key variables used in all three ITSA models. All variables are aggregated at weekly level to avoid missing values and having enough data points.

Variable (n= 396)	**Mean**	**Std. Dev**	**Min**	**Max**
Crash Frequency	40.24	10.27	3	68
Number of Deaths	0.15	0.43	0	4
Total Injuries	24.96	9.22	2	60
Number of serious injuries	1.14	1.26	0	7
Via on-demand ridesharing Availability	0.47	0.49	0	1
Time since Via Availability	44.38	59.89	0	187

Table 2. Results from the ITSA model representing the association between Via availability and other independent variables with the weekly number of traffic crashes. The variable of interest (Time Since Via Availability) is shown in bold text

Number of observations = 393
Prob > chi2 = 0.0000
Log likelihood = -1458.235

	Coef.	Std. Err.	P>|z|	[95% Conf. Interval]	
Total number of crashes per week (Dependent Variable)					
Time	0.07	0.01	0.00	0.05	0.09
Via Availability	-3.12	1.98	0.12	-6.99	0.76
Time Since Via Availability	**-0.10**	**0.02**	**0.00**	**-0.13**	**-0.06**
Constant	31.87	1.54	0.00	28.86	34.89

Table 3. Results from the ITSA model representing the association between Via availability and other independent variables with the weekly number of injuries caused by traffic crashes. The variable of interest (Time Since Via Availability) is shown in bold text

Number of observations = 393
Prob > chi2 = 0.0005
Log likelihood = -1449.868

	Coef.	Std. Err.	P>|z|	[95% Conf. Interval]

Number of total injuries per week (dependent variable)					
Time	0.04	0.01	0.00	0.022952	0.064018
Via Availability	-3.33	1.87	0.08	-7.00727	0.339258
Time Since Via Availability	**-0.05**	**0.02**	**0.00**	**-0.08752**	**-0.01861**
Constant	20.25	1.37	0.00	17.57519	22.92678

Table 4. Results from the ITSA model representing the association between Via availability and other independent variables with the weekly number of serious injuries caused by traffic crashes. The variable of interest (Time Since Via Availability) is shown in bold text

	Coef.	Std. Err.	P>|z|	[95% Conf. Interval]	
Number of observations =	393				
Prob > chi2 =	0.0005				
Log likelihood =	-1449.868				
Serious Injuries					
Time	-0.001	0.00	0.25	0.00	0.00
Via Availability	-0.272	0.30	0.37	-0.87	0.32
Time Since Via Availability	0.003	0.00	0.20	0.00	0.01
Constant	1.469	0.19	0.00	1.10	1.84

APPENDIX AS: BIBLIOGRAPHY

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Chapter 4: Impacts of On-demand Ride Services on the Number of Traffic Crashes – A Case Study of RideAustin in Austin, TX

ABSTRACT

On-demand ridesharing services are rapidly growing and are predicted to continue to do so, as they offer millions of trips to potential riders every day. The impacts of ridesharing services on travel behavior, traffic congestion, and the environment have been examined in depth through empirical studies; however, their impact on the number of traffic crashes has been neglected. Past studies exploring the safety impacts of ridesharing services have considered only the *availability* of a ridesharing service; however, we argue that the mere presence of a ridesharing service does not guarantee either a positive or a negative impact on traffic safety. Rather, it is the usage frequency of a service that is likely to make an impact. This study aims to analyze the impacts of ridesharing services on the number of traffic crashes and injuries, using RideAustin, a community-based ridesharing service in Austin, TX, as a case study. It adopts the difference-in-difference approach to investigate how RideAustin affects traffic crashes at the U.S. census block group level, while controlling for sociodemographic characteristics and built environment variables. The trip level data from RideAustin used in this study pertains approximately 1.4 million trips from 2016 to 2017; traffic crash and injury data from the Texas Department of Transportation for the period 2012-2020 pertains to about 373,000 accidents. Difference-in-difference models demonstrated that the number of traffic crashes only decreased when the number of trips in a block group increased a certain threshold. Mere availability of the services and very low usage (<1 ride per block group) was found to have no significant impact on traffic safety. The findings from this study will enable a better understanding of the safety benefits of ridesharing services, thereby helping transportation and policy planners reduce the number of traffic crashes in urban areas.

INTRODUCTION

Mobility on Demand (MOD), which utilizes real-time data to fill mobility gaps by providing ridesharing & multimodality in transportation systems, is tremendously popular in the United States and around the world. It was developed based on the shared economy, and links the components of transportation supply and demand with trip planning without any breaks (Shaheen et al., 2017). On-demand ridesharing services, recognized as ride-sourcing, share trips and mobility modes between users with the same origins and destinations and improve trip reliability by decreasing travel time and cost (Rayle et al., 2014; Shaheen and Cohen 2019).

Multiple studies have been conducted to explore the social, economic, and environmental benefits and advantages of on-demand ridesharing services and have shown that innovative partnerships between MOD services and public transit agencies can improve transportation equity for the underserved population and increase the efficiency of public transit ridership in low-density routes (Lucken et al., 2019). It has also been suggested that MOD may be able to complement traditional fixed-route transit systems in metropolitan areas during low-demand ridership hours (Volinski 2019) or substitute for the fixed-route transit in small cities and rural areas (Koffman 2004; Tsay et al., 2016). Replacing low-ridership conventional transit services with ride-sourcing can reduce travel time, decrease operational costs, and boost transit performance, particularly when provided with the last-mile connection (Yan et al., 2019). Another important advantage is the benefit to the environment that results from the 22% reduction in travel distance realized by ride splitting, which significantly decreases the amount of gas emissions (Liu et al., 2021).

Despite the positive effects of a ride-sourcing system on trip efficiency, equity, and accessibility, there is still some uncertainty about its broader impacts. Empirical evidence raises concern about the impacts of sharing mobility on car ownership, but there is no evidence that it has decreased private vehicle usage; indeed, it may have slightly increased it (Anderson 2014; Clewlow and Mishra 2017; Rayle et al., 2016). Exploring the effects of ride sourcing on individual travel patterns, however, indicates that in the long term, ride splitting users may shift from purchasing private vehicles to ridesharing (Zheng et al., 2019). Similarly, there are differing views on the effects of on-demand ridesharing services on *traffic congestion*, with some suggesting that adopting ridesharing can decrease traffic congestion (Alexander and González 2015; Li et al., 2016) and others espousing that it has no impact due to increased demand for driving and vehicle miles traveled (Anderson 2014; Schaller Consulting 2017). MOD can be also considered a factor in predicting *crashes and fatalities*. There are opposing views about the potential effects of on-demand ride services on the number of traffic crash incidents and fatalities, and very few studies have explored changes in the trends of traffic crashes and fatality changes in the MOD context (Brazil and Kirk 2020; Dills and Mulholland 2018; Morrison et al., 2018).

The rapid expansion of the on-demand ridesharing market makes it crucial to understand the impacts that it has on the transportation systems. This study aims to understand the environmental impacts of on-demand ridesharing services by addressing and clarifying the gaps in the existing body of literature through 1) employing a diff-in-diff analysis and examining the effects of a ridesharing service in Austin, Texas, and 2) applying a new method for identifying the effects from on-demand ridesharing services on vehicle traffic and crashes. The remainder of the paper is organized as follows. Section 2 reviews the available relevant literature, Section 3 introduces the study methodology and describes the data and the employed method, Section 4 presents the results, and Section 5 provides a discussion of the findings and a summary of the conclusions.

LITERATURE REVIEW

The effects of MOD and ride sourcing services have been the subject of several recent studies. The emerging literature conceptualizes the effects of MOD services through two lines of research: 1) effect of ridesharing on alcohol-involved crashes; and 2) effects of ridesharing on vehicle ownership, traffic congestion, and road usage.

Uber technology was one of the first ridesharing services to receive attention from scholars because of its potential to reduce the vast number of drunk driving incidents in the United States. Its effect on the shift in the total number of drunk drivers and weekend and holiday-specific traffic fatalities was investigated, using data from U.S. metropolitan counties during the period of 2005 to 2014. Results from binomial and Poisson regression models indicated no association between the deployment of Uber and the number of traffic fatalities (Brazil and Kirk 2016). The entry of two Uber services, Uber Black and Uber X, into the California market was explored for the period of 2009 to 2014, using a difference-in-difference approach, and the results revealed a reduction in the alcohol-related motor vehicle homicide rate (Greenwood and Wattal 2015).

In 2018, Dills and Mulholland used county-level data from 2007 through 2015 to investigate the impacts of the introduction of Uber as an emerging ridesharing mode in the U.S. and found that its presence decreased the number of fatal accidents and some types of crimes. In their research, the effects of Uber on crime were categorized according to incidents that might not occur because of a new transportation option, such as DUIs (driving under the influence), drunkenness and disorderly conduct, aggravated assault, and motor vehicle thefts (Dills and Mulholland 2018).

Although the initial empirical evidence pointed out an average association between ridesharing and crashes, the results were mixed. Therefore, Morrison and his colleagues addressed the inconsistency of the empirical findings by considering physical variations across geographic samples. They employed interrupted time-series analyses of traffic crashes and Uber ridesharing in four US cities with populations of more than 200,000: Las Vegas and Reno, Nevada; Portland, Oregon; and San Antonio, Texas. Their results indicated a reduction in alcohol-related accidents that could be attributed to Uber; however, the findings differed across case studies due to the different structures and topology of the cities (Morrison et al., 2018).

Brazil and Kirk (2020) updated their study on the relationship between Uber availability and traffic fatalities by employing more recent data of Uber ridership and testing whether the association relies on local and physical attributes of the built environment. Multivariate regression modeling of the data from 100 of the most populated metropolitan areas in the United States between 2009 and 2017 revealed that Uber availability does not affect traffic fatalities. Instead, they found that Uber's presence can increase traffic fatalities in areas with a high population density (Brazil and Kirk 2020).

Likewise, a recent study declared a 3% increase in fatal accidents involving cars and pedestrians in U.S. cities due to the introduction of ridesharing services (Barrios et al., 2019). Other reported results of ridesharing availability are increased arterial vehicle miles traveled, extra fuel consumption, more hours of delays in traffic annually, and growth in the number of new car registrations. The results are more significant in cities with greater access to public transit, carpools, and high vehicle ownership. Cities with higher demand for Uber experience more significant traffic congestion and risk of accidents than small cities with limited access to public transit services (Hall, Palsson and Price 2018; Erhardt et al., 2019; Schaller 2018).

The literature demonstrates wide discrepancies between geographical areas; hence, it is necessary to understand the relationships between the presence of on-demand ridesharing services and changes in the number of crash incidences in different contexts. This study utilizes an interrupted time-series analysis to investigate the effects of an on-demand ridesharing service on vehicle crashes in Austin, Texas. Diff-in-diff is a popular method that is used in the literature to evaluate traffic changes (Dills and Mulholland 2018; Greenwood and Wattal 2015; Morrison et al., 2018). This evaluation can provide urban planners with new insights that will enable them to make more suitable policies for developing technology-based transportation services. Furthermore, evaluating the safety performance of the existing on-demand ridesharing services in different geographical areas can provide policymakers with valuable information that will facilitate their implementing improvements into similar projects.

The following questions formed the basis for this research:

(1) Does the deployment of an on-demand ridesharing service impact the number of crashes in its service area?

(2) How is the use of an on-demand ridesharing service associated with injuries caused by traffic crashes in a metropolitan area?

METHODOLOGY

Data and Variables

The following are the reasons for our selection of Austin, Texas as the city in which to explore the relationship between the availability of demand-responsive transport services (DRT) and traffic crashes.

(1) Austin is home to RideAustin, which is one of the largest DRT systems in the nation and is a community based non-profit DRT service that provided more than two million trips to riders in its first year of operation.

(2) In 2016, Uber and Lyft, the two largest ride-hailing services, ceased their Austin operations due to differences with the city government on background checks of drivers. Their absence shifted the demand for ridesharing services to RideAustin, simplifying the data that would form the basis for this research.

(3) The majority of research on DRT has focused on large metro areas and cities, but those findings may not be applicable to small- and medium-sized cities.

(4) The ridership data for 2016 and 2017 was made public by RideAustin, and we were able to use the information for our research study.

Data used in this research was obtained from multiple sources. The trip level ridership data for RideAustin was downloaded from the online database, DataWorld, which provides a dataset of 1,494,002 trips taken during June 2016 to April 2017 and is the only data available publicly for download. Each trip record includes the date, time, latitude, and longitude of origin and destination points, as well as the time and distance required to complete the trip. The spatial distribution of RideAustin trips is shown in Figure 1, where every dot represents one trip. trip

The Texas Department of Transportation (TXDOT) Crash Record Information System (CRIS) was utilized for obtaining data on all of the traffic crashes reported to the police within the Austin metro area between 2012 to 2020. Each traffic crash record includes information on the date, time, location, severity, number of injuries, and number of deaths. After refining the data by removing records with missing information, 257,955 crash records remained in the dataset. The spatial distribution of traffic crashes is shown in Figure 2, where each point depicts one traffic crash during the study period. We used crash data from 2012 to 2020 to have enough observations before and after the launch of RideAustin. This period was chosen for our analysis for several reasons. First, since RideAustin was launched in 2016, we decided to include the maximum period in our analysis after the start of the RideAustin service. Still, we did not want to include data after the onset of the COVID-19 pandemic. Therefore, our dataset only included a few months of data from 2020. Second, to have an equal time period before and after the introduction of RideAustin and enough data points to run the difference-in-difference series analysis, we included data for an almost-equal period (approx. four years) of time before and after the start of the RideAustin service.

Sociodemographic, built environment, and traffic-related data was obtained from the mapping software, Maptitude, by Caliper Corporation. Table 1 depicts a summary of the variables and sources from which the data was obtained. The data was aggregated at the block group level to include socio-demographic and built environment variables.

The variables included in the analysis are described below,

1. **Number of trips per block group** : The number of RideAustin trips per block groups during 2016-2017 (duration for which ridership data is available). We geocoded all trips and spatially joined the points of origin of each trip with the block group in which they were located. Then we divided the number of trips by the population of each block group to get "Number of trips per capita per block group" for each block group. We did this to standardize the number of trips based on population.
2. **Number of traffic crashes per capita per block group:** The crashes reported to police and registered in The Texas Department of Transportation (TXDOT) Crash Record Information System (CRIS) were collected from 2012-2020 and spatially joined with block groups and then divided by the population to calculate number of traffic crashes per capita per block group.

3. **Number of injuries per capita per block group:** The number of injuries recorded in each traffic crash from the Crash Record Information System (CRIS) database were collected from 2012-2020 and spatially joined with block groups and then divided by the population to calculate number of injuries per capita per block group.
4. **Population Density:** Population of the block group divided by area to get number of people per square mile.
5. **Intersection Density:** Number of intersections per square mile. This is used to check how dense the street network is, which is an important determinant of traffic crashes in literature.
6. **Annual average daily traffic:** This is the annual average daily traffic for each block group collected from HERE traffic data base through Maptitude[3] mapping software by Caliper corporation.
7. **Road Network length:** This is the total length of street/road network in a block group.

Methods

To evaluate the impact of the availability and usage of demand-responsive transport (DRT) systems on traffic safety, we used the difference-in-difference (DiD) approach to measure the variances in the traffic crashes and traffic injuries before and after the deployment of RideAustin in 2016. DiD is a quasi-experimental technique that is used to measure the effect of certain interventions and policy measures on an outcome variable by comparing differences in control and treatment groups over time and before and after the intervention. A statistically significant difference between the treatment and control groups before and after intervention indicates that the intervention had a significant impact on the outcome variable. For this study we used the

[3] https://www.caliper.com/maptovu.htm

number of crashes and injuries per capita per block group as our dependent variables. Crashes and injuries were measured on a per capita basis to control for differences in populations of block groups. We used census block groups as our unit of analysis to account for small-scale and localized variations in crashes, as a block group is the smallest geographic unit with available socio-demographic and related data. Our data includes a total of 7697 block groups within the study region which were selected based on the geographic boundaries of the city.

Previous studies on the impacts of public transit and demand-responsive transport systems assumed that the mere presence or absence of a service impacts the surrounding areas as well as the targeted area, and used the unavailability of these services in an area as a proxy to define treatment and control groups (Barreto et al., 2021). This research, however, assumes that DRT services may reduce traffic crashes and injuries because 1) people will have less exposure to traffic as they switch from modes such as walking and biking to using DRT services, and 2) the DRT service will likely decrease the overall traffic volume and thus the number of traffic incidents. These assumptions can only hold true if a DRT service is used by the residents to the extent that it impacts traffic volumes/exposure rates.

We tested several models by varying the defining criteria for the treated group. For the first model, we chose all block groups having at least one RideAustin trip as the treatment group and all other block groups as control groups. This model assumed that block groups with mere availability/just one ride on RideAustin would impact on the number of traffic crashes.

For the other six models, the criteria for selecting the treatment group are given below,

1. Model 1: Block groups with at least 1 ride were considered as treatment groups.
2. Model 2: Block groups with at least 10 rides were considered as treatment groups.
3. Model 3: Block groups with at least 50 rides were considered as treatment groups.

4. Model 4: Block groups with at least 100 rides were considered as treatment groups.
5. Model 5: Block groups with at least 250 rides were considered as treatment groups.
6. Model 6: Block groups with at least 500 rides were considered as treatment groups.

The criteria for selecting the treatment groups were based on both the presence of the service and its actual usage to evaluate the impacts of the ridership on traffic safety.

A summary of the dependent and independent variables used in the difference-in-difference model is given in Table 2. The two dependent variables are the number of crashes and the number of serious injuries per capita per block group. Two dummy variables were used in the model. First, the time variable corresponds to the implementation of RideAustin and has a value of 0 before the implementation of RideAustin (before 2017) and a value of 1 after implementation. The variables of RideAustin shown with different subscripts indicate the availability of RideAustin within a block group. Its value changes with the value for the threshold to select the treated group; therefore, each variation is denoted by its subscript. The diff-in-diff interaction term (DiD) is the product of the values of the two dummy variables (Time x RideAustin availability). The subscripts indicate the variable values for each of the six treatment and control groups mentioned above.

RESULTS

Traffic Crashes

The six diff-in-diff models employed to evaluate the impact of RideAustin on traffic crashes were based on the criteria selected for the treatment and control groups. Table 3 illustrates the results of examining whether the availability of RideAustin is associated with any change in the traffic crash rates per block group and presents the summary statistics (estimates and p-values) of all six diff-in-diff models, along with the R squared/adjusted R squared values. The DiD (interaction term) reflects the impact of availability of RideAustin on traffic crashes.

The results depicted in Table 3 indicate that the coefficient for the DiD term is positive but statistically insignificant when the treatment group is selected based on at least one trip DiD_0. However, when the number of trips for selecting the treatment group is increased, the coefficients for the DiD term show a significant negative association with the number of crashes. The coefficient value for DiD_{10} is 0.03 and not statistically significant, while the coefficient values for **DiD_{50}, DiD_{100}, and DiD_{250}** are respectively -0.1013, -0.1488, and -0.1603 and are significant at 98 and 99 confidence intervals. These results indicate that the impact of RideAustin on the number of traffic crashes becomes more obvious with increased usage of the service. In Model 6, where the number of RideAustin rides increases to at least 500 rides per block group, the associations between ridership and crashes are significant, but the coefficient value is less than that for Models 4 and 5. This indicates that increasing the ridership to at least 500 rides per block group decreases the level of positive associations between RideAustin ridership and vehicle crashes.

Traffic Injuries

The results for serious injuries per capita per block group are shown in Table 4. The relationship between RideAustin and the number of serious traffic injuries for the DiD_0 and DiD_{10} models is negative and statistically significant. As the criteria for selecting the treatment group increases, the coefficients obtain a higher negative value and are more statistically significant. The coefficient for the DiD terms increases from -0.0095 in the first model to -0.1255 in the last model when the threshold is set at 500 trips per block group. The negative association between traffic injuries and RideAustin is significant for Models 3, 4, 5, and 6; however, Model 6, that explores the effects of RideAustin ridership on traffic injuries in counties with at least 500 rides per capita, has a smaller coefficient than Models 3, 4, and 5 that illustrate counties with ridership of at least 50, 100, and 150 per capita. These results support the assumption that the impacts of RideAustin on traffic crashes become evident when the criteria to determine whether or not a block group was treated is set at a higher value. This indicates that when more trips are taken on a DRT service such as RideAustin, the number of crashes is likely to decrease.

DISCUSSION AND CONCLUSION

The aim of this study was to examine the impacts of demand-responsive transportation services on the number of traffic crashes and injuries. RideAustin, an on-demand ridesharing service that offered approximately three million rides to people in Austin, Texas from 2016 to 2020 (Hernandez 2020), was used as a case study. Unlike past studies that used the availability, presence, introduction, and resumption of on-demand ridesharing services in different geographical areas to evaluate the traffic impacts (Brazil and Kirk 2020; Dills and Mulholland 2018; Morrison et al., 2018), this study used the frequency of usage of the RideAustin service to evaluate its impacts on traffic safety and assumed that the mere availability of a service cannot significantly impact traffic safety. The key findings of this research are described below.

First, a diff-in-diff analysis of the data indicates that there are statistically significant and negative associations between the ridesharing ridership and traffic crashes of the treated block groups and the control block groups. This result confirms the studies that reported lower risks for vehicle crashes for app-based motorcycle taxi drivers compared with regular motorcyclist taxies in Vietnam (Nguyen-Phuoc et al., 2020), the reduced impact of Uber on alcohol-involved crashes in U.S. cities (Morrison et al., 2018), the significant drop in the number of serious traffic crash injuries after the deployment of Uber in Great Britain (Kirk et al., 2020), and the reduction of traffic accidents attributed to Uber and Cabify services in Madrid (García et al., 2021).

Second, the results revealed a negative association between vehicle traffic injuries and RideAustin ridership frequency, which echoes the results of Dills and Mulholland 2018; Greenwood and Wattal 2015; and Morrison et al., 2018.

Third, the relationship between RideAustin and traffic crashes and injuries are dependent upon the treated block groups being selected based on the number of trips. The relationship is not significant if the treated block group is selected based only being in a service area. These findings are in agreement with several other studies that evaluated the impacts of policy intervention and found that the availability or presence of a facility or service is not sufficient to make a difference (Bhattacharya et al., 2012; De Juan et al., 2020; Lovenheim and Walsh 2018; Sinha and Laha 2019). It is the actual usage of services or a facility that can have an impact. For example, as shown in our results, the value of the difference-in-difference term decreases with an increase in the usage frequency (from 0.03 in the first model to -0.168 in the last model and -0.0095 to -0.1255 in the crash and injury models, respectively). As the difference-in-difference terms and number of ride variables are both related to time, and based on changes in pattern over time, the inconsistency in relations could be attributed to this factor.

Fourth, although the number of traffic and injury crashes decreases with an increase in the number of those utilizing the on-demand service, the significance of the model for at least 500 rides per county is less than that of counties with at least 50, 100, and 250 rides. This result reveals that counties with a higher demand for on-demand ridesharing services face greater traffic congestion and a higher risk of vehicle accidents than smaller counties (Hall, Palsson, and Price 2018; Erhardt et al. 2019; Schaller 2018).

Overall, on-demand ridesharing services such as RideAustin have the potential to decrease vehicle ownership, affect individuals' decision to transition from private cars to ridesharing, and reduce the overall traffic congestion and crashes in urban areas. However, the potential advantages of on-demand ridesharing are still uncertain since studies have revealed that platforms such as Uber have increased traffic congestion and the number of crashes and fatalities in high dense and compact areas (Brazil and Kirk 2020; Li et al., 2022). Urban and built environment features such as population and employment density, network design, diversity of land use, and distance to other modes of transportation can moderate the efficiency of on-demand ridesharing services but enhancing the efficiency and equity of ridesharing will require developing and implementing strategies that adjust with the urban features of different geographical areas. Since policymakers necessarily cope with the principles and regulations of these platforms, considering the heterogeneity in the effects of on-demand ridesharing services can assist them in making appropriate decisions while improving mobility via MOD services. Therefore, city and transportation planners should be aware of the disparities in urban forms and built environment characteristics when approving the initiation of on-demand ridesharing service platforms.

The results of this study indicate that subsidizing and incentivizing on-demand ridesharing services in urban and rural could be helpful policy interventions, as there is a positive relationship between the MOD services and a smaller number of traffic crashes. Regular auditing of the ridership trends of existing MOD services will ensure that they are not merely available in an area but also are used by the residents.

Still the effects of ridesharing services on an increased number of trips are not clear in the literature. Therefore, studying the impacts of RideAustin on vehicular traffic was beyond the scope of this study. To our knowledge, RideAustin provided around 1.4 million trips in less than one year. Since this service is a ridesharing service, this study assumes that many of these trips were shared by more than one passenger (we do not have an exact figure), which would result in the reduction of drive-alone trips and vehicular traffic.

In addition, we are not stating a causal relationship between traffic crashes and an-demand ridesharing services. Still, we present that, in areas where people frequently use ridesharing services, the number of traffic crashes is lower than in areas where these services are not frequently used. Studying the impacts of ridesharing services on vehicular traffic could be a future research question and could help clarify this relationship even more.

Study Limitations

Although this study is a good attempt to evaluate the safety impacts of DRT services, it does have some limitations described below,

The data obtained from the CRIS data only includes traffic crashes that were reported to the police, and the literature shows that traffic crashes are usually under-reported, as not every crash that occurs is reported.

Several crashes included in the CRIS database did not contain information of some important variables such as the longitudes and latitudes. Since our analysis required that all the crash points be mapped so that they could be joined with the block groups, we had to remove all of the crashes lacking the latitude and longitude information, which reduced the number of observations.

The ridership data for RideAustin available online is only for the year 2016-2017. However, our analysis period after the introduction of RideAustin spans from 2016-2020. The inclusion of ridership data for a longer temporal scale would increase the reliability of the results.

This study included the total number of crashes and injuries in the analysis. The number of fatalities in the analysis would give more insights into the impact of demand responsive services on traffic safety. However, traffic fatalities are rare incidents, due to which we did not have enough data available to do a diff-in-diff analysis on traffic fatalities or severe injuries.

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FIGURES

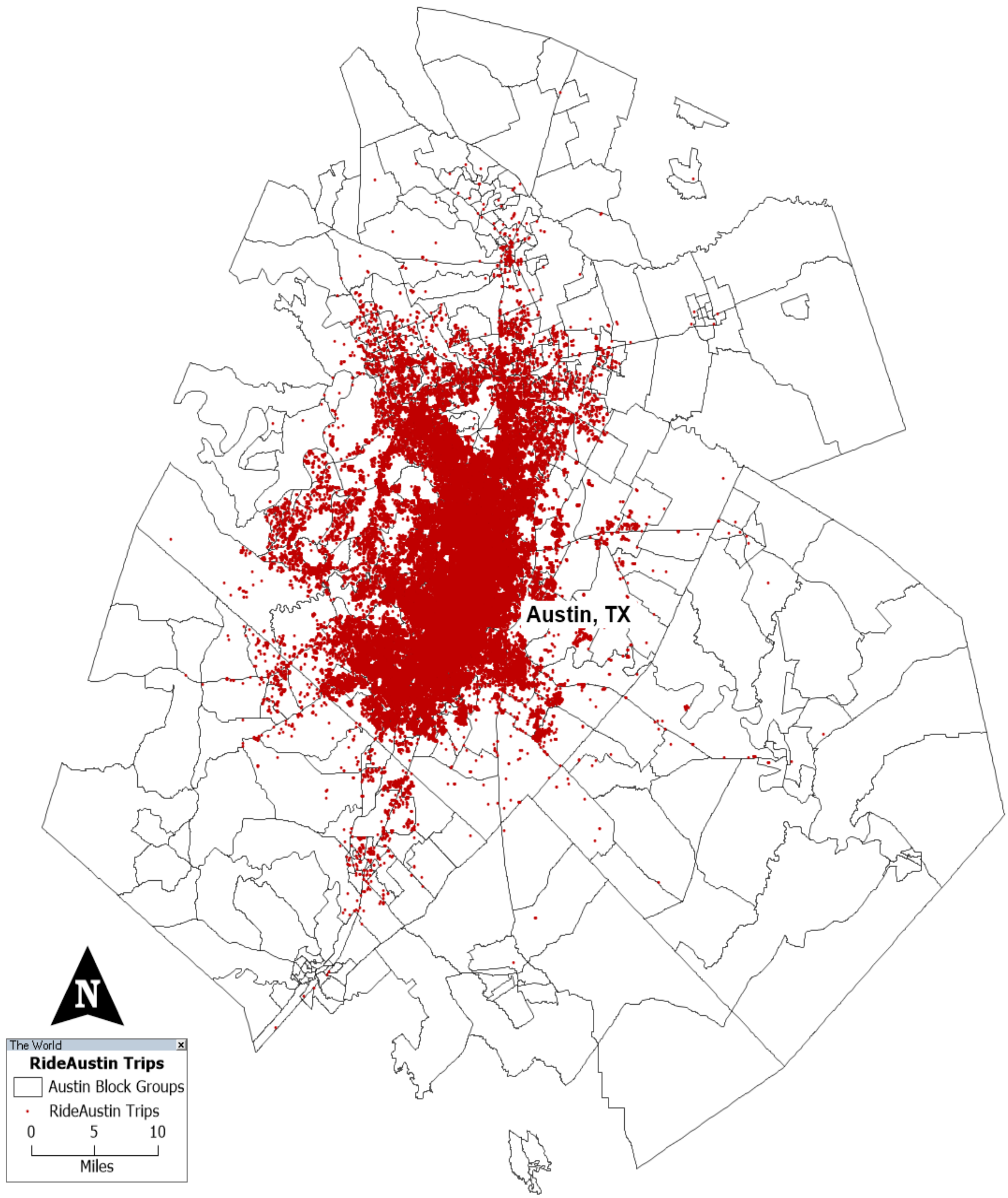

Figure 1. Spatial distribution of RideAustin trips in which each red dot depicts one RideAustin

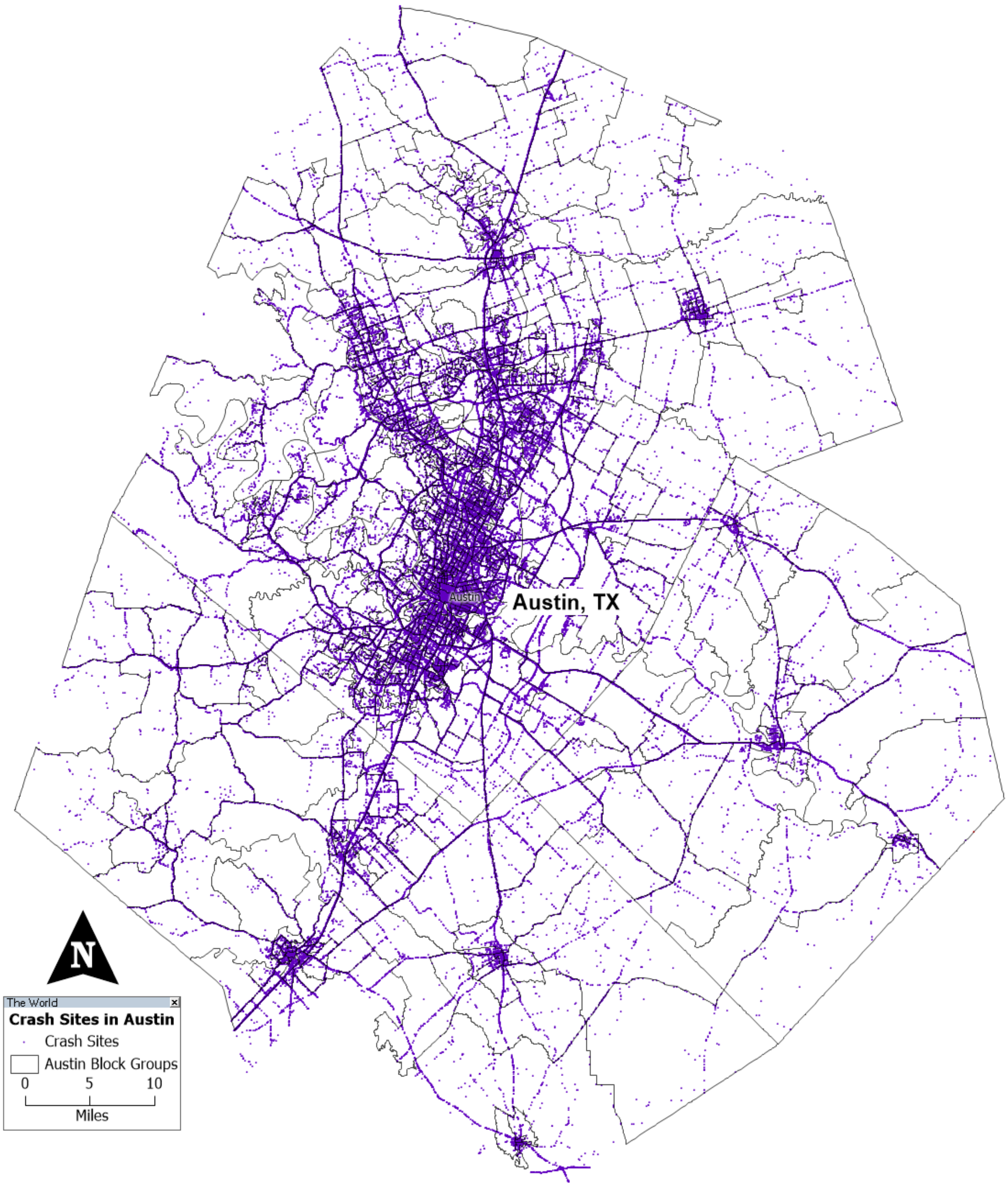

Figure 2. Spatial distribution of traffic crashes in which each point depicts a crash site

TABLES

Table 1. Sources of Data and Variables

Data Category	Variables	Source
Ridership	Number of trips per block group	RideAustin/ DataWorld (2016-2017)
Traffic crashes	Number of traffic crashes per capita per block group	TxDOT CRIS (2012-2020)
	Number of injuries per capita per block group	
Socio-demographic	Population density	Maptitude (2015-2019 ACS)
Traffic	Annual average daily traffic	
Built environment	Intersection density	
	Road network length	

Table 2. Summary of Variables Measured at Block Group Level

Variables	N	Mean	SD	Min	Max
Dependent Variables					
Ln Crashes Per Capita Per Block Group	7,697	-4.62	1.10	-8.16	0.39
Ln Injuries Per Capita Per Block Group	7,697	-5.32	1.25	-8.70	0.16
Independent Variables					
DiD_0	7,697	0.38	0.49	0.00	1.00
DiD_{10}	7,697	0.33	0.47	0.00	1.00
DiD_{50}	7,697	0.29	0.45	0.00	1.00
DiD_{100}	7,697	0.26	0.44	0.00	1.00
DiD_{250}	7,697	0.21	0.41	0.00	1.00
DiD_{500}	7,697	0.17	0.37	0.00	1.00
$RideAustin_0$	7,697	0.88	0.33	0.00	1.00
$RideAustin_{10}$	7,697	0.77	0.42	0.00	1.00

$RideAustin_{50}$	7,697	0.67	0.47	0.00	1.00
$RideAustin_{100}$	7,697	0.60	0.49	0.00	1.00
$RideAustin_{250}$	7,697	0.50	0.50	0.00	1.00
$RideAustin_{500}$	7,697	0.38	0.49	0.00	1.00
Time	7,697	0.43	0.50	0.00	1.00
Intersection Density	7,697	344.12	304.11	0.00	2021.67
Average Daily Traffic	7,697	71650.15	84636.53	586.20	800900.60
Population Density	7,697	4032.57	4593.09	8.28	53614.90
Number of RideAustin Trips	7,697	31.10	38.87	1.00	433.00
Road Network Length	7,697	19.98	21.29	0.00	164.68

Table 3. RideAustin Ridership Frequency and Vehicle Traffic Crashes [Dependent Variable: Log (Traffic Crashes Per Capita)]

Predictors	**Model1 (DiD_0)**		**Model2 (DiD_{10})**		**Model3 (DiD_{50})**		**Model4 (DiD_{100})**		**Model5 (DiD_{250})**		**Model6 (DiD_{500})**	
	Est	***p***	***Est***	***p***	***Est***	***p***	***Est***	***p***	***Est***	***p***	***Est***	***p***
(Intercept)	0	1	0	1	0	1	0	1	0	1	0	1
DiD	0.0093	0.727	-0.01892	0.349	-0.04605	0.009	-0.06223	<0.001	-0.06075	<0.001	-0.04851	0.001
RideAustin	-0.0963	<0.001	-0.11705	<0.001	-0.05412	<0.001	0.00406	0.761	0.02891	0.03	0.03406	0.01
Time	-0.0199	0.437	0.00352	0.85	0.02177	0.166	0.03055	0.033	0.02474	0.052	0.01323	0.251
AADT	0.4517	<0.001	0.45719	<0.001	0.45161	<0.001	0.44172	<0.001	0.43687	<0.001	0.43494	<0.001
RideAustin Trips	-0.087	<0.001	-0.08826	<0.001	-0.08637	<0.001	-0.08375	<0.001	-0.08271	<0.001	-0.08277	<0.001
Intersection Density	0.3168	<0.001	0.33198	<0.001	0.32579	<0.001	0.31284	<0.001	0.30566	<0.001	0.30204	<0.001
Population Density	-0.211	<0.001	-0.20127	<0.001	-0.20986	<0.001	-0.21926	<0.001	-0.22352	<0.001	-0.2247	<0.001
Road Network Length	0.0435	<0.001	0.03411	0.002	0.04466	<0.001	0.05169	<0.001	0.05483	<0.001	0.05563	<0.001
R^2 / R^2 adj	**0.377 / 0.376**		**0.381 / 0.381**		**0.374 / 0.373**		**0.371 / 0.370**		**0.370 / 0.370**		**0.370 / 0.369**	

Table 4. RideAustin Ridership Frequency and Vehicle Traffic Injuries [Dependent Variable : Log (Traffic Injuries Per Capita)]

Predictors	**Model1 (DiD_0)**		**Model2 (DiD_{10})**		**Model3 (DiD_{50})**		**Model4 (DiD_{100})**		**Model5 (DiD_{250})**		**Model6 (DiD_{500})**	
	Est	***p***	***Est***	***p***	***Est***	***P***	***Est***	***p***	***Est***	***p***	***Est***	***p***
(Intercept)	0	1	0	1	0	1	0	1	0	1	0	1
DiD	-0.00802	0.771	-0.02744	0.189	-0.05082	0.005	-0.06199	<0.001	-0.06305	<0.001	-0.03737	0.009
RideAustin	-0.03741	0.003	-0.04169	0.002	0.04864	<0.001	0.11406	<0.001	0.13821	<0.001	0.11829	<0.001
Time	-0.05225	0.048	-0.03736	0.053	-0.02217	0.171	-0.01691	0.249	-0.02117	0.104	-0.03986	0.001
AADT	0.41977	<0.001	0.42202	<0.001	0.40789	<0.001	0.39559	<0.001	0.39227	<0.001	0.39387	<0.001
RideAustin Trips	-0.08191	<0.001	-0.08243	<0.001	-0.07882	<0.001	-0.07666	<0.001	-0.07864	<0.001	-0.08185	<0.001
Intersection Density	0.32169	<0.001	0.32805	<0.001	0.30926	<0.001	0.29007	<0.001	0.28012	<0.001	0.28118	<0.001
Population Density	-0.16135	<0.001	-0.15732	<0.001	-0.17176	<0.001	-0.18233	<0.001	-0.18263	<0.001	-0.17828	<0.001
Road Network Length	0.03865	0.001	0.03474	0.002	0.0473	<0.001	0.05502	<0.001	0.05468	<0.001	0.05131	<0.001
R^2 / R^2 adj	**0.389 / 0.388**		**0.389 / 0.389**		**0.396 / 0.395**		**0.402 / 0.402**		**0.406 / 0.406**		**0.404 / 0.403**	

Chapter 5: Integrating Shared Autonomous Vehicles into Existing Transportation Services: Evidence from a Paratransit Service in Arlington, Texas

ABSTRACT

This study investigates the potential benefits of integrating shared autonomous vehicles and an existing transportation system by exploring a recently initiated project that integrates autonomous vehicles (AVs) with an existing on-demand ridesharing service, Via, in Arlington, Texas. We first identified the spatial patterns of the ridership on a localized scale, using geographically weighted regression (GWR) for the existing paratransit service, Handitran. Assuming that the existing ridership will be combined in the future with shared autonomous vehicles (SAVs), we looked at integration options, based on the spatial patterns of supply and demand and payment options for the riders. The results suggest that the paratransit service, Handitran, is currently used by a small proportion of the eligible population, whose travel patterns differ based on their age. For instance, younger users usually ride Handitran for traveling to work, recreational activities, and routine chores, while senior riders often use the service for medical and recreational trips. The results of the geographically weighted regression (GWR) model indicate that the major determinants of Handitran usage are the population's percentage of older adults, racial distribution, and household vehicle ownership; the coefficients of these factors vary across the City. The results of hot-spot analyses reveal that the integration of the services will improve the efficiency of the existing transportation system by responding to the excess rider demand, particularly in the downtown area. Finally, we describe the implications of implementing policies for AV integration in cities, service providers, and other stakeholders and suggest future research topics.

Keywords: *Shared autonomous vehicles; Paratransit; Geographically weighted regression; Integrated mobility, Mobility as a service*

INTRODUCTION

Alleviating the need for owning a vehicle and promoting the use of public transit may be simultaneously accomplished by integrating transportation services [1]. Several studies have proposed combining fixed-route transit systems in dense areas with demand-responsive services that serve those in less transit-demanding locations [2–5]. Recently, transit agencies have partnered with rapidly growing, privately-owned transportation network companies (TNCs) that use an online platform or mobile application to connect commuters with drivers who are operating their own vehicles [9] in an attempt to combine multiple mobility modes, increase the cost-effectiveness of travel, and provide more options for existing and future transit users [6]. Sharing repetitive and pre-planned trips through on-demand services reduces the number of miles traveled and the length of time required to reach destinations compared to conventional ridesharing services such as taxis [7]. Therefore, partnering with mobility-on-demand (MOD) companies to integrate public transit into TNCs enhances the efficiency and quality of public transport services, particularly for low-income, elderly, and disabled people and those who reside in rural areas [8]. Although various studies have explored integrating fixed-route transit and demand-responsive services, discussions about integrating future technologies such as shared autonomous vehicles into existing public transit services are still limited [9–11], despite their promising potential [12, 13]. Recent literature on the potential synergies between AVs and ridesharing touts shared autonomous vehicles (SAVs) as having unique advantages over other public transit modes, such as lower travel costs and more trips served per ride [12], greater travel convenience [14], and the ability to mitigate adverse environmental effects [12]. A rich body of research addresses factors contributing to the deployment and adoption of AVs; however, most of them assume that AVs are an updated version of personal human-driven cars [15–19]. Rapid advancements in the field of information and communication technology (ICT) equip AVs with a much higher potential than a personal automobile for enhancing mobility options and reducing manual driving efforts, and the interactions between existing transportation services and future SAVs need further exploration.

To address the research gap, we explored the potentials of an integrated transportation network, including an SAV and an existing paratransit service. Our focus was on RAPID (rideshare, automation, and payment integration demonstration), a SAV project that aims to integrate Level 4 AVs into existing transportation services in Arlington, Texas. The RAPID project combines AV and MOD technologies to develop an efficient and accessible transit network in a low-density urban setting where conventional fixed-route transit is impractical. The project also provides wheelchair-accessible vehicles as part of its autonomous fleet. The ways that the SAVs can play a complementary role in their integration with the existing on-demand ridesharing paratransit service were explored, as were the spatial patterns of trips at a block group level. Sociodemographic factors were controlled using geographically weighted regression (GWR) techniques to identify local and spatial differences while exploring travel patterns. Block groups are the smallest geographical scale used in such a study to the best of our knowledge, giving more targeted and local transportation insights. Most of the previous research was developed based on aggregated data at relatively large geographical scales where multiple modes of public transit are available (e.g., counties, cities, census tracts), but studies of midsized cities with no fixed-route public transit option are currently lacking [18, 20, 21].

The remainder of this paper is organized as follows. Section 2 describes the conceptual framework of transportation integration while addressing the features of SAVs and paratransit services in the existing literature. The research methodology follows and iterates the details of the case study, followed by descriptions of the data collection and analysis. In the results section, we detail the significant findings, and in the discussion and conclusion section, we summarize the results and potential policy implications.

LITERATURE REVIEW

During the last few decades, designing and operating an integrated public transit system has become a subject of great interest [20, 22, 23]; however, studies on the integration of AVs into existing transportation services have only been conducted recently. The first efforts to study AVs as a potential enabling technology for improving future urban mobility researched systematic approaches to design and evaluate autonomous mobility-on-demand (AMoD) systems. To estimate the effects of different SAV fleet sizes and environmental benefits regarding the relocation of self-driving shared vehicles with personal mobility, transportation scholars often utilized agent-based simulation models and espoused that a reasonable fleet of SAVs has the potential to replace conventional vehicles [12, 24]. For instance, Spieser et al. [25] suggested that deploying a fleet of SAVs the approximate size of one-third of all personal transportation can meet an entire population's mobility needs.

Synergistic opportunities between AVs and public transit systems differ based upon the City's organizational structure and demand characteristics. In Singapore, Shen and colleagues [10] proposed preserving bus routes in high-demand areas while replacing low-demand bus routes with shared AVs. They developed an agent-based supply-side simulation, and the results indicated that a combination of 90% high-demand bus routes with 10% AVs could improve the service quality, sustainability, and efficiency of existing bus services. The result of a study by Levin and colleagues [9] indicates that integrating a transit service with a small fleet of SAVs can reduce the transportation system's total travel time. Another agent-based simulation of the supply and demand interactions of an integrated AV and public transit system in a major European city revealed that suppliers should consider the level of service and the operational cost to achieve an optimal fleet size. Some strategies, such as combining AV and public transit fare systems, encourage the demand for ridesharing and reinforce service integration [11]. Exploring the economic impacts of substituting conventional buses with demand-responsive transit (DRT) services in low-to-medium density areas indicates that service fare and vehicle capacity can determine the demand for new service integration [26]. In summary, factors such as the fleet size and vehicle capacity; the quality and the level of the service, the fares charged, operational costs, hailing strategies, transit frequency, and fleet management are among the factors that have been studied to understand the balance between public transit and SAVs through simulation of SAVs system platforms [11, 27–29].

The studies mentioned above proposed a simulation-based approach to designing and evaluating integrated AV and public transportation systems. A few studies have also explored the potential of AVs to resolve transportation issues by integrating solutions while analyzing the social dynamics, social preferences, attitudes, and consumer concerns [18, 30, 31]. A recent study suggests that for efficient and economic integration of public transit services into on-demand ride-sourcing services, there is a need to understand factors affecting riders and drivers' travel demand and supply in an integrated system [32]. The results from an empirical study in Atlanta showed that the residents would be interested in integrating their high-quality mass transit with AVs if they felt that such integration could improve their trip time and productivity [18]. A recent study suggests that accessibility and safety are the primary concerns of people considering adopting an integrated transportation system [33].

A substantial gap remains in the synergistic opportunities provided by AVs and existing transportation services. As cities and transportation agencies begin to integrate and improve their transit services, it is crucial that they understand the travel patterns and factors that influence the existing ridership that is expected to utilize SAVs. Successful policy development for integrating transit services requires recognizing the travel behavior and patterns of the services that are expected to operate through the system.

Past studies have been primarily conducted in large cities with ample public transit access, such as Singapore, Lisbon, and Toronto [21, 24, 34, 35], but defining the role of SAVs in future transportation systems is different in urban settings with no access to a comprehensive and robust public transit service. Accordingly, this study aims to understand the patterns of existing usage and potential interaction between an SAV fleet with an existing ridesharing service by answering the following questions:

1. How and to what extent is the existing paratransit service currently used by the residents of a city?
2. What forces shape the existing ridership at the block group level?
3. What opportunities can be considered a result of the potential integration of SAVs into the current service?

We examined the travel behaviors of the users of Handitran, specialized paratransit service in Arlington, Texas, to begin answering the questions, as the RAPID SAV is projected to operate in areas currently served by Handitran: downtown Arlington and on the University of Texas at Arlington campus. We compared the usage patterns of the Handitran service inside and outside the proposed RAPID SAV service area to predict the possible demand and ridership patterns for the new service. This study will help AV planners predict SAV service usage by identifying the paratransit service's actual users and understanding the SAV-paratransit interaction will enable the City's administration to make data-driven decisions and further optimize the existing services and the proposed SAVs. To perform our study, we used trip data from the Handitran service for all rides requested during 2019.

The Handitran riders were categorized into two groups: adults above the age of 65 and persons under the age of 65 with disabilities. This population segment was addressed as the transportation-disabled population and was studied, using a wide range of techniques that varied from focusing on the demographic characteristics of travelers to spatial and geographic factors that influence the traveling behavior of the elderly [36–40]. We then compared the Handitran usage patterns inside and outside the RAPID service zone and explored the factors affecting the paratransit ridership to predict the future integration of the SAV ridership. The differences in trip characteristics when an alternative mode of public transit is available, and the potential integration of the future SAV service into the current paratransit service were investigated. While previous research mainly relied on regression models to identify transit ridership determinant factors, this study utilized a GWR model to evaluate the spatial ridership of Handitran paratransit service.

DATA AND METHODOLOGY

Data

Study area

This study was conducted in the City of Arlington, Texas, which has the distinction of being one of the largest cities in the United States without a mass-transit service [41]. Arlington is a medium-sized city that is located in the middle of the DFW metropolitan area, which is considered one of the fastest-growing metro areas in the United States. The 2019 population of Arlington was 392,462, a 7% increase from 365,438 in 2010 (ACS-2019). The number of people aged 65 or older was 40,101 (10.2% of the total population) in 2019, up from 29,752 (8.1% of the total population) in 2010 (American Community Survey 2019). Due to its strategic location in the heart of the fast-growing DFW metro area, population growth is expected to continue.

Arlington's leadership role in implementing app-based, on-demand services and SAV technologies in the Dallas Fort Worth (DFW) region made it an attractive location in which to perform this research and analyze the potential integration of SAV services with existing transit options. It has an app-based, on-demand ridesharing service under the Via[4] platform and is also served by the Handitran paratransit service [42]. In 2020, the City was granted a $1.7 million Integrated Mobility Innovation (IMI) award by the Federal Transit Administration (FTA, 2020). While some findings may not be directly applicable to cities of all types and characteristics, this study provides valuable insight for cities of comparable size and demographics.

Handitran service and trip data analysis

Arlington's Handitran is a federally assisted transportation program under Title VI of the Civil Rights Act of 1964 and related statutes that provide rides to eligible people (City of Arlington Handitran, 2014). Handitran rides can be booked online via the website or by telephone. To be eligible for the service, an individual must be either a "senior citizen" or "transportation disabled." Senior citizens are defined as persons 65 years of age or older; the transportation-disabled are those who, because of a functional limitation (caused by either a physical, medical, or mental condition), cannot independently operate a motorized vehicle, either on a permanent or temporary basis.

Handitran is an important mobility option that serves the entire City of Arlington and includes up to 1.5 miles outside the city limits. The downtown area will be served by an SAV service (RAPID) that will be integrated with the on-demand ridesharing service (Via). We used a dataset based on all the Handitran rides requested during 2019 to explore the characteristics and features of the service. Figure 1 shows the distribution of trips based on their points of origin. In 2019, there were

[4] An app based, on-demand ride service providing shared rides at subsidized rates in the City of Arlington, TX

373,202 trips requested from Handitran, including trips that were cancelled or not taken, with an average of 231 trips per passenger.

Analytical Methods

The data analysis was performed in three steps. First, we analyzed the trip data for Handitran, a service for the transportation-dependent population in Arlington, to disaggregate the riders and gain a better understanding of the occasional and frequent users of the paratransit and to determine how the different categories of riders use the service. Second, we used the geographically weighted regression technique, which explores relationships between paratransit ridership and sociodemographic and geographical features at an aggregated level, to explore the determinant factors of ridership for Handitran. Finally, we evaluated the potential for integrating the paratransit service into a newly initiated shared autonomous vehicles service in Arlington.

Trip Data Analysis

The trip level data for all the trips requested from the Handitran service in 2019 was analyzed, based on the age of the users, to determine the role, if any, that age plays in the usage patterns. We also analyzed the travel patterns for which the Handitran services were requested, based on the time of day and purpose of the trips.

Geographical weighted regression (GWR)

For analyzing the determinant factors of the ridership, we used a geographically weighted regression model, which was more effective than a linear regression model. Linear regression models are beneficial for understanding relationships between dependent and independent variables, but they generally do not consider the effects of geographical or spatial variations [6] in the model. Sociodemographic characteristics play a crucial role in shaping transit usage behaviors and patterns, but their spatial features vary across geographical areas.

Geographically weighted regression models, which account for spatial non-stationarity of variable values over space in a model, were first proposed by Brunsdon et al. [8]. They are an extension of linear regression models, as they account for spatial variations. The GWR model can be mathematically described as shown in eq (1). GWR is a popular analytical technique that is used in the literature to explore local-scale variations in variables of interest [43–46].

$yi = \beta_0(ui , vi) + p \sum k \, \beta_k(ui , vi)xik + \varepsilon i$ (1)

where,

(ui ,vi) are the coordinates (latitudes and longitudes) of a location

β_k represents the parameters that need to be estimated, is a function of the location, and is calculated for each spatial unit (block group in this analysis)

εi is the error term

To find a model with a better fit, we ran ordinary least square regression (OLS) and GWR, using the same set of predictor variables; the number of Handitran rides was used as the dependent variable. The OLS regression model resulted in a very low R-squared value (0.20), and the residuals plots showed a clustering behavior. Therefore, we chose GWR because of its higher R-squared value and random residuals and for its ability to explain variations at a local scale [47, 48]. The spatial statistics tool in the ArcGIS Pro software was used to run the GWR model.

Seven sociodemographic variables at the block group level were found to be significant in the GWR model: total population; percentage of population 65 and older; distribution of white, Asian, and non-English-speaking people; share of people with bachelor's or higher degrees; and the share of households without a vehicle. The data for these variables were collected from the five-year American Community Survey (ACS) at a block group level and was validated by the pairwise correlation test.

We chose block groups as the spatial unit of analysis for several reasons. First, they are the most granular geographical level for which census data is available from the American Community Survey, and they are more analogous to neighborhoods than census tracts. Second, our study area is the City of Arlington, which is a mid-size town and consists of 32 census tracts and 355 block groups. Considering a higher spatial unit of analysis such as a census tract would reduce the number of observations and result in a lack of variation in the key variables within the case study area for running a regression model. Third, block groups have been extensively used in the literature where the research questions involve variables related to sociodemographic characteristics [49–52].

DATA ANALYSIS AND RESULTS

Trip data analysis

Handitran travel pattern

Research shows that paratransit services do not operate at their maximum capacity, mainly because of the lack of coordination between paratransit agencies and contractors hired to provide the services [53]. Table 1 shows the usage patterns of the Handitran service in 2019. Only 1,618 customers used the service, which is less than 2% of the population eligible for the service, based on their age or disability status. Not only is the number of active users low, but most of the trips were taken by an even smaller number of users. Data shows that over 50% of all Handitran paratransit rides in 2019 were made by only 12% of its users. The limited use of Handitran service by the eligible population could stem from the quality of the service and hailing and fare strategies. In addition, the service is not available to all potential users due to the fleet size, capacity of the service, and the hailing strategies set by the Handitran management. Another reason for the low usage could be the lack of advertisement for the services, which leaves many unaware of the option. It is also highly likely that many of the eligible users do not know about the service or know how to use it due to the lower educational attainment levels and lack of English-speaking skills.

Trip characteristics by age group

Some studies suggest that the frequency of trips requested by individuals decreases after age 65 [54]. Table 2 shows the distribution of users in each age category (over and under 65), the total and the average number of trips using Handitran data. Overall, the ridership is significantly high in the group under 65 years of age. This could be associated with the purpose of each age group using the service. 25% of their Handitran trips by younger users are work-related, while only 7% of trips by older users are for work purposes. This could be one of the reasons for higher trip frequencies by younger users.

To evaluate whether the travel patterns of the two groups (over and under 65 years of age) are statistically different, we ran a difference in means test (t-test) for trip distances and trip durations for both groups. The results of the test, shown in Table 3, revealed that there is a statistically significant difference between the trip distances of the two age groups; the hypothesis that the differences are not equal to 0 is statistically significant at a 95% confidence level.

The results of the t-test for trips durations for both age groups are shown in Table 4. It can be observed that there is a statistically significant difference in the trip durations of the two groups, with younger people taking longer trips on average.

Trip purpose by age group

Figure 2 illustrates the distribution of trip purposes based on the two age groups. The trip purposes for the Handitran paratransit are categorized as work, school, medical, essential personal trips (ESP), such as going to a bank, grocery store, pharmacy, etc., and recreation. The results indicated that there is a notable difference between the two age groups' purposes for their trips. The pie chart shows that users under 65 make a higher share of work- and school-related trips, while older users make more medical and recreational trips.

Temporal patterns by age group

In addition to the aforementioned trip characteristics, it is important for the optimal allocation of resources to understand the distribution of trips pertaining to the time of the day. Understanding the temporal usage patterns of the Handitran service is vital to uncovering certain characteristics of passengers' daily activities and the potential for integrating multiple services, such as the new SAV RAPID service. Such temporal usage patterns can be effectively understood via a graph, as illustrated in Figure 3. The plots in Figure 3 (a & b) display the temporal patterns of usage for both age groups and further divide the usage into two categories: weekdays and weekends. The plots show the number of rides taken on Handitran during the operating hours (7 AM to 10 PM on weekdays; 8 AM to 9 PM on Saturdays).

There is a clear difference in the temporal usage patterns of the two age groups and days of the week. During weekdays, users tend to make more trips in the early morning, with peak usage between 8-9 AM for both age groups. During weekends, the trips peak almost one hour later (9 and 10 AM) than on weekdays for both age groups. Evening peaks vary widely between the age groups and the two temporal categories. Evening peaks tend to last longer during weekdays, starting at 1 PM for older users and 2 PM for younger users. The plots also show that younger users take advantage of the service more frequently than older users; in fact, they made more than 10,000 trips on average during peak hours, while older users averaged slightly more than 4,000 trips per day. These temporal patterns correspond, to a large extent, to trip purposes for each group. As younger users take Handitran trips for work, the peak hour for these users is between 7-9 AM in the morning. On the other hand, the peak hour for older people is between 8-10 AM indicating that older people start their daily activities later in the day than younger people.

Results of the GWR

The GWR model was used to analyze the determinant factors of ridership for the Handitran service. Descriptive statistics for the variables are presented in Table 5.

Table 6 shows the output of the GWR model. The GWR-adjusted R-squared value of 0.44 is twice that of the OLS model. The GWR model evaluated each element (block group) at a local scale in relation to its neighbors. Neighbors were the block groups with similar characteristics that were spatially located next to the block group under study. This process was performed for each block group, and a coefficient was assigned to every unit.

Figure 4 (a-g) shows the distribution of the coefficient values of all the independent variables, with the dependent variable at the block group level. The large and small polygons represent the Via and RAPID service areas, respectively. The local scale maps from GWR allow us to understand the type/strength of the relationship of the variables, with independent variables at a micro (block group) scale. We anticipated that understanding the determinants of the existing ridership by considering spatial differences would help in devising relevant strategies for integrating the new transportation service. The small and big polygons show the Handitran and RAPID service areas, respectively. Because of variations in the absolute values of coefficients, we used a standard deviation scale for easy comparison of the independent variables. The red color represents statistically significant negative coefficient values, indicating that the relevant variable has a negative relationship with Handitran ridership. The darker red color shows higher (negative) coefficient values, while the lighter red/orange color shows lower negative coefficient values, ranging from -0.5 to -2.5 standard deviations. The blue color represents statistically significant positive coefficient values, showing a positive relationship of the variable with Handitran ridership. The dark blue color represents higher coefficient values, while the light color shows lower values ranging between 0.5 to 2.5 standard deviations. The white color represents values between 0.5 and -0.5 standard deviations, where the relationship between the independent variable with the number of Handitran Trips is not statistically significant. The maps show that the coefficients of all independent variables are not globally uniform but vary significantly in different parts of the City, indicating different usage patterns. Variations in coefficient values across spaces are given in Table 7.

Potential for Service Integration

In recent years, the transportation sector has experienced technological advancements, new modes of transit, and increasing growth of app-based on-demand ride services. The improvement of transit services and provision of a better mobility experience are possible through integrating multiple modes in terms of ride-booking options (smartphone apps) and modes of payments (online payment for services). Integration of the two systems could likely improve the quality of service, provide a better mobility experience to users, reduce traffic congestion, enhance the overall system performance, and lower the operating and maintenance costs. Based on the existing usage patterns, we find the following advantages to integrating multiple modes to improve the overall system.

Ridership / Clientele

Handitran provides services for the entire City of Arlington, while the proposed Arlington RAPID services will only be available in the areas in and around the UTA campus and downtown. Although the service area for RAPID is minimal compared to Handitran (about 1% of the total Handitran service area), it will serve some of the City's largest activity centers. Since the population of the RAPID service area is unknown, we used the number of Handitran trips per square mile to compare the usage patterns and as a proxy for the future demand and potential of integrating both services. As shown in Table 8, the number of trips per square mile in the RAPID service area was about 28% larger than that of the whole Handitran service area in 2019. Hence, there is considerable excess demand for using Handitran in the designated RAPID service area. Accordingly, the RAPID integration could improve the efficiency of Arlington's existing transportation system by servicing the excess demand for ridership in the City's downtown area.

Existing user locations

The RAPID project is projected to include a wheelchair-accessible vehicle to provide services to people with disabilities. To understand the potential for transit demand from the perspective of the transportation-disabled population, we used ArcGIS software to run an optimized hot-spot analysis of Handitran users, based on their home locations, comparing hot and cold spots with the proposed RAPID service area, The results are shown in Figure 5. The black polygon shows the proposed RAPID service area, the red color shows the users' hot-spots, and white indicates that there are not spatially significant hot-spots. It is clear from the map that Handitran users are clustered in the downtown/UTA area, and the hot-spots are partially located within and surrounding the RAPID service zone, indicating a higher demand for paratransit services.

Existing Demand Distribution and Future Extension Potential

While it is important to know that many of the Handitran users are clustered in the downtown area, it is also important to see their usage patterns based on the spatial distribution of the number of trips. Intuitively, it seems that trips should be clustered in areas where users are; however, the hot-spot analysis of the trips showed a different pattern. Figure 6 shows the results of the hot-spot analysis of trips based on their origins. We used Maptitude, a spatial analysis software, rather than the ArcGIS-optimized hot-spots option, to run the analysis for origin points of trips, as ArcGIS requires that the features be aggregated to a polygon. For example, it uses the number of trips per block/block group to create a hot-spot map, while we opted to run hot-spots based on actual trip locations. Small and big polygons show the RAPID and Via on-demand service areas, respectively. The red areas show hot-spots, and the blue areas show cold spots. Hot-spots show spatially significant clustering of high values, while cold spots show spatially significant clustering of low values (in this case, the number of Handitran trips). These hot-spots show that although many Handitran users live in the downtown area, most of the trips originate from the southern part of the City. We also see a major effect of the Via service because all the hot-spots are located outside the Via service area. These patterns show the inter-dependence of multiple services and the potential for integration because all the services currently operate individually while competing with other services. The trip hot-spots data could also be useful for the future expansion of the RAPID service area.

Interaction with alternative transit modes and service

Unlike other cities of the same size, Arlington does not have a fixed-route public transit system. At present, Handitran only serves the transportation-disabled and elderly populations, while the Via on-demand rideshare service is available to anyone in the City. As of 2019, Handitran served the entire City of Arlington, plus 1.5 miles outside the city boundaries, while Via's service area was limited to specific sections of the City[5]. Therefore, it is important to understand the interactions of paratransit services with other public transit modes – Via, in this case.

Table 9 shows a comparison of Handitran trips in areas where Via is and is not available, and it is evident that people who reside in areas that don't have Via services take more and longer trips on Handitran. The statistics show that 62% of Handitran trips originate from areas where Via services are unavailable; only 37% originate from block groups served by Via. These statistics show how the unavailability of an alternative mode impacts other modes. Without integration, both services

[5] Via's service area was expanded to the entire city of Arlington in January 2021.

may be present in an area but are more likely to compete rather than to complement each other. On the other hand, an integrated service can significantly improve the efficiency of all modes/services.

Potential for payment integration

Another avenue of integration is the payment platform for these services. Currently, Handitran payments can only be made with cash or a monthly pass. According to the service policy, no passenger can be denied services for his/her inability to pay the fare, so a "fare-owed form" is filled out by any passenger unable to pay at the time of the ride. Those completing the form are obligated to pay later, but no data is available about how many actually do so. There is, however, data that shows that cash payments and fare-owed procedures can adversely affect the quality and efficiency of the service. Table 10 shows the distribution of modes of payments for Handitran trips. Approximately 34% of trips are paid for with cash, and around 16% do not pay at the time of the ride. This payment collection system is very inefficient and results in less revenue. Since Handitran does not have an existing smartphone app or online mode of payment, its revenue collection could be enhanced if it were integrated with RAPID.

DISCUSSION AND CONCLUSION

This study explored the advantages of integrating existing transportation services and proposed a shared autonomous vehicle (SAVs) service. We focused on an existing Handitran paratransit service and the RAPID SAV project piloted by the City of Arlington, Texas. Unlike past studies that evaluated integrated AV and public transit services by designing concrete scenarios based on agent-based simulation platforms [10, 11], we explored the potential for SAV/PT rideshare integration by determining and understanding the travel patterns of paratransit users that may be the future consumers of the integrated services.

Data analysis of the ridership of Arlington's paratransit service indicated significant differences in the travel behaviors and patterns of the two studied age groups. A large percentage of the riders were shown to be younger than 65, rode more frequently and for longer distances than their older counterparts, and utilized the service more for work and school purposes than those older than 65. This finding may be due to life cycle changes and travel behavior shifts in older adults, such as retirement [57], and their need for more medical and recreational trips. While there is no direct empirical evidence to identify the potential users of integrated public transit services and SAVs, this finding could imply that younger adults are more likely to rideshare through future integrated services. This result is beyond the primary public transit integration goals that are usually suggested to improve the mobility needs of senior adults [8]. Although it appears that the RAPID SAVs could provide a more convenient and flexible mobility option for elderly adults than driving their own vehicle, it is not possible at this time to accurately draw conclusions about the relationship between age and the adoption of SAVs. Our findings, however, do previous support studies in the US indicating that older adults are more likely to drive a private vehicle than utilize AVs [58], but younger people are more inclined to opt for an SAV [59]. Because many older adults for whom the existing paratransit services were designed do not take advantage of them, it is not expected that they will use SAVs to the extent that younger adults will.

According to the GWR results, the future RAPID service will operate in an area that shows a significant elasticity coefficient with existing paratransit in terms of sociodemographic attributes at the block-group level. In the blocks in which the integrated RAPID ride will be available, race (share of the white and Asian populations) has the highest negative association with the existing ridership. The level of education (share of the population with a bachelor's degree) and lack of access to a vehicle (share of households with no vehicles) also negatively affect the existing ridership at the block level. This result reveals that in the RAPID service area, a part of the population that includes some white and Asian people with higher education and those with no access to a vehicle is less likely to use the current paratransit frequently. On the other hand, the results suggest that some RAPID service area blocks with a significant share of the 65 and above population have a greater tendency to use the current paratransit. These findings indicate the potential synergies for integrating RAPID into existing transit, including paratransit and Via on-demand rideshare, to provide services with unique advantages to residents of this particular area [12]. Although little has been done to identify t*he sociodemographic features* of potential SAV users [60, 61], our findings shed light on the findings from empirical studies suggesting that residents of densely populated regions, students, and highly trained individuals have more positive attitudes and perceptions towards AVs [62, 63].

Our findings also indicate that the deployment of SAVs and existing paratransit and ridesharing services are not mutually exclusive. A comparison of paratransit service usage within and outside the RAPID service area showed that the demand for trips per square mile in the RAPID service area was about 128% of the total trips generated per square mile across the entire Handitran service area in 2019. Despite the presence of the Via rideshare service in Arlington's downtown area in 2019, there has also been a considerable demand for using Handitran in the RAPID service area. This demand may be effectively met through the integration of RAPID SAVs by reducing travel time [9], improving service quality, and utilizing transit services more efficiently [10]. Therefore, we anticipate that the integration of the RAPID on-demand SAV service will improve the efficiency of the existing transportation system in Arlington by responding to the demand for riders in the downtown area through encouraging SAV ridesharing and improving the efficiency of all the services [11]. The high-demand hot-spots that we have identified in this work can aid city officials in determining future expansion areas for the service.

The introduction of the RAPID service in Arlington also offers opportunities for payment integration. Currently, more than one-third of Handitran service payments are made with cash, paid directly to the drivers at the time of the service. Compared to the application-based payment approaches, this method is sub-optimal and inefficient. Integration of the payment methods of the two services could offer the Handitran users more flexibility and convenience and significantly improve their trip experience.

POLICY RECOMMENDATIONS AND FUTURE RESEARCH

A number of policy recommendations can be drawn from the analysis of sociodemographic determinants of ridership, spatiotemporal patterns of usage, interactions of multiple transit modes/services, and the potential for integration. These recommendations can benefit the stakeholders, the City's policy and decision-makers, and the companies providing the transit service in their planning, design, and optimization of mobility services for existing as well as future projects.

The analysis of trip characteristics and usage patterns indicates that a very small percentage of eligible users (~2%) use the service, and the majority of the users are younger than 65. We hypothesize that this could be due to two reasons. First, many of the City's residents are not aware of the service because it is not advertised. Second, the application process for determining eligibility takes time and extra effort that could become a stumbling block for the potential population, who might otherwise sign up for the service. Integration of the services and the access to Handitran through a smartphone application could improve the visibility of the service and also ease the application process for new customers by providing them with an online registration facility on the app.

The temporal distribution of trips reveals that there is a higher demand on weekdays than on weekends. High demand periods during weekdays are 7 to 9 in the morning and 1 to 5 in the evening. The evening peak for older adults lasts longer than that for younger users. The spatial distribution of trips at the block group level shows a wide range of variations across the City, indicating diverse demand levels in different areas. It is expected that the distribution of vans in high-demand areas and the trips of longer durations can improve the quality and efficiency of the service; however, a simulation-based study that evaluates the distribution of resources (vans and drivers) and impacts of integration with other modes and services are needed.

Finally, the sociodemographic determinants of ridership from the geographically weighted regression model suggest that the effects of sociodemographic characteristics vary significantly across the City. A variable showing a very strong relationship with ridership in the northern parts of the City may show an opposite behavior in the south. These results indicate that a strategy for optimizing the service quality in one area may not be effective in others; therefore, the City or the service providers should customize any intervention. A survey designed to reveal the preferences of potential users in specific areas could help in determining the suitability of future plans. Although this study provides a good foundation for understanding the spatiotemporal patterns of transit ridership of older adults and the likely interaction of multiple services/modes, it could be expanded in the future studies by adding more sociodemographic variables and the data that covers a longer period of time.

Conflict of Interest Statement

On behalf of all the authors, the corresponding author states that there is no conflict of interest.

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FIGURES

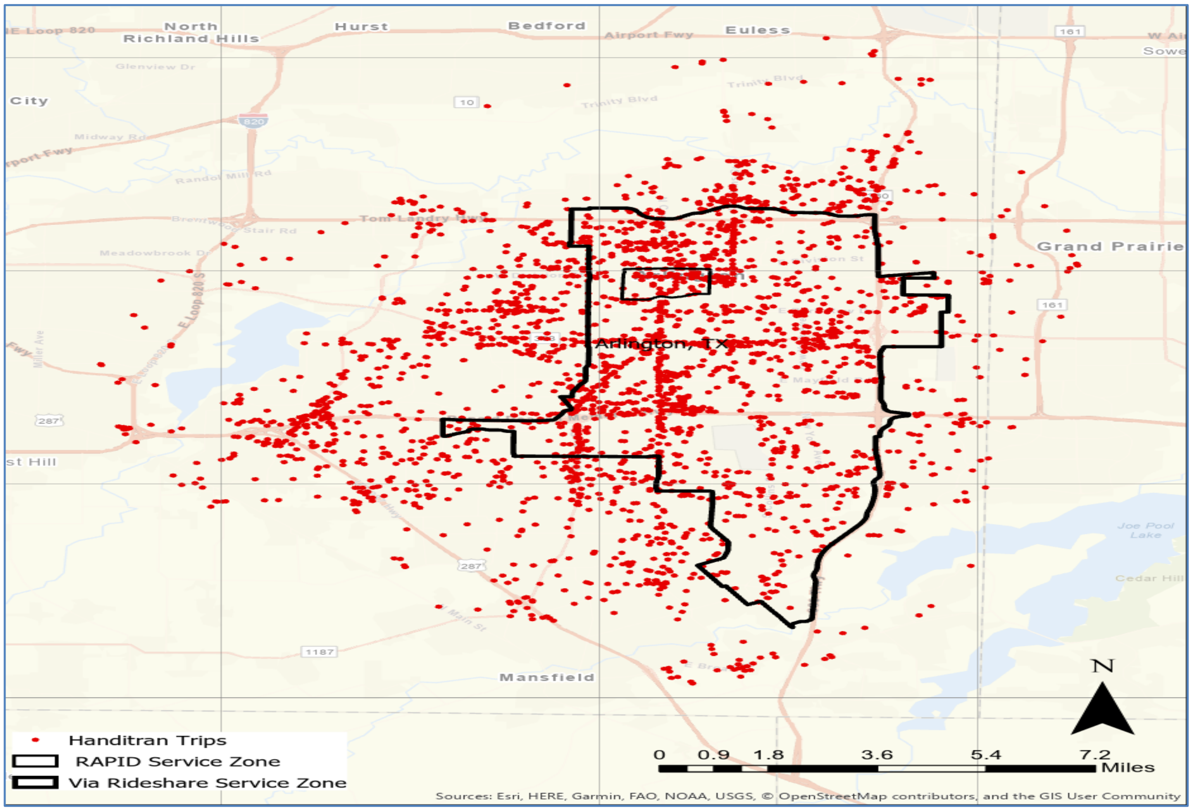


Figure 1. Spatial distribution of trips completed by Handitran in 2019

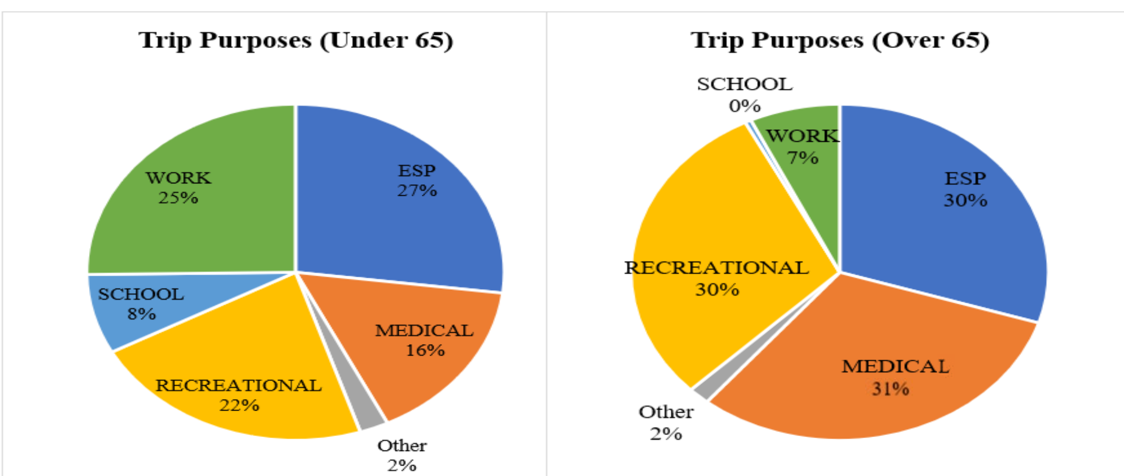


Figure 2. Trip distribution by purpose.

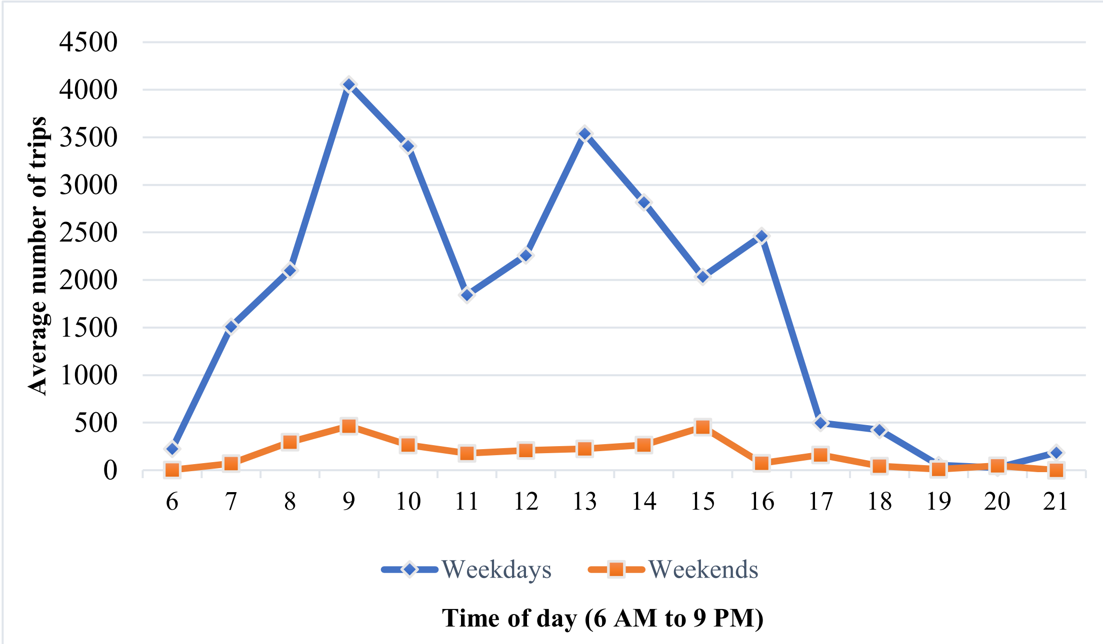


Figure 3 (a). Temporal distribution of daily average number of trips made by users 65 years of age

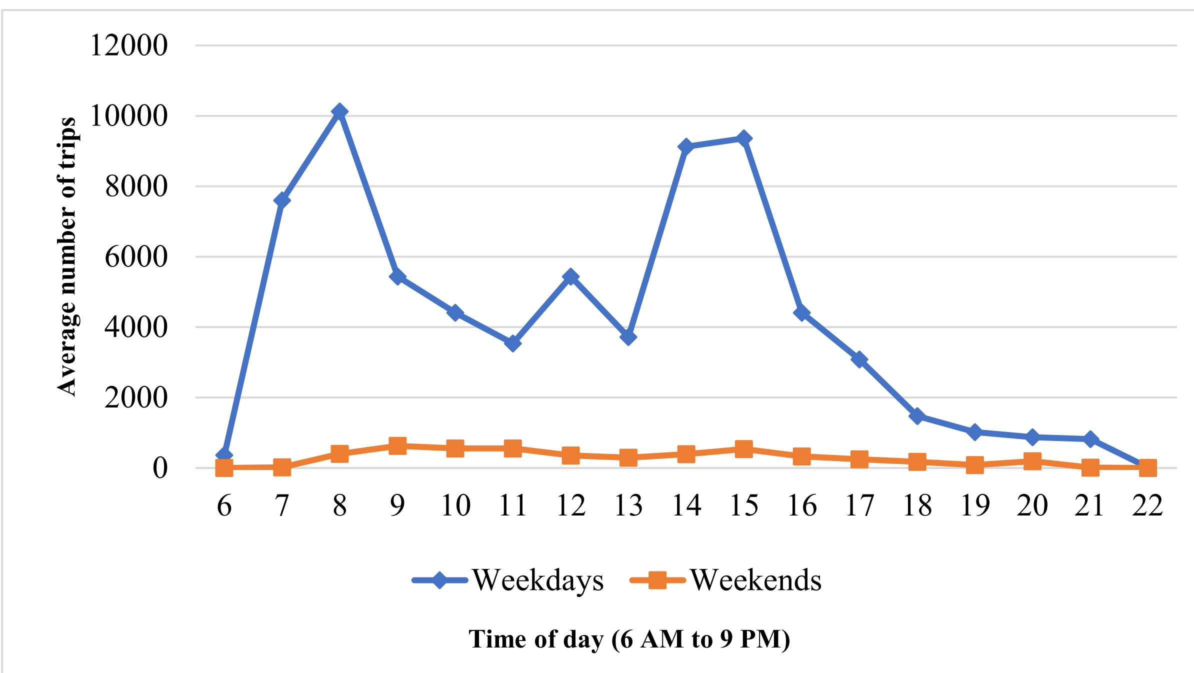
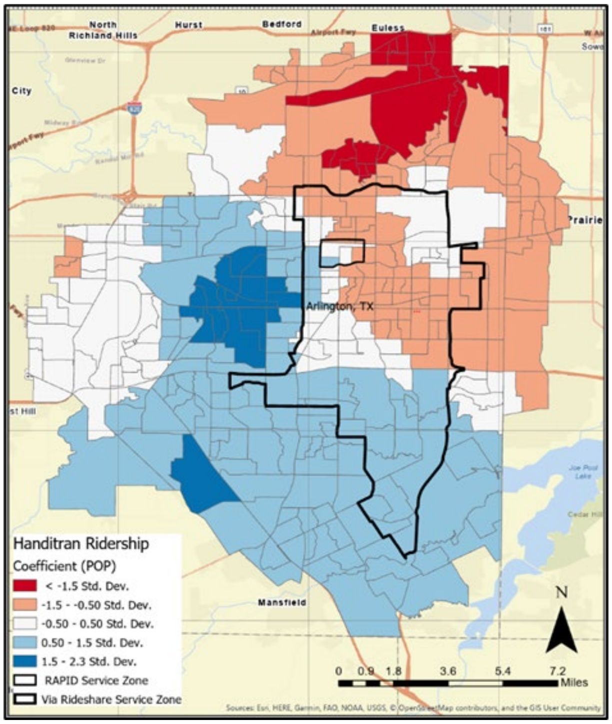
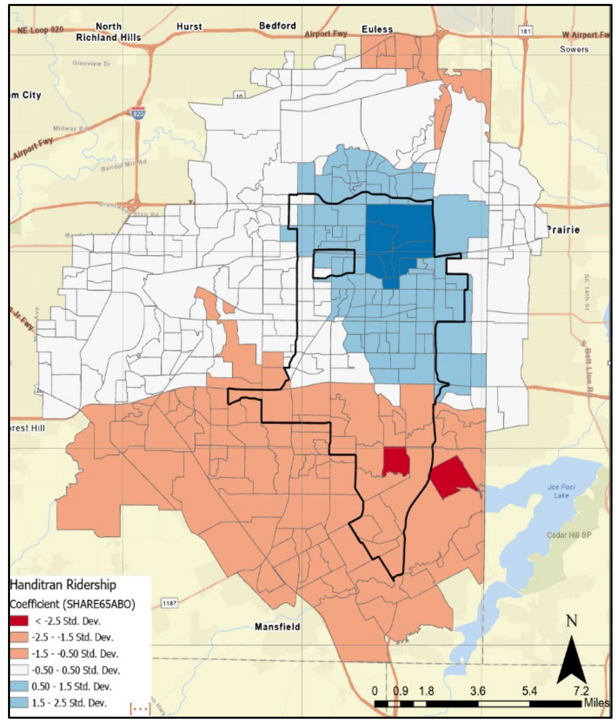


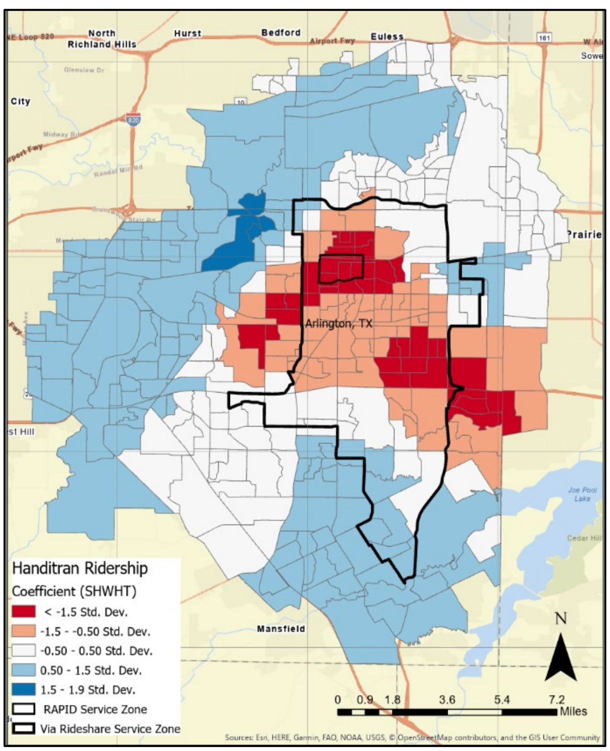
Figure 3 (b). Temporal distribution of daily average number of trips made by users under 65 years of age



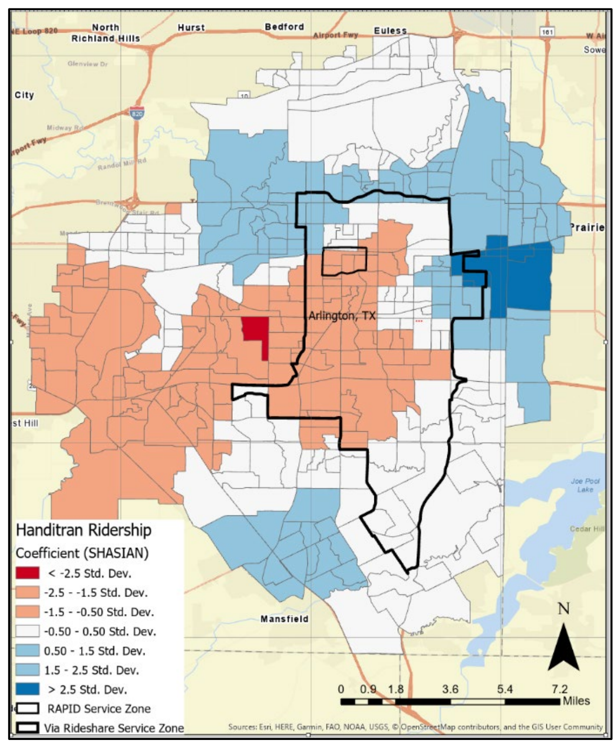
(a) Total population



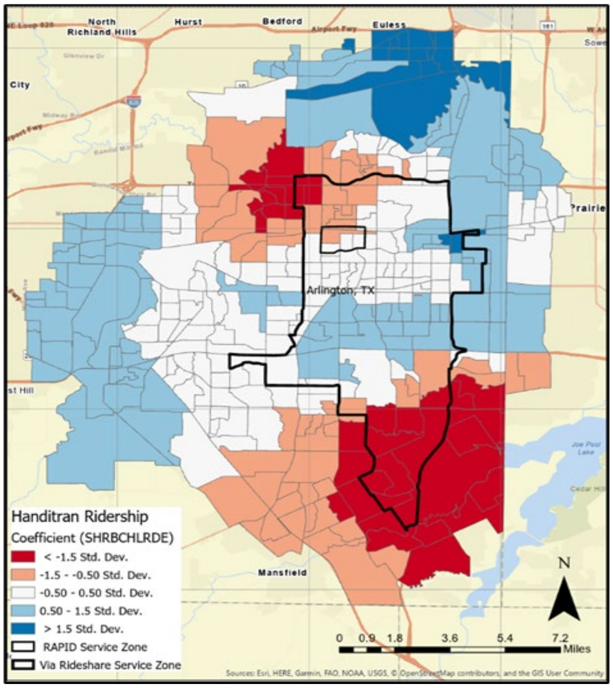
(b) Share of 65 and above



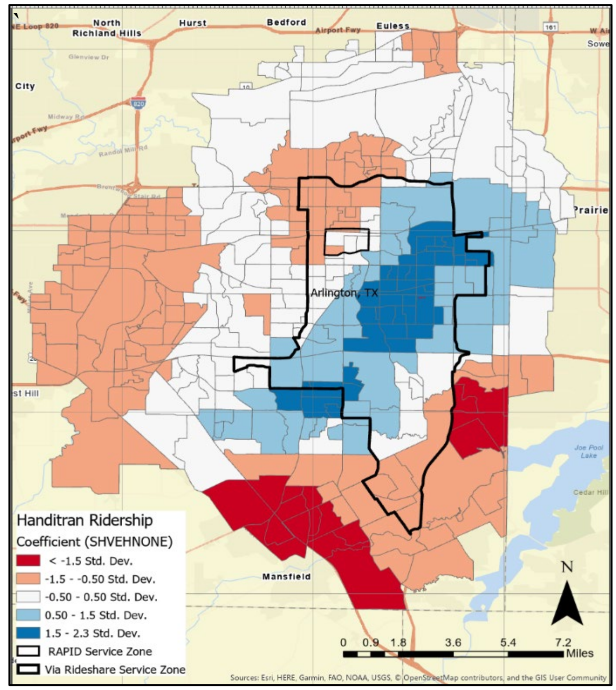
(c) Share of White population



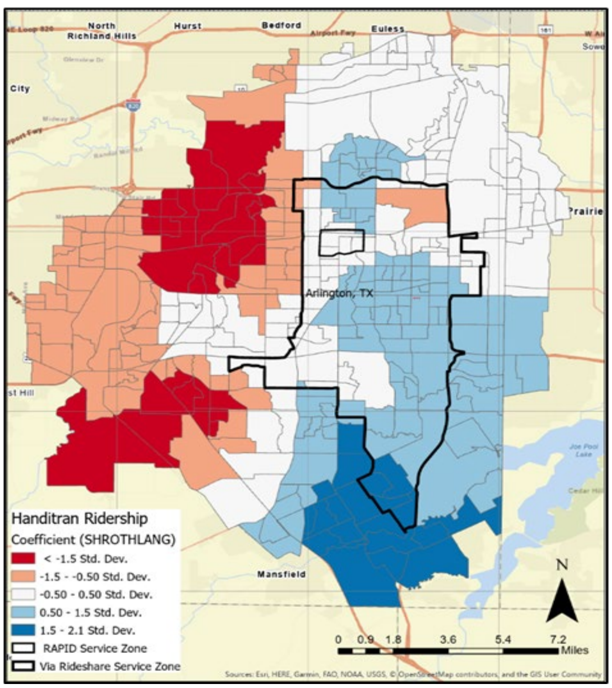
(d) Share of Asian population



(e) Share of bachelors or higher degree



(f) Share of households with no vehicles



(g) Share of non-English speakers

Figure 4 (a-g). Local coefficient values of independent variables vs. the dependent variable (number of Handitran trips per block group); color scale shows the value of each coefficient

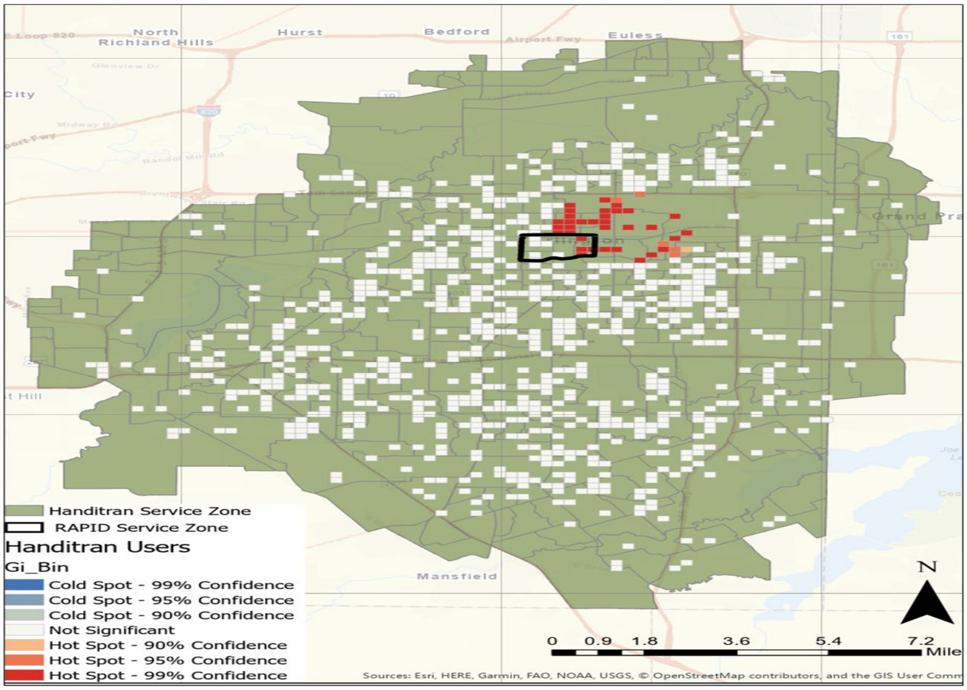


Figure 5. Hot-spots of Handitran user locations

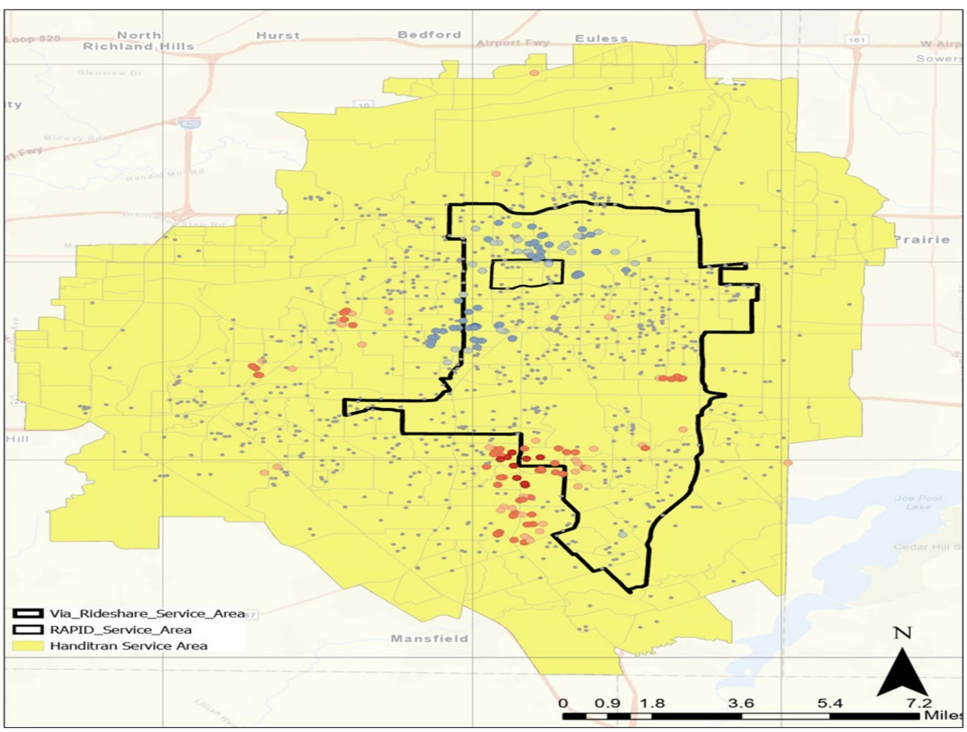


Figure 6. Hot-spots of Handitran trips based on points of origin

TABLES

Table 1. Handitran trip data summary (2019)

Attribute	Data
Total Population in Handitran Zone	573,867
65+ Population (ACS- 2014-2018) without Disabilities	35,368
People with Disabilities	57,386 (10% of the overall population has a disability: City of Arlington)
Eligible People	92,754
Total Users	1,618 (~ 1.74 % of Eligible Users)
Total Trips	373,202
Average Trips per User	231
Only 12% of the users make over 50% of all trips	

Table 2. Summary of trip data by age group

	Age Group		
	Under 65	Over 65	Total Population
Users			
Number of users	422	277	699
Percentage	60%	40%	100%
Trips			
Total Number of Trips	75,580	30,206	105,786
Percentage	71%	29%	100%
Average Number of Trips	179.10	109.05	151.34

Table 3. t-test for trip distances of two groups

Two-sample t-test with equal variances						
Group	Observations	Mean	Std. Err	Std. Dev	[95% Conf. Interval]	
Under 65	75,580	6.780989	0.015088	4.147858	6.751418	6.810561
Over 65	30,206	6.075029	0.022283	3.87279	6.031353	6.118705
Combined	105,786	6.57941	0.012556	4.083662	6.554802	6.604019

Diff		0.70596		0.027713	0.651642	0.760278

Ha: diff < 0	**Ha: diff != 0**	Ha: diff> 0
Pr(T < t) = 1.0000	**Pr(|T| > |t|) = 0.0000**	Pr(T > t) = 0.0000

Table 4. T-test for trip durations in two groups

Two-sample t- test with equal variances						
Group	Observations	Mean	Std. Err	Std. Dev	[95% Conf. Interval]	
Under 65	75,580	18.62929	0.030948	8.508019	18.56864	18.68995
Over 65	30,206	16.8618	s0.047864	8.318655	16.76798	16.95561
Combined	105,786	18.1246	0.026109	8.491951	18.07343	18.17578
Diff		1.767494		0.05755	1.654697	1.880292

Ha: diff < 0	**Ha: diff != 0**	Ha: diff> 0
Pr(T < t) = 1.0000	**Pr(|T| > |t|) = 0.0000**	Pr(T > t) = 0.0000

Table 5. Descriptive statistics of variables in the GWR model

Variable Type	Variable	Mean	SD
Dependent Variable	Number of Handitran Rides	221.3	286.9
Independent variable	Total Population	1764	1070
	Share of 65 and above	10.9	8.03
	Share of White Population	62.7	22.3
	Share of Asian Population	5.7	7.7
	Share of bachelor's degree/more	27.5	17.6
	Share of HHs with no vehicle	4.5	6.5
	Share of Non-English speakers	30.3	17.6

Table 6. Summary of the GWR model

------- Analysis Details -------	
Number of Features	335
Dependent Variable	Number of Handitran Trips

Explanatory Variables	Total Population Share of 65 and above Share of White Population Share of Asian Population Share of bachelor's degree or higher Share of households with no vehicles Share of non-English speakers
---------- Model Diagnostics -----------	
R-squared	0.59
Adjusted R-squared	**0.45**

Table 7. Variation in coefficient strengths across space

Variable	Spatial variation in relationship with Handitran Ridership		
	Strong	Neutral	Weak
Total Population	South	West	North
Share of 65 and above	Center	West, East	South
Share of White Pop.	Northwest, South	Northeast, Southwest	Center
Share of Asian Population	East, Northwest	North, South	Center, West
Share of bachelor's degree/more	West, Northeast	South, Northwest	Center
Share of HHs with no vehicles	Center	North	South, West
Share of non-English speakers	West, Northwest	Northeast	South, Southeast

Table 8. Comparison of Handitran service usage within and outside of the RAPID service area

Service Zone	Total area (sq miles)	Total Completed Trips in 2019	Trips per square mile
Handitran (existing)	199	149,012	1,410
RAPID (proposed)	1.09	1,972	1,809
% Of RAPID	1.04	1.32	128.3

Table 9. Trip comparison based on the availability of Via services

	Availability of Via Services

	NO	YES	Total
Average Distance	7.13	5.36	6.46
Total Number of Trips	80,541	48,766	129,307
Trip Distribution Percentage	62.29%	37.71%	100%

Table 10. Modes of payments for Handitran trips

Type	Share	Percentage
Cash to driver	51,825	34.78%
Credit Card	89	0.06%
Fare Owed	23,694	15.90%
Monthly pass	71,726	48.14%
Ticket	7	0.00%
Volunteer pass	1,669	1.12%
Total	149,010	100.00%

Chapter 6: Policy Implications and Future Research Opportunities

POLICY IMPLICATIONS

This dissertation provides an in-depth analysis of several aspects of DRT systems. As the DRT systems have the potential to contribute positively to making transportation systems more efficient and sustainable, several policy implications need to be viewed. This chapter explains the policy implications of the finding of this dissertation that could be applied to DRT systems in low-density, rural cities that lack mass transit systems.

Firstly, the insights from travel patterns of the RAPID (SAV) users showed significantly different patterns of usage based on the time of the day and the day of the week. The usage trends showed higher ridership numbers on Wednesdays and Thursdays and early and late afternoon times. These patterns indicate the spatial and temporal patterns of the concentration of demands of the RAPID service. These insights could be used to implement strategies for balancing supply and demand and improving service efficiency in order to provide services in areas and times of need. Managing the supply of services that meets the demand levels could keep the travel times under a certain threshold to keep the satisfaction levels of existing users and attract new customers to switch from their existing modes of transit to RAPID.

Planning the service schedules for the service will help with better service reliability and accessibility to attract more users.

The finding from the Ordered Logistic Regression models indicates that the existing mode of transit and user perceptions about the RAPID service plays a vital role in user acceptance of the SAV service. Safety is an important factor, as users with higher levels of perception about the safety of RAPID were more likely to be frequent users. Users with Uber, Lyft, Walking, and Biking as their usual mode of commute are more likely to be frequent users than users who take private vehicles as their usual mode of transport. This provides an opportunity for RAPID service to attract users from other modes to be loyal RAPID customers. This could be achieved by offering safe, accessible, and reachable services when users need them the most. The likelihood of attracting users from other modes could be exploited by removing the barriers in multi-modal transport and providing options to users to be able to switch between the modes and be able to move from one service to the other. The strategies, if measured and applied in the right way, could significantly improve the ridership numbers of the RAPID service.

In terms of traffic safety, the findings from the RideAustin service indicate that the impact of the service on traffic crashes was more obvious when the number of trips taken in that area was beyond a certain threshold. This indicates that the mere presence of a service is not likely to make any significant difference unless the service has a large clientele and shares a good proportion of all vehicular trips in an area. This underscores the important point that policymakers and decision-makers should focus more on service quality instead of the mere provision of a service. Regular auditing of ridership patterns could be a very useful means to take account of current ridership trends and the potential of improving the service and ridership. Strategies to incentives and subsidize DRT services could be helpful in improving ridership numbers that could result in a reduction of traffic crashes.

Ridership analysis of Handitran data indicates sub-optimal usage (2% use the service), and most of the users are younger than 65 years of age. The likely reason could be attributed to a lack of awareness by eligible users and the difficult sign-up process for potential users. These barriers to onboarding new users could be addressed by strategies to advertise the service so that the majority of the population is aware of the availability of this service. The sign-up process could be made easier and simpler by integrating Handitran with existing DRT services that already have running smartphone applications. That could help attract more users and benefit the eligible, transit-dependent populations.

The results from the Geographical Weighted Regression (GWR) model indicate that the relationship of socio-demographic variables varies significantly across the space in the study area. This indicates that all socio-demographic groups have different responses and travel patterns. This indicates that policymakers should implement strategies that are focused on each socio-demographic group instead of using a one fits all approach. These tailored interventions could help improve the service quality and the user base.

FUTURE RESEARCH OPPORTUNITIES

The RAPID SAVs study was based on a survey responded to by current users of the service. To understand the likelihood of users switching from other modes to RAPID, it is important to also analyze the behaviors of potential users, which could be included in a future study. That will provide better insights into user preferences and their willingness to switch existing modes of transit they use. The cost of traveling and willingness to pay to use SAV services are vital factors in the acceptance of these services. The RAPID SAV service study could not include the impacts of the cost of traveling as the service was available free of cost to UTA students. A study in the future to analyze the impacts of travel cost and how it impacts users willing to pay to get better insights for acceptance of such services.

Traffic safety studies were based on data collected from the Texas Department of Transportation's (TxDOT) Crash Record Information System (CRIS). Although the data is a great resource for the analysis of traffic crashes, it only includes traffic crashes that were reported to the police. Future research using any alternative sources of data, such as crowdsourced data, could be used future research. Data for RideAustin was available only for one year; future studies could include data for a longer duration to have a better insight into the impact of DRT services on traffic crashes.