Emerging Mobility Services and Technologies:

Understanding User Adoption and Travel Impacts

by

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ABSTRACT

With rapid advances in technology development and public adoption, it is crucial to understand how these services will shape the future of travel depending on the extent to which people will use these services; impact the transportation and infrastructure systems such as changes in the use of transit and active modes of travel; and influence how technology developers create and update these transportation technologies to better serve people's mobility needs. This dissertation explores how two major emerging services, namely ridehailing services and autonomous vehicles (AVs), will be used in the future when they are widely available and vastly used, and how they may impact the transportation infrastructure and societal travel patterns. The four proposed chapters use comprehensive quantitative and qualitative methods to explore the status of these technologies from theory, through robust modeling frameworks, to practice, by investigating the recent AV pilot deployments in real-world settings. In the second chapter, it was found that increased frequency of ridehailing use is significantly associated with a decrease in bus usage, suggesting that ridehailing functions more as a substitute for buses than as a complement and implying that transit agencies should explore ways to incorporate ridehailing services in their plans to enhance transit usage. Next, the third chapter showed that interest in using AVs for running errands had a positive and significant effect on AV ownership intent, even after accounting for a host of variables. The fourth chapter depicted how ridehailing experiences have a considerable effect on the willingness to ride AV-based services in both private and shared modes, suggesting that experience is crucial for future adoption of these services. Then, two recent real-world AV experiences are explored in the fifth chapter. Lessons learned from these experiments reinforced the importance of first-

hand experiences in promoting AV awareness and trustworthiness, potentially leading to greater degrees of adoption. Finally, the results and discussions presented in this dissertation strengthen the body of literature on key emerging transportation technologies and inform policymakers and stakeholders to properly prepare cities and the public to welcome these technologies into our transportation system in an efficient, equitable, and complementary way.

DEDICATION

To my parents, Jane and César (*in memoriam*); my brother, Thúlio; and my grandparents, Manoel and Laurinda.

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1. INTRODUCTION

The transportation industry has been facing major changes with the emergence of innovative mobility services and technologies. Rapid advancements in digital platforms, data analytics, and artificial intelligence have given rise to several new transportation options that are changing the way people move and interact with urban environments. This dissertation aims to explore the adoption patterns and travel impacts of emerging mobility services and technologies, with a particular focus on understanding user behaviors, societal implications, and the challenges and opportunities associated with their integration and adoption.

The traditional model of transportation, centered around private vehicle usage and reliance on public transit, has been disrupted by a wide range of emerging mobility services. These include ridehailing services, bike-sharing platforms, electric scooters, autonomous vehicles, among others. These services offer convenient and flexible alternatives to traditional modes of transportation, promising many societal benefits, including reduced congestion, improved air quality, and enhanced accessibility.

Understanding user adoption is a key aspect of studying emerging mobility services and technologies. It is essential to delve into the factors that influence individuals' decisions to adopt or reject these new transportation options, and the extent to which these individuals will, in fact, engage with these technologies. Factors such as convenience, cost, reliability, perceived safety, and environmental concerns play crucial roles in shaping user behaviors and choices. Examining the underlying motivations and barriers to adoption can provide insights into designing effective policies, strategies, and interventions to promote sustainable and inclusive transportation systems.

With the effects of the COVID-19 pandemic on travel patterns that linger for some people after all restrictions are lifted, travel behaviors and opinions are uncertain. This is especially true when we consider the future of transportation and how society will fully adapt to emerging technologies. Although each emerging transportation technology mentioned before has its pros and cons and could be discussed in deeper levels, this dissertation will focus on exploring user adoption and travel impacts of two major ones: *ridehailing services* and *autonomous vehicles*.

The advent of ridehailing services, highlighted by industry giants like Uber and Lyft, has disrupted the transportation landscape, reshaping the way we travel, and challenging the traditional dominance of public transit systems. One key appeal of ridehailing services is their convenience and flexibility. These platforms offer door-to-door service on-demand, eliminating the need to navigate fixed transit routes and adhere to predetermined schedules. The ability to easily request a ride with the tap of a smartphone has attracted users who value personalized transportation experiences tailored to their specific needs and preferences. Furthermore, ridehailing services have filled a gap in transportation by addressing the first- and last-mile connectivity challenge. Many transit riders face difficulties accessing transit stations or completing their journey from transit stops to their final destinations. Ridehailing services provide an alternative that complements transit by seamlessly connecting passengers from their doorstep to the transit station, enhancing the overall travel experience. While the cost of individual rides on ridehailing services may be higher than a single transit fare, the convenience and perceived value may offset the price differential for some users. Additionally, the transparency of pricing and the absence of ticketing barriers associated with transit systems contribute to the appeal of ridehailing services, particularly for occasional riders or those who find the transit fare structure complex or inconvenient.

Similarly, autonomous vehicles (AVs) promise a future of sustainable and efficient automated transportation. With the ability to communicate with each other and infrastructure, AVs can optimize traffic flow, reduce congestion, and minimize fuel consumption. This efficiency is expected to result in reduced travel times and environmental benefits, such as decreased emissions and improved air quality. However, given that the technology is still in the early stages of societal adoption and many still do not have access to it, it is rather challenging to assess the extent to which people will, in fact, embrace the technology and use it as part of their travel routine. With safety concerns or simply lack of knowledge playing a significant role in preventing potential AV adoption, in addition to behaviors and attitudes subject to change given major disturbances (e.g., COVID-19 pandemic, financial crisis), understanding how, and how much, AVs will be used is crucial to prepare for their widespread availability.

Moreover, assessing the travel impacts of these emerging mobility services and technologies is vital to evaluate their effectiveness and raise awareness regarding their potential unintended consequences. While these services have the potential to reduce private vehicle ownership, congestion, and greenhouse gas emissions, their true impact on travel behavior patterns, mode shifts, and overall mobility patterns remains a complex and evolving area of research. As a result, four major issues are identified and discussed below.

Issue #1: Ridehailing services replacing transit rides

As ridehailing services continue to gain popularity, concerns have been raised about their impact on transit ridership. Public transit has long been a crucial component of urban transportation, providing an affordable and sustainable alternative to private vehicle ownership. However, in recent years, many transit agencies have experienced a decline in ridership, which was exacerbated after the COVID-19 pandemic. Several factors contribute to this decline, including changing demographics, urban sprawl, and shifts in travel preferences. Notably, the emergence of ridehailing services in the last decade has introduced a new element that has influenced transit usage patterns.

Despite the advantages of ridehailing services, concerns arise regarding equity and accessibility. Public transit often serves as a lifeline, sometimes the only transportation method available, for low-income individuals, seniors, and individuals with disabilities who heavily rely on its affordable and inclusive nature. The rise of ridehailing services may inadvertently exclude these vulnerable populations due to cost or digital literacy, exacerbating existing transportation inequities. In addition, the proliferation of ridehailing services may lead to increased vehicle miles traveled and traffic congestion in some urban areas. If users shift from sustainable transit options to single-occupancy ridehailing trips, the potential environmental benefits of reduced vehicle ownership and public transit usage may be severely diminished.

Rather than viewing ridehailing services as direct competitors, many transit agencies have started exploring partnerships and integration options. Some agencies have integrated ridehailing services into their transit apps, offering seamless multimodal trip planning and ticketing. Such collaborations present an opportunity to improve the quality of transit services, extend coverage in underserved areas, and provide innovative solutions that combine the strengths of both transit and ridehailing services, ultimately better serving users.

The relationship between ridehailing services and transit usage is, however, complex and multifaceted. While ridehailing services have undoubtedly impacted transit ridership, the overall implications and magnitude of this impact vary across cities and demographics. While some transit agencies have experienced ridership declines, others have observed minimal or no changes. In auto-dominated areas, transit is simply a weak competitor and can rarely beat the efficiency and comfort of private vehicles. As a result, people rely on their vehicles to meet their travel needs. In the past decade, ridehailing services (e.g., Uber and Lyft) have been providing on-demand curb-to-curb mobility through the convenience of a smartphone app and, with the benefits they provide to riders, some have simply replaced transit use with ridehailing services. Although many scholars clearly state that ridehailing is replacing transit in certain places, there is a large gap in the literature that deeply explores various nuances that comprise the complex relationship between transit and ridehailing services (Gehrke et al., 2019; Dong, 2020).

Issue #2: AVs leading to zero-occupancy trips

Despite of their promised benefits, the widespread adoption of AVs also brings forth potential challenges that need to be addressed. One such concern is the occurrence of zero occupancy trips, where AVs operate without any passengers on board, which threatens to undermine the very benefits they promise to deliver, especially in terms of sustainability.

These *"zombie miles"* may occur when AVs travel with no passengers between drop-offs and pick-ups, as well as empty return trips to a designated parking or service areas. Zero-occupancy trips can be caused by poor distribution of AVs given a service area, resulting in increased congestion, energy consumption, and air pollution. In the future, one way AVs can be used is to run errands for people, such as picking up kids from school, laundry, packages, or groceries. Although the idea of AVs running errands sounds appealing, it may result in some concerning consequences, especially if people start using them more frequently and carelessly with no barriers or disincentives on their end.

Once these services are widely adopted, the perceived usefulness of AVs for that purpose could lead to increased demand for AVs, which may result in greater AV ownership levels. As individuals recognize the potential benefits of owning their AVs, they tend to be more likely to consider purchasing or leasing one. This may lead to changes in travel behaviors and mobility patters. For instance, individuals may prefer to make more small purchases at different stores and let the AV make multiple trips, as opposed to having one major day during the week or a chain of trips to run their errands. This shift may significantly impact the land use, congestion levels, and air quality.

Thus, given their convenience, potential increase in productivity and time savings, safety, and potential cost savings associated with AVs running errands, it is very compelling for individuals to embrace autonomous transportation. However, it is important to recognize and address the potential negative consequences associated with this emerging trend, especially the undesired zero-occupancy trips, so we can reach an AV-powered errand ecosystem that maximizes benefits while minimizing challenges.

Issue #3: Insufficient utilization of shared rides within the context of AV ridehailing services

AVs are expected to revolutionize the transportation field, especially when integrated with ridehailing service providers. The economic and environmental benefits should be realized once people are consistently taking shared ridehailing rides in AVs, due to fares getting cheaper and reduction of vehicles needed on the roads, which leads to a more efficient and sustainable way of using these services.

Unfortunately, convincing people to share rides in the future has been extremely challenging, especially after the COVID-19 pandemic which led people to avoid interacting with strangers to some degree. Most individuals still prefer the convenience of their solo rides. Convincing passengers to embrace in shared rides requires addressing various concerns such as longer travel times, potential discomfort sharing space with strangers, and preferences for door-to-door service.

In addition to general preference for private rides, lack of trust or perceived safety are major factors that prevent people from sharing AV rides. Given they will share a driverless ride with a complete stranger, it is reasonable to expect at least a robust background checks and constant monitoring systems, emergency protocols, and safety features to create trustworthiness and encourage passengers to share their AV rides in the future.

Understanding and identifying different types of users are essential for the creation of strategies to overcome the skepticism of sharing rides with strangers so that policymakers can promote regulations and incentives that may target individual groups. By exploring and tackling these barriers that prevent individuals from fully emerging in such shared future, society can fully unlock AV’s potential to transform urban mobility efficiently and equitably.

Issue #4: Low adoption rates of AV services in real-world scenarios

Although modeling efforts and simulations are vital for exploring minor nuances and specific variables regarding AV technology adoption, sometimes they may be disconnected from reality, either from limited technical capabilities to unravel many playing factors in a single problem, or maybe people's opinions simply do not quite match their real-world preferences and proclivities. A great opportunity to explore how people will actually adopt to AV services is by going from theory to practice by actually deploying these services and exploring travel patterns from a real-world setting.

Knowing that AVs are a relatively new technology, and many people are still unaware of the AV concepts and capabilities, real-world implementation is a great opportunity to raise awareness, build trust, and explore the extent to which users may use these services. Once AVs are common in a region, it may subconsciously bring individuals a greater sense of safety, especially when operations appear to be successful, reliable, with minor or no issues.

As discussed before, there are many ways AVs could be deployed in a region, such as on demand, for delivering meals, running errands, or as a shuttle in a fixed area. Real world implementation allows policymakers and developers to in-depth explore these context-specific solutions and barriers. The way AVs are customizable to specific settings is extremely important when developing strategies to ensure they will enter specific markets in a desirable way that will not cause disturbances while still facing high levels of adoption, meeting people's mobility needs.

Finally, exploring AV deployments in real-world while exploring user needs and preferences in different scenarios are critical for a successful AV-like service. These experiences and programs provide opportunity to collect rich up-to-date information from real users, observing how they engage and interact with these services, potentially changing their travel patterns. Additionally, these pilot projects promote collaboration between AV developers and stakeholders, bringing different mindsets with different goals to a common ground, creating an environment that collectively aims to promote a precise and sustainable adoption of AVs.

Conclusions on the four issues

In order to address the challenges and harness the potential of these emerging transportation options, a balanced approach is required. Public transit agencies, policymakers, and ridehailing service providers must collaborate to create integrated, sustainable, and equitable transportation systems that meet the diverse needs of communities.

However, despite the promises and benefits of emerging mobility services and technologies, several challenges exist that need to be addressed. Technical issues related to safety, cybersecurity, data privacy, and interoperability pose significant concerns. Additionally, regulatory frameworks, insurance policies, and public acceptance play crucial roles in shaping the future of these technologies.

Addressing these challenges requires interdisciplinary research, collaborations between academia, industry, and policymakers, and the development of comprehensive strategies and frameworks to guide their responsible and sustainable integration into our transportation system.

These are major issues that this dissertation attempts to address. This dissertation seeks to bridge this knowledge gap by exploring empirical research efforts and analyzing large-scale data sets to gain a comprehensive understanding of the travel impacts associated with these emerging technologies. The proposed dissertation aims to contribute to the growing body of knowledge base surrounding emerging mobility services and technologies. By understanding the dynamics of user behavior, evaluating travel impacts, and addressing challenges and opportunities, we can foster the development of sustainable, efficient, and inclusive transportation systems that meet the needs of our evolving urban environments and enhance the quality of life for individuals and communities.

In addition to introductory and concluding chapters, this dissertation will be heavily composed of four content chapters that have the objective of answering the following research questions:

- **Chapter 2 – The Impact of Ridehailing Service Use on Bus Ridership: A Joint Modeling Framework**

  Research question: To what degree does an individual's frequency of using ridehailing services impact their bus use, even after jointly accounting for a host of sociodemographic variables and attitudinal constructs?

- **Chapter 3 – Understanding Interest in Personal Ownership and Use of Autonomous Vehicles for Running Errands: A Joint Model Exploration**

  Research questions: What are the factors that influence intentions to own an AV? To what degree would people be interested in sending AVs to run errands?

- **Chapter 4 – A Multidimensional Analysis of Willingness to Share Rides in a Future of Autonomous Vehicles**

  Research questions: In a future of AV-based ridehailing services, what are the factors that influence the willingness to use such services privately and in a shared (with strangers) mode?

- **Chapter 5 – Autonomous Vehicles (AVs) in the Real World: A Tale of Two AV Pilot Deployments in Arizona**

  Research questions: How do user opinions and perceptions vary depending on the nature of the AV deployment? What lessons were learned from these experiences?

The following four chapters contain abstract, introduction, data description, methodology, results, and conclusion sections. Finally, the last chapter provides a conclusion of the dissertation.

2. THE IMPACT OF RIDEHAILING SERVICE USE ON BUS RIDERSHIP: A JOINT MODELING FRAMEWORK

ABSTRACT

Transit ridership has been on the decline for several years. One key contributing factor is the rise of ridehailing service usage and its impact on transit use. This study attempts to provide a comprehensive and holistic assessment of the impacts of ridehailing service use on transit ridership while controlling for a host of socio-economic, demographic, and attitudinal factors. Using detailed survey data collected in four automobile-centric metropolitan areas of the US, this study jointly models the frequency of using ridehailing services and the extent to which an individual has changed bus use due to ridehailing. The results indicate that ridehailing use frequency is significantly associated with a decrease in bus use, suggesting that ridehailing serves as a substitute for bus use (more than it serves as a complement). The findings suggest that transit agencies need to explore pathways towards leveraging ridehailing services to better complement transit usage.

2.1 Introduction

Transit has been experiencing a decline in ridership over the past decade in the United States (Boisjoly et al., 2018). While the COVID-19 pandemic has undoubtedly played havoc with transit ridership during 2020 and 2021, the fact remains that transit ridership was on the decline even prior to the onset of the pandemic (Graehler et al., 2019), and ridership levels after the pandemic do not appear to be recovering as fast as desired (Magassy et al., 2023), especially due to the surge in work-from-home and hybrid work modalities (Vickerman, 2021). In the largest metro areas, transit ridership varies from 60%-70% of pre-pandemic levels (National Transit Database, 2023)As transit agencies look to the future and contemplate how they can enhance their service to stem the tide, there is a critical need to better understand the contribution of various factors to the decline in transit ridership. Transit remains a mode of transportation that is critical to the movement of people, particularly serving those who may not have access to (or be able to use) an automobile. During the pandemic, it became apparent that transit is a critical mode of transportation helping essential frontline workers to get to and from their jobs.

There are a number of reasons that have likely contributed to the decline in transit ridership over the past decade in particular. In most markets across the US, transit is not competitive when compared to the private automobile. As such, except for small shares of individuals, many travelers naturally gravitate toward the use of the automobile for meeting mobility needs. With rising incomes and greater employment opportunities available following the great recession, it is to be expected that individuals would acquire private automobiles for transportation purposes. During the years preceding the pandemic, the nation saw record numbers of new and used vehicles being bought and sold in the US (Woodall, 2016), clearly suggesting that the appetite for automobile-oriented private mobility continues unabated. Other reasons that contribute to transit decline include the continued sprawl of land use patterns (both residential and employment) that render transit use challenging, reconfiguration of transit service in efforts to attract choice riders (which often occurs at the expense of serving more captive riders), and the affordability and reliability of the personal automobile mode (Taylor et al., 2009; Chakraborty and Mishra, 2013; Boisjoly et al., 2018).

In addition to the reasons for transit decline noted in the prior paragraph (which have existed for decades now), a more recent phenomenon that may have adversely impacted transit ridership is the rise of ridehailing services (e.g., Uber and Lyft) that provide on-demand curb-to-curb mobility through the convenience of a smartphone app. The app allows users to summon rides and automates the process of tracking and paying for rides. These services have gained considerable traction over the past decade in cities around the world thanks to their convenience and affordability (relative to traditional taxi transportation).

Ridehailing services may impact transit patronage in a number of ways. An individual may utilize ridehailing services instead of transit, thus creating a substitution effect with transit losing riders to ridehailing services. An individual may use ridehailing services to connect to and from transit stations/stops, essentially creating first- and last-mile connectivity that would enable convenient transit access and egress. In this scenario, transit would gain ridership thanks to the availability of ridehailing services. And finally, ridehailing services may not impact transit ridership at all; it could take the place of another mode of transportation or simply generate a net new trip that would not have been undertaken otherwise. There may be other ways in which ridehailing services and transit interact with one another, especially with a number of transit agencies establishing partnerships with ridehailing service providers (e.g., APTA, 2020; Shaheen and Cohen, 2020), but the fact remains that the relationship generally boils down to one of substitution, complementarity, or no-effect.

Explorations of the relationship between ridehailing service and transit use have been undertaken and documented in the literature. Some studies point to instances where ridehailing has served to enhance transit connectivity and usage, but in most instances, it is clear that ridehailing is a transit substitute. Ridehailing also substitutes for the use of other modes (most notably, traditional taxi and personal automobile), but most survey research to date clearly shows that ridehailing serves as a substitute for transit. However, past studies exploring the relationships between ridehailing and transit use have largely been descriptive in nature (e.g., Rayle et al., 2016; Clewlow and Mishra, 2017; Young and Farber, 2019) or have relied on models that do not fully account for the complex relationships that govern the impact of ridehailing on transit use (e.g., Hall et al., 2018; Gehrke et al., 2019; Dong, 2020).

This study attempts to provide a more comprehensive assessment of the impacts of ridehailing service use on transit ridership while controlling for a host of socio-economic, demographic, and attitudinal factors. Using detailed survey data collected in four automobile-centric metropolitan areas of the US, namely, Phoenix, Austin, Atlanta, and Tampa, this study simultaneously models the frequency of using ridehailing services and the extent to which an individual has changed use of bus services due to ridehailing service usage. The frequency of ridehailing use and the change in bus usage are treated as endogenous variables, with the frequency of ridehailing use directly affecting bus use change. In addition, the simultaneous equations model incorporates latent attitudinal constructs that capture modal and lifestyle proclivities of the survey respondents, thus accounting for the effects of attitudes that are likely to influence the nature of the relationships of interest. The model is estimated in a single step using the Generalized Heterogeneous Data Model (GHDM) framework developed by Bhat (2015); this methodological framework enables the efficient estimation of joint model systems that incorporate error correlations across endogenous variables, thus accounting for the presence of correlated unobserved attributes that may be simultaneously affecting multiple endogenous variables. The study focuses exclusively on bus use change because metropolitan areas differ considerably with respect to the presence and nature of rail service in their transportation ecosystem. Bus use may increase (complementarity), decrease (substitution), or experience no change as a result of ridehailing service use.

2.2 Data

This subsection presents a brief description of the dataset used in this study. An overview of the survey and the sample characteristics is presented first; a more in-depth examination of the endogenous variables and attitudinal statements of interest in this study is presented second.

2.2.1 Characteristics of the Sample

In the Fall of 2019, a comprehensive survey was administered in four major metropolitan areas of the United States: Phoenix, Austin, Atlanta, and Tampa. All four areas are located in warmer climates of the country and are characterized by dispersed land use patterns and rather poor levels of transit service (and very low transit mode shares). The survey was aimed at collecting rich information about people's attitudes and perceptions towards emerging mobility services and transportation technologies besides their socio-economic, demographic, and routine mobility characteristics. The same survey instrument was administered in all four metropolitan regions, thus ensuring consistency in data collection. The sampling methodology had to be customized to some degree in each region to maximize response rate. Respondents were recruited by sending invitations to hundreds of thousands of e-mail addresses and several thousand mailing addresses. The random set of addresses was obtained from a commercial vendor. Individuals who completed the survey and provided all requisite information were provided a $10 gift card as an incentive and token of appreciation. The complete sample across all four areas comprised 3,465 individuals. Full details about the survey and the sample are contained in a series of reports (Khoeini et al., 2021).

The analysis in this effort is focused on understanding the relationship between ridehailing service use (frequency) and change in bus use. As such, the analysis sample includes only the subset of individuals who actually use ridehailing services. All non-users and those who indicated their bus use changed, but not due to ridehailing use, were eliminated from the analysis sample. In addition, records with missing or obviously erroneous data were excluded from the analysis sample. The final resulting analysis sample comprised 1,336 respondents. Table 1 shows the characteristics of this subsample of respondents.

The sample characteristics show a level of variability that is appropriate for model development and estimation. Even though the sample characteristics may not perfectly mirror population census distributions, that does not present a problem in the context of a modeling effort of the kind undertaken in this work. Females are over-represented, comprising just over 60 percent of the sample. The lowest age group depicts the highest presence in the sample, with 37.7 percent of the analysis sample falling into the 18-30-year age group. All other age groups are well represented in the sample. Nearly 93 percent of the respondents have a driver’s license, nearly 59 percent are full or part-time workers, and about 14 percent are neither workers nor students. The sample depicts a high level of educational attainment with a little over 38 percent having a Bachelor's degree and about 29 percent having a graduate degree. About 73 percent of the sample respondents are White, 12.4 percent are Asian or Pacific Islander, and 8.7 percent are Black.

The income distribution shows a rich variation with a healthy representation of individuals in every income bracket. In terms of household size, 42.3 percent of individuals reported living in households with three or more people while 22.3 percent constituted single person households. A little over 60 percent reside in stand-alone homes and nearly 30 percent reside in condo/apartment units. Nearly 60 percent own their home, while 35 percent are renters. Just about 5.5 percent of individuals report living in households with no vehicles; nearly 25 percent are in households with one vehicle; and 30.5 percent are residing in households with three or more vehicles. This distribution suggests that this is a sample with a high level of household vehicle availability. The sample is composed more heavily of individuals from the Austin and Atlanta areas due to a higher level of ridehailing service use in those areas.

2.3 Endogenous Variables and Attitudinal Indicators

Table 1 also depicts distributions on the behavioral endogenous variables of interest. Both frequency of ridehailing service usage and change in bus use after adoption of ridehailing service are ordered dependent variables with three categories each. It is found that about two-thirds of the sample uses ridehailing services rarely (less than monthly); just over one-quarter of the sample uses ridehailing services monthly; and only 6.7 percent use these services weekly. In terms of change in bus usage, only 4.2 percent report an increase in bus use due to adoption of ridehailing services. On the other hand, 18.5 percent report a decrease in bus usage. Most individuals (77.3 percent) report no change in bus use due to ridehailing service usage.

Table 1 Socio-Economic and Demographic Characteristics of the Sample

Individual characteristics (N = 1,336)		*Household characteristics (N = 1,336)*	
Variable	**%**	**Variable**	**%**
Gender		**Household annual income**	
Female	60.4	Less than $25,000	12.9
Male	39.6	$25,000 to $49,999	11.8
Age category		$50,000 to $74,999	16.3
18-30 years	37.7	$75,000 to $99,999	12.8
31-40 years	15.8	$100,000 to $149,999	21.2
41-50 years	15.3	$150,000 to $249,999	15.9
51-60 years	15.7	$250,000 or more	9.1
61-70 years	10.5	**Household size**	
71+ years	5.0	One	22.3
Driver's license possession		Two	35.4
Yes	92.6	Three or more	42.3
No	7.4	**Housing unit type**	
Employment status		Stand-alone home	61.1
Student (part-time or full-time)	12.9	Condo/apartment	29.7
Worker (part-time or full-time)	58.8	Other	9.1
Both worker and student	14.1	**Homeownership**	
Neither worker nor student	14.1	Own	59.7
Education attainment		Rent	35.0
High school or less	7.2	Other	5.3
Some college or technical school	25.6	**Vehicle ownership**	
Bachelor's degree(s)	38.4	Zero	5.5
Graduate degree(s)	28.8	One	24.7
Race		Two	39.3
Asian or Pacific Islander	12.4	Three or more	30.5
Black or African American	8.7	**Location**	
Multi race	3.7	Atlanta, GA	34.2
Native American	0.6	Austin, TX	42.4
Other	1.5	Phoenix, AZ	16.7
White or Caucasian	73.2	Tampa, FL	6.7
		Endogenous Variables	
Frequency of ridehailing service usage		**Change in bus use due to ridehailing service**	
Weekly	6.7	Increase	4.2
Monthly	25.8	No change	77.3
Rarely	67.4	Decrease	18.5

One of the key objectives of the modeling exercise undertaken in this chapter is to explicitly account for latent attitudinal constructs that may impact the endogenous variables of interest. The latent attitudinal constructs are endogenous variables themselves as well and are influenced by exogenous socio-economic and demographic characteristics. Three latent constructs are considered in this study. They are *pro-environment attitude*, *mobility service perception*, and *transit-oriented lifestyle*. Each latent construct is captured using three attitudinal variables or indicators in the data set. These indicators are highly correlated with one another and constitute an important dimension of the latent construct. Figure 1 depicts the three stochastic latent constructs and their corresponding attitudinal indicators. In the interest of brevity, each and every attitudinal statement is not described in detail here as the distributions depicted in the figure are self-explanatory.

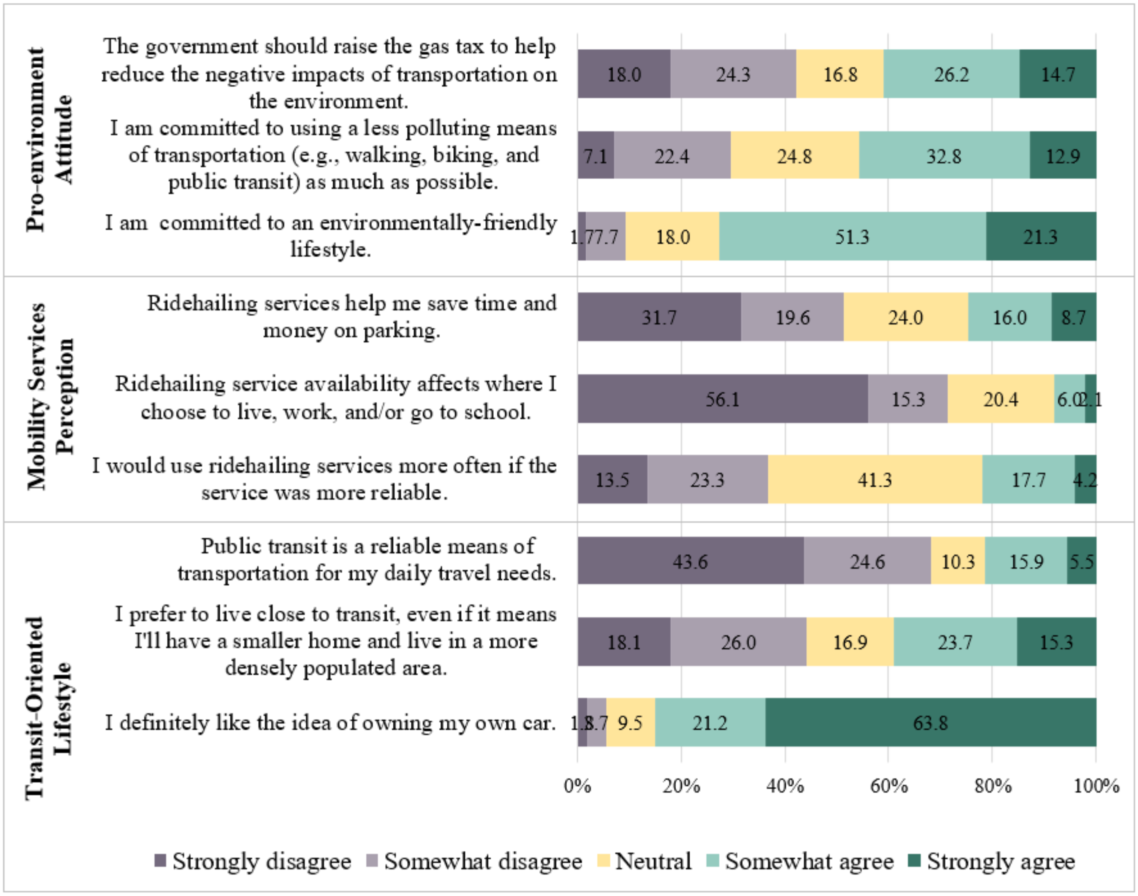

Figure 1 Distribution of Attitudinal Indicators of Latent Variables (N = 1,336)

Figure 2 (a) presents a bivariate descriptive chart of the two dependent variables. The pattern suggests a relationship between the two dimensions of interest, but a multivariate modeling framework is needed to truly capture the relationship between these two behavioral phenomena while controlling for other socio-economic, demographic, and attitudinal variables. As expected, the greatest change in bus use occurs among those who use ridehailing services very frequently (weekly basis). The number of individuals who indicate that they use ridehailing weekly is small (N=90); within this group, nearly nine percent indicated that they increased bus use, but 40 percent indicated that they decreased their bus use as a result of ridehailing service usage. Among those who use ridehailing services more sparingly, nearly 80 percent report no change in bus use due to ridehailing. Only four percent increased bus use, while the remainder (16 percent of rare users and 19.4 percent of monthly users) decreased bus use. Clearly, frequency of ridehailing service usage does have implications for change in bus use, and the percentage of individuals decreasing bus use greatly exceeds the percent of individuals increasing bus use (due to ridehailing service usage). This is the first indication that ridehailing substitutes for, and takes away, bus ridership (more than it complements and adds to bus ridership).

It is worth mentioning that not all individuals present in the sample were current bus users (using bus *at least* less than monthly for *work/school* or *errands/shopping/social/recreational* purposes). In fact, only a quarter of them reported being current bus users. Looking at the bivariate relationship between bus use change after using ridehailing by bus user status presented in Figure 2 (b), it is clear that bus users were more impacted than their counterparts with decrease in bus use (22.9 percent), while 14.4 percent of them reported an increase in bus usage, suggesting that ridehailing services may have served them to complement their transit rides. For individuals who were currently not bus users (about 75% of the sample), 17% of them reported a decrease in bus usage, which suggests that ridehailing services shifted these users away from transit. Interestingly, seven individuals (0.7%) reported an increase in bus usage after using ridehailing services. This unexpected result may be because these individuals used transit for purposes other than the ones mentioned above.

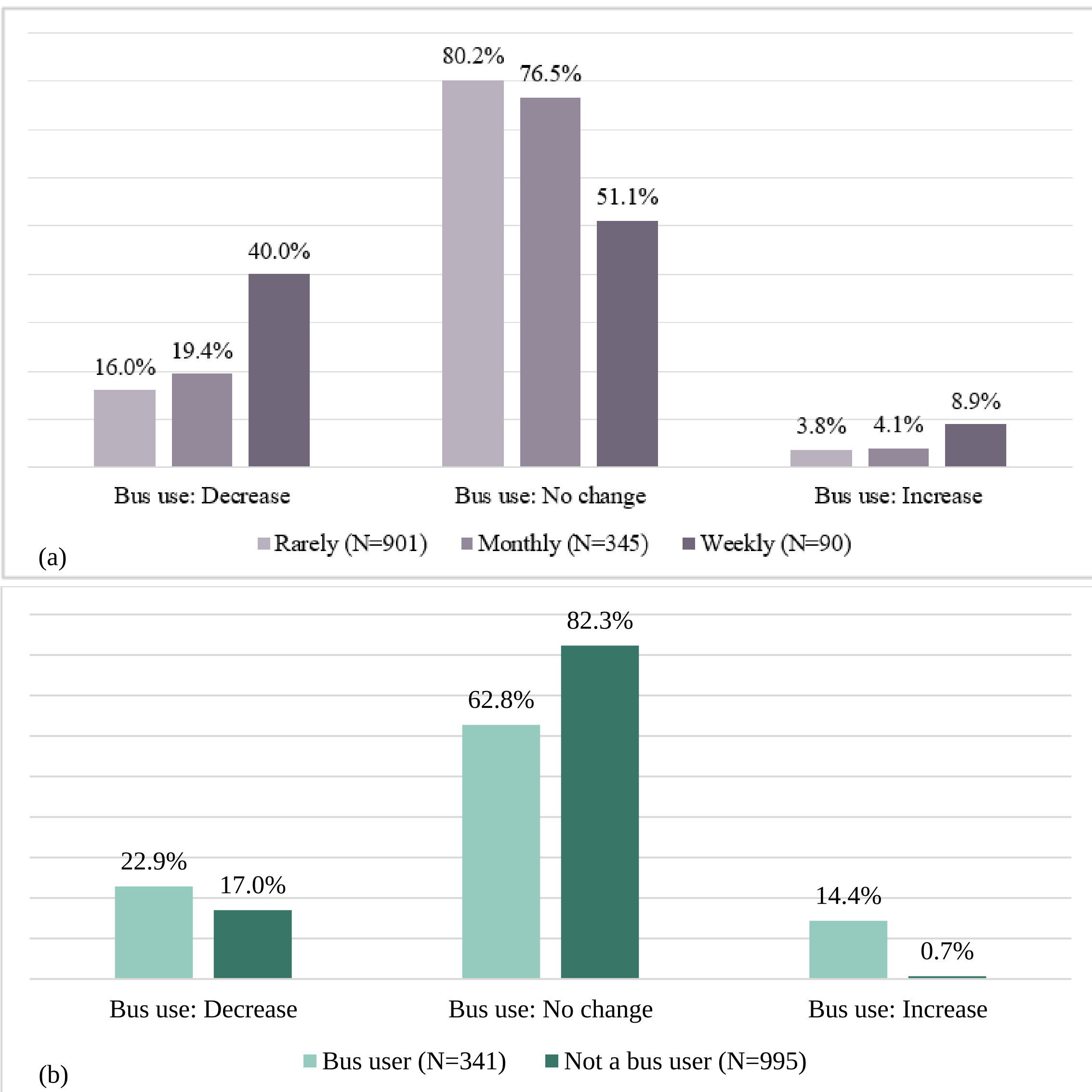

Figure 2 Bus Use Change by (a) Ridehailing Services Usage Frequency and (b) Bus User Status (N = 1,336)

2.4 Modeling Approach

This subsection presents the modeling framework and methodology. The modeling framework should be capable of accounting for multiple endogenous variables and the influence of latent attitudinal constructs (which are endogenous themselves). The overall model structure is presented first, while the model formulation and estimation methodology are presented second.

2.4.1 Model Structure

A simplified representation of the model structure is depicted in Figure 3. The analytic framework centers on developing a joint model of ridehailing service use frequency and bus use change. The determinants of the main outcome variables include individual-level variables spanning socio-economic, demographic, and household characteristics as well as attitudinal/lifestyle factors that are also known as psycho-social factors. The factors are not directly observable but are treated as latent stochastic constructs revealed through an individual's responses to a set of attitudinal statements.

Exogenous variables include socio-economic and demographic variables together with select travel or mobility routines that may be treated as exogenous for purposes of this study. There is a direct effect between the two endogenous variables, with the frequency of ridehailing service use affecting change in bus use. Exogenous variables can directly influence the behavioral outcomes of interest. At the same time, they may also influence the endogenous variables through an intermediate set of latent attitudinal constructs. The three latent attitudinal constructs influence the endogenous variables and are themselves influenced by exogenous variables. As they are stochastic in nature, error correlations may be computed for the latent constructs; and by virtue of their stochasticity, they are able to engender an implied correlation between the two endogenous variables themselves. It is desirable to estimate the entire model structure in one step for purposes of parameter efficiency and representation of jointness in the behavioral outcomes of interest. The Generalized Heterogeneous Data Model (GHDM) developed by Bhat (2015) offers a computationally efficient and robust approach for parameter estimation. The estimation methodology will be presented in the full dissertation.

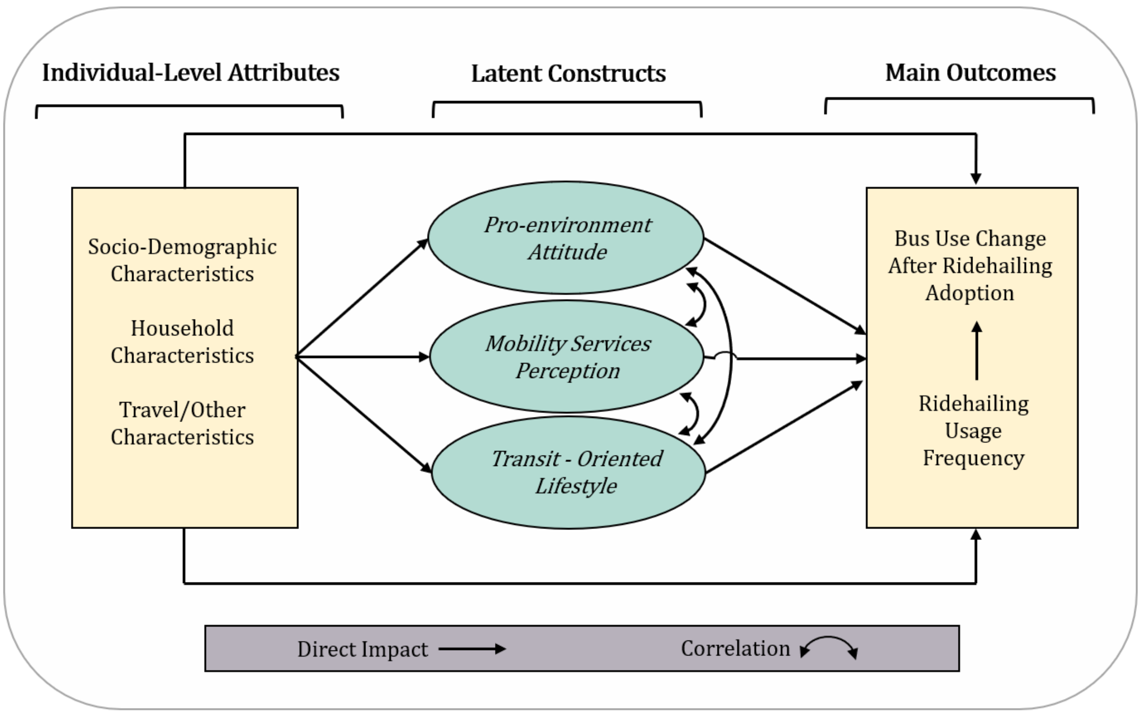

Figure 3 Modeling Framework

2.4.2 Model Estimation Methodology

As the outcomes as well as the indicators are ordinal in nature, the GHDM model for this study is formulated for exclusively ordinal outcomes. Consider the case of an individual

$q \in \{1, 2, ..., Q\}$. Let $l \in \{1, 2, ..., L\}$ be the index of the latent constructs and let z_{ql}^* be the value of the latent variable l for the individual q. z_{ql}^* is expressed as a function of its explanatory variables as,

$$z_{ql}^* = \boldsymbol{w}_{\boldsymbol{ql}}^{\mathrm{T}} \boldsymbol{\alpha} + \eta_{ql} \,, \tag{1}$$

where $\boldsymbol{w}_{\boldsymbol{ql}}$ $(D \times 1)$ is a column vector of the explanatory variables of latent variable l and $\boldsymbol{\alpha}$ $(D \times 1)$ is a vector of its coefficients. η_{ql} is the unexplained error term and is assumed to follow a standard normal distribution. Equation (1) can be expressed in matrix form as,

$$\boldsymbol{z}_{\boldsymbol{q}}^* = \boldsymbol{w}_{\boldsymbol{q}} \boldsymbol{\alpha} + \boldsymbol{\eta}_{\boldsymbol{q}} \,, \tag{2}$$

where $\boldsymbol{z}_{\boldsymbol{q}}^*$ $(L \times 1)$ is a column vector of all the latent variables, $\boldsymbol{w}_{\boldsymbol{q}}$ $(L \times D)$ is a matrix formed by vertically stacking the vectors $(\boldsymbol{w}_{\boldsymbol{q1}}^{\mathrm{T}}, \boldsymbol{w}_{\boldsymbol{q2}}^{\mathrm{T}}, ..., \boldsymbol{w}_{\boldsymbol{qL}}^{\mathrm{T}})$ and $\boldsymbol{\eta}_{\boldsymbol{q}}$ $(D \times 1)$ is formed by vertically stacking $(\eta_{q1}, \eta_{q2}, ..., \eta_{qL})$. $\boldsymbol{\eta}_{\boldsymbol{q}}$ follows a multivariate normal distribution centered at the origin and having a correlation matrix of $\boldsymbol{\Gamma}$ $(L \times L)$, i.e., $\boldsymbol{\eta}_{\boldsymbol{q}} \sim MVN_L(\boldsymbol{0}_{\boldsymbol{L}}, \boldsymbol{\Gamma})$, where $\boldsymbol{0}_L$ is a vector of zeros. The variance of all the elements in $\boldsymbol{\eta}_{\boldsymbol{q}}$ is fixed as unity because it is not possible to uniquely identify a scale for the latent variables. Equation (2) constitutes the structural component of the framework.

Let $j \in \{1, 2, ..., J\}$ denote the index of the outcome variables (including the indicator variables). Let y_{qj}^* be the underlying continuous measure associated with the outcome variable y_{qj}. Then,

$$y_{qj} = k \text{ if } t_{jk} < y_{qj}^* \leq t_{j(k+1)} \,, \tag{3}$$

where $k \in \{1, 2, ..., K_j\}$ denotes the ordinal category assumed by y_{qj} and t_{jk} denotes the lower boundary of the k^{th} discrete interval of the continous measure associated with the j^{th} outcome. $t_{jk} < t_{j(k+1)}$ for all *j* and all *k*. Since y_j^* may take any value in $(-\infty, \infty)$, we fix the value of $t_{j1} = -\infty$ and $t_{j(K_j+1)} = \infty$ for all *j*. Since the location of the thresholds on the real line is not uniquely identifiable, set $t_{j2} = 0$. y_j^* is expressed as a function of its explanatory variables and other observed dummy variable endogenous outcomes (only in a recursive fashion, if specified),

$$y_{qj}^* = \boldsymbol{x}_{\boldsymbol{qj}}^{\mathrm{T}}\boldsymbol{\beta} + \boldsymbol{z}_{\boldsymbol{q}}^{*\mathrm{T}}\boldsymbol{d}_{\boldsymbol{j}} + \xi_{qj}, \tag{4}$$

where $\boldsymbol{x}_{\boldsymbol{qj}}$ is an $(E \times 1)$ vector of size of explanatory variables including a constant as well as including the possibility of other dummy variable endogenous outcome variables. $\boldsymbol{\beta}$ $(E \times 1)$ is a column vector of the coefficients associated with $\boldsymbol{x}_{\boldsymbol{qj}}$ and $\boldsymbol{d}_{\boldsymbol{j}}$ $(L \times 1)$ is the vector of coefficients of the latent variables for outcome *j*. ξ_{qj} is a stochastic error term that captures the effect of unobserved variables on y_{qj}^*. ξ_{qj} is assumed to follow a standard normal distribution. Jointly, the continuous measures of the *J* outcome variables may be expressed as,

$$\boldsymbol{y}_{\boldsymbol{q}}^* = \boldsymbol{x}_{\boldsymbol{q}}\boldsymbol{\beta} + \boldsymbol{d}\boldsymbol{z}_{\boldsymbol{q}}^* + \boldsymbol{\xi}_{\boldsymbol{q}}, \tag{5}$$

where $\boldsymbol{y}_{\boldsymbol{q}}^*$ $(J \times 1)$ and $\boldsymbol{\xi}_{\boldsymbol{q}}$ $(J \times 1)$ are the vectors formed by vertically stacking y_{qj}^* and ξ_{qj} , respectively, of the *J* dependent variables. $\boldsymbol{x}_{\boldsymbol{q}}$ $(J \times E)$ is a matrix formed by vertically stacking the vectors $\left(\boldsymbol{x}_{\boldsymbol{q1}}^{\mathrm{T}}, \boldsymbol{x}_{\boldsymbol{q2}}^{\mathrm{T}}, ..., \boldsymbol{x}_{\boldsymbol{qJ}}^{\mathrm{T}}\right)$ and $\boldsymbol{d}$ $(J \times L)$ is a matrix formed by vertically stacking $\left(\boldsymbol{d}_{\boldsymbol{1}}^{\mathrm{T}}, \boldsymbol{d}_2^{\mathrm{T}}, ..., \boldsymbol{d}_{\boldsymbol{J}}^{\mathrm{T}}\right)$. $\boldsymbol{\xi}_{\boldsymbol{q}}$ follows a multivariate normal distribution centered at the origin with an identity matrix as the covariance matrix (independent error terms). $\boldsymbol{\xi_q} \sim MVN_J(\boldsymbol{0_J}, \mathbf{I_J})$. It is assumed the terms in $\boldsymbol{\xi_q}$ are independent because it is not possible to uniquely identify all correlations between the elements in $\boldsymbol{\eta_q}$ and all correlations between the elements in $\boldsymbol{\xi_q}$. Further, because of the ordinal nature of the outcome variables, the scale of $\boldsymbol{y_q^*}$ cannot be uniquely identified. Therefore, the variances of all elements in $\boldsymbol{\xi_q}$ is fixed to one. The reader is referred to Bhat (2015) for further nuances regarding the identification of coefficients in the GHDM framework.

Substituting Equation (2) in Equation (5), $\boldsymbol{y_q^*}$ can be expressed in the reduced form as

$$\boldsymbol{y_q^*} = \boldsymbol{x}_q\boldsymbol{\beta} + \boldsymbol{d}\left(\boldsymbol{w}_q\boldsymbol{\alpha} + \boldsymbol{\eta}_q\right) + \boldsymbol{\xi}_q\,, \tag{6}$$

$$\boldsymbol{y_q^*} = \boldsymbol{x}_q\boldsymbol{\beta} + \boldsymbol{d}\boldsymbol{w}_q\boldsymbol{\alpha} + \boldsymbol{d}\boldsymbol{\eta}_q + \boldsymbol{\xi}_q\,. \tag{7}$$

On the right side of Equation (7), $\boldsymbol{\eta_q}$ and $\boldsymbol{\xi_q}$ are random vectors that follow the multivariate normal distribution and the other variables are non-random. Therefore, $\boldsymbol{y_q^*}$ also follows the multivariate normal distribution with a mean of $\boldsymbol{b} = \boldsymbol{x}_q\boldsymbol{\beta} + \boldsymbol{d}\boldsymbol{w}_q\boldsymbol{\alpha}$ (all elements of $\boldsymbol{\eta_q}$ and $\boldsymbol{\xi_q}$ have a mean of zero) and a covariance matrix of $\boldsymbol{\Sigma} = \boldsymbol{d}\boldsymbol{\Gamma}\boldsymbol{d}^{\mathrm{T}} + \mathbf{I_J}$.

$$\boldsymbol{y_q^*} \sim MVN_J(\boldsymbol{b}, \boldsymbol{\Sigma})\,. \tag{8}$$

The parameters that are to be estimated are the elements of $\boldsymbol{\alpha}$, strictly upper triangular elements of $\boldsymbol{\Gamma}$, elements of $\boldsymbol{\beta}$, elements of $\boldsymbol{d}$ and t_{jk} for all j and $k \in \{3, 4, ..., K_j\}$. Let $\boldsymbol{\theta}$ be a vector of all the parameters that need to be estimated. The maximum likelihood approach can be used for estimating these parameters. The likelihood of the q^{th} observation will be,

$$L_q(\boldsymbol{\theta}) = \int_{v_1=t_{1y_{q1}}-b_1}^{v_1=t_{1(y_{q1}+1)}-b_1} \int_{v_2=t_{2y_{q2}}-b_2}^{v_2=t_{2(y_{q2}+1)}-b_2} \cdots \int_{v_J=t_{Jy_{qJ}}-b_J}^{v_J=t_{J(y_{qJ}+1)}-b_J} \phi_J(v_1, v_2, \ldots, v_J \mid \boldsymbol{\Sigma}) dv_1 dv_2 \ldots dv_J \ , \qquad (9)$$

where, $\phi_J\left(v_1, v_2, \ldots, v_J \mid \boldsymbol{\Sigma}\right)$ denotes the probability density of a J dimensional multivariate normal distribution centered at the origin with a covariance matrix $\boldsymbol{\Sigma}$ at the point $(v_1, v_2, \ldots, v_J)$. Since a closed form expression does not exist for this integral and evaluation using simulation techniques can be time consuming, the One-variate Univariate Screening technique proposed by Bhat (2018) was used for approximating this integral. The estimation of parameters was carried out using the *maxlik* library in the GAUSS matrix programming language.

2.5 Model Estimation Results

This section presents the estimation results for the joint model system. The entire model structure was estimated in one step using the GHDM methodology. The factor loadings, effects of exogenous variables on the latent factors and behavioral dimensions of interest, and the relationship between the endogenous variables are estimated simultaneously, thus recognizing the jointness in the complex interrelationships that characterize ridehailing and bus use.

2.5.1 Latent Construct Model Components

Table 2 presents estimation results for the latent variable component of the model system. The table presents factor loadings for attitudinal indicators that define the latent constructs as well as model coefficients depicting the influence of exogenous variables on the latent constructs. As noted earlier, there are three latent constructs defined by three attitudinal indicators each. The factor loadings are all intuitive and significant, clearly indicating that they are appropriate indicators for the latent constructs defined in this study.

Table 2 Determinants of Latent Variables and Loadings on Indicators (N = 1,336)

Explanatory Variables (base category) Note: Base categories for attributes (*) are the excluded categories not appearing in the table.	**Structural Equations Model (SEM) Component**					
	Pro-environment Attitude		Mobility Services Perception		Transit-oriented Lifestyle	
	Coef	t-stat	Coef	t-stat	Coef	t-stat
Individual characteristics						
Age (*)						
18-30 years	—	—	0.59	16.47	—	—
18-40 years	-0.14	-6.29	—	—	—	—
31-65 years	—	—	—	—	-0.37	-16.13
Education (*)						
High school or less	—	—	—	—	0.32	9.29
Graduate degree(s)	0.31	13.61	—	—	—	—
Race (White)						
Non-White	—	—	0.66	18.46	—	—
Employment status (not a student)						
Student	0.38	13.91	—	—	—	—
Household characteristics						
Household income (*)						
Up to $25,000	—	—	0.34	8.43	—	—
Up to $50,000	—	—	—	—	0.50	20.98
$100,000 to $150,000	-0.25	-10.73	—	—	—	—
$100,000 or over	—	—	-0.34	-11.13	—	—
Household structure (not a nuclear family)						
Nuclear family	—	—	—	—	-0.39	-15.48
Correlations between latent constructs						
Pro-environment attitude	1	—	0.68	4.61	0.95	7.56
Mobility services perception			1	—	0.80	5.64
Transit-oriented lifestyle					1	—
Attitudinal Indicators	**Loadings of Latent Variables on Indicators (Measurement Equations Model Component)**					
The government should raise the gas tax to help reduce the negative impacts of transportation on the environment.	0.62	22.47				
I am committed to using a less polluting means of transportation (e.g., walking, biking, and public transit) as much as possible.	0.91	24.07				

I am committed to an environmentally-friendly lifestyle.	0.45	18.18				
Ridehailing services help me save time and money on parking.			0.66	17.67		
Ridehailing service availability affects where I choose to live, work, and/or go to school.			0.42	17.81		
I would use ridehailing services more often if the service was more reliable.			0.32	17.25		
Public transit is a reliable means of transportation for my daily travel needs.					0.80	26.98
I prefer to live close to transit, even if it means I'll have a smaller home and live in a more densely populated area.					0.65	26.01
I definitely like the idea of owning my own car.					-0.58	-22.83

A host of exogenous variables influence the latent attitudinal constructs. It was found that there was no significant gender effect across all three latent constructs. This is somewhat inconsistent with findings reported in the literature (e.g., Lavieri and Bhat, 2019; Sikder, 2019; von Behren et al., 2021), but is a result in this study that proved insensitive to the model specification. Younger individuals are more likely to view mobility services positively, consistent with earlier findings in the literature that have consistently shown that younger individuals use mobility services more than others (e.g., Rayle et al., 2016; Alemi et al., 2018; Sikder, 2019). Older individuals exhibit a higher degree of pro-environment attitude and a lower degree of transit oriented lifestyle, consistent with the literature (e.g., Cervero, 2007; Wiernik et al., 2013; Lavieri and Bhat, 2019; Sharda et al., 2019). In general, those in the middle age groups are in a lifecycle stage where concerns about employment, household obligations, child care, and financial security tend to be greater, and hence less emphasis is placed on environmental and transit oriented lifestyles (Wiernik et al., 2013; McCarthy et al., 2017).

As expected, a higher education level is associated with a greater degree of pro-environment attitude, similar to findings reported by Kang et al. (2021) and Blazanin et al., (2021). Students depict a higher level of pro-environment attitude than others. At the same time, those with a lower education level (high school or less) appear more transit oriented than others; this, however, is largely because these individuals are in a lower income bracket and depend more heavily on transit for their mobility (leading to a greater proclivity towards a transit oriented lifestyle). The household income and structure effects are intuitive as well. Lower income individuals depict a more positive perception of mobility services, because they use them for mobility and find them convenient and affordable to do so (at least for short trips). Lower income individuals are also more inclined to be transit oriented. On the other hand, higher income individuals – who tend to own and use cars more than other groups – are less pro-environment and less favorable about mobility services (largely because they do not have a need to use mobility services on any regular basis). These findings are consistent with those reported in the literature (e.g., Cervero, 2007; Sharda et al., 2019). Finally, households that have a nuclear family structure (multiple adults with at least one child) are less likely to score high on the transit-oriented lifestyle, which is consistent with the notion that transit is not very conducive to meeting the complex mobility needs of households with children.

2.5.2 Bivariate Model of Behavioral Outcomes

Table 3 presents estimation results for the bivariate model of behavioral outcomes. The key finding is that, after controlling for all socio-economic, demographic, and attitudinal effects in a joint behavioral modeling framework, ridehailing usage has a statistically significant negative impact on bus use. An increasing frequency of ridehailing usage has the effect of decreasing bus use. Although there have been efforts to leverage ridehailing to complement and enhance transit usage (Shaheen and Cohen, 2020), the results of this study unequivocally show that ridehailing is taking ridership away from bus service – particularly in automobile-oriented metropolitan areas that are generally characterized by dispersed land use patterns and relatively poor transit service (note that this effect of ridehailing usage frequency on bus use may be considered as a "true" causal effect, after accommodating the spurious unobserved correlation between the two endogenous variables engendered by the stochastic latent constructs).

Table 3 Estimation Results of the Joint Ridehailing Use and Bus Use Change Model (N = 1,336)

Explanatory Variables (base category)	**Main Outcome Variables**			
	Ridehailing Use (rarely, monthly, weekly)		Bus Use Change (decrease, no change, increase)	
	Coef	t-stat	Coef	t-stat
Endogenous variable				
Ridehailing use frequency	—	—	-0.17	-10.59
Latent constructs				
Pro-environment attitude	-0.25	-6.36	—	—
Mobility services perception	0.07	1.29	-0.32	-9.25
Transit-oriented lifestyle	0.46	9.57	0.42	10.99
Individual characteristics				
Age (*)				
31-65 years	—	—	0.25	7.78
Over 65 years	-0.75	-14.85	—	—
Race (White)	—	—		
Non-White	-0.07	-1.57	—	—
Employment (not a student)				
Student	—	—	0.22	7.46
Household characteristics				
Household income (*)				
$50,000 to $100,000	—	—	0.22	7.22
$150,000 or more	0.49	14.50	—	—
Household size (*)				
One	0.22	7.52	—	—
Three or more	—	—	0.20	7.37
Household vehicles (zero or at least two)				
One	—	—	-0.14	-5.26
Travel & built environment characteristics				
Weekly VMT (up to 75 & over 100 mi)				
76 to 100 mi	—	—	-0.31	-7.40
Population density (≥ 3,000 person/sq mile)				
Low density (< 3,000 person/sq mile)	-0.25	-10.51	—	—
Location (Austin, Phoenix, Tampa)				
Atlanta	0.15	5.59	—	—
Thresholds				
1|2	0.44	15.13	-1.08	-26.59
2|3	1.59	45.32	1.69	35.81
Correlation				
Ridehailing use	—	—	0.03	—
Data Fit Measures	**Joint (GHDM) Model**		**Independent (IOP) Model**	
Log-likelihood at convergence	-1838.49		-1850.23	
Log-likelihood at constants	-1925.09			
Number of parameters	82		32	
Likelihood ratio test	0.045		0.039	
Average probability of correct prediction	0.361		0.359	

Note: Base categories for attributes (*) are identified by the excluded categories.

All other effects are as expected and consistent with previous findings in the literature. Pro-environment attitude is associated with a proclivity towards lower level of ridehailing use, a positive perception of mobility services is associated with an inclination towards higher level of ridehailing use and a decreased level of bus use, and a transit-oriented lifestyle is associated with higher levels of ridehailing and increased bus use (suggesting transit oriented individuals use ridehailing to complement transit as opposed to substitution). These findings are similar to those reported in the literature (Rayle et al., 2016; Dong, 2020; von Behren et al., 2021).

Socio-economic and demographic characteristics significantly influence ridehailing use frequency and change in bus usage arising from the use of ridehailing services. Consistent with prior research, those over the age of 65 years are more likely to use ridehailing services sparingly when compared to younger age groups (Rayle et al., 2016; Alemi et al., 2018). Whereas those in the middle age group depict a tendency to increase bus use after adopting ridehailing, the positive coefficient for the 31-65 years group suggests that frequent ridehailing users in this group are more likely to use ridehailing to complement transit than other age groups.

There is a modest race effect with non-whites likely to use ridehailing services on a less frequent basis. This finding is somewhat contradictory to findings reported in the literature where it has been found that minority groups use ride-hailing services to a greater degree than Whites, even after controlling for income (Clewlow and Mishra, 2017; Deka and Fei, 2019). It should be noted that this data set is derived from four automobile-oriented sprawled metropolitan regions; as such, some findings may not be perfectly comparable to those reported in the literature. In a sprawled region, non-whites are likely to find it challenging to use mobility services on a frequent basis due to poor transit services (hence limited opportunities to use mobility services as first-mile/last-mile connectors) and higher costs associated with the need to traverse longer distances. Students on the other hand are likely to use ridehailing services to connect with transit; they report a higher level of transit use after using ridehailing services.

A higher income is associated with a proclivity for higher frequency of ridehailing use, a finding that mirrors the literature (e.g., Lavieri and Bhat, 2019; Dong, 2020). The middle-income group appears to show a tendency to increase bus use after ridehailing adoption. This is because they are able to use the service to connect to transit, particularly for commuting; they have enough income to use the service frequently as a first-mile/last-mile connector, but not enough income to undertake the entire commute journey by ridehailing. Individuals living alone show a greater proclivity to use ridehailing services more frequently, while those in larger households show a propensity to increase bus use after ridehailing adoption. The former finding is consistent with that reported by Sikder (2019), and the latter finding reflects the fact that not all individuals in larger households have access to an automobile and are now able to leverage ridehailing services to complement and elevate their bus use.

In one-vehicle households (which are generally vehicle-deficient households where one or more household members often depend on bus service to meet mobility needs), the greater use of ridehailing services is associated with a propensity to reduce bus use. Individuals in these households have clearly substituted the use of bus transit with ridehailing service. The amount of weekly travel influences bus use change. Those who have a large travel footprint (76-100 miles per week), depict a tendency to reduce bus use and substitute bus use with ridehailing services. In the four metro regions covered by this survey sample, meeting such extensive mobility needs using bus service is challenging, and hence ridehailing services are a superior alternative (thus leading to a proclivity to reduce bus use). Lower density living is associated with a higher probability of using ridehailing services less frequently; those in low density neighborhoods are likely to own cars and would find regular use of ridehailing cost prohibitive due to distances that need to be traversed. Respondents from Atlanta report a proclivity to use ridehailing services more frequently, presumably due to high density pockets, severe traffic congestion, and opportunities to connect to major transit (e.g., MARTA rail lines). The error correlation across the dependent variables of interest is very small, suggesting that the inclusion of the direct effect of ridehailing use frequency on bus use change captures the relationship between them quite effectively. Consequently, the remaining error correlation that would arise from the presence of correlated unobserved attributes that affect both endogenous variables is modest.

From a goodness-of-fit standpoint, the joint model is found to offer significantly better fit than a corresponding independent model system in which error correlations engendered through the endogenous treatment of latent attitudinal constructs are ignored (restricted to zero by virtue of treating attitudinal variables as exogenous variables, similar to socio-economic and demographic variables). This shows that modeling latent attitudinal constructs and behavioral outcomes of interest in an integrated framework that recognizes endogeneity is critical to capturing the jointness in attitudes and behaviors.

2.6 Study Implications and Conclusions

This study focuses on the interaction between ridehailing service usage and change in bus use that results from the use of ridehailing services. The study utilizes a data set comprising respondents from the metro regions of Phoenix, Atlanta, Austin, and Tampa. The survey specifically asked individuals to convey their attitudes toward ridehailing services, the frequency with which they used ridehailing services, and the extent to which their bus use has changed due to ridehailing usage. In order to better understand and isolate the effect of ridehailing services on bus use change, this study adopts a simultaneous equations modeling framework in which joint relationships among multiple endogenous variables are captured explicitly. The model system accounts for the influence of latent attitudinal factors and treats them as endogenous variables as well.

The findings of this study clearly show that ridehailing usage negatively impacts bus use. Descriptive statistics as well as model estimation results indicate that ridehailing use frequency is significantly associated with a decrease in bus use, suggesting that ridehailing serves as a transit substitute (more than it serves as a complement). Despite attempts to have ridehailing services provide first-mile/last-mile connectivity and serve as a complement to transit, this has not happened – at least in auto-oriented metropolitan regions with dispersed land use patterns and rather limited transit service. After accounting for a host of socio-economic, demographic, and attitudinal factors, the effect of ridehailing is that it takes away from bus ridership.

The results are not surprising. Ridehailing is convenient, flexible, agile, faster (than transit), and personalized – these are many of the traits that render a mode appealing. It is more expensive, but also more affordable than traditional taxi and unlikely to be cost-prohibitive for short trips of a few miles (more than 60 percent of daily trips in the United States are five miles or less). Ridehailing also removes the hassle of driving and parking. It is clear why ridehailing is highly competitive and able to take trips away from public transit. As shared mobility services increasingly make their way into the transportation landscape (potentially shared, electrified, and automated to a greater degree in the future), the future of transit is under threat – and the threat has been exacerbated by the pandemic and the new remote modalities of work, school, and shopping embraced by the public. Transit ridership was already on the decline prior to the pandemic, and this analysis shows that ridehailing contributed significantly to the decline (the survey data pertains exclusively to the pre-pandemic period).

Municipalities and transit agencies need to explore strategies to enhance service and ridership, particularly in auto-oriented regions that have dispersed land use patterns. Partnering with ridehailing services so that first-mile/last-mile connectivity to transit is enhanced, payment systems are integrated, and the cost of ridehailing access/egress segments is highly subsidized would help transit agencies utilize emerging mobility services more effectively to boost ridership. Transit agencies themselves could reconfigure their service to expand coverage and enhance connectivity and accessibility with a focus on key travel corridors, market segments, and destinations. Recent attempts at reconfiguring services have worked to increase ridership in a few areas; examples include the Houston and Seattle metro areas (Descant, 2018) and the Northern Kentucky area (Tindale-Oliver, 2021). In all of these regions, transit services were expanded, routes were redrawn to bring about more direct connections and enhance both speed and reliability, access to destinations and people with mobility limitations was improved, and public input was considered throughout the process of reconfiguration.

Agencies may need to consider charging an additional fee for ridehailing services and use the revenue obtained to enhance transit services and mobility options for residents. Ridehailing services have already shown to increase congestion (Diao et al., 2021) and this study shows that they take ridership away from transit too. The levying of a fee would help manage the demand for ridehailing services while providing additional revenue for enhancing transit services and access for disadvantaged groups. Transit agencies will be in a better position to provide customized mobility, similar to the RideChoice program currently offered by Valley Metro in the Greater Phoenix region for transportation disadvantaged groups (Valley Metro, 2021). Concerted efforts aimed at increasing awareness about transit options, influencing attitudes and values, and changing perceptions may further help stem the loss of transit ridership.

The future of transit remains uncertain. In the absence of significant investments in service and technology, partnerships with new and emerging mobility providers, and enhancements in service configuration that boost accessibility, it is likely that transit will continue to experience declines in ridership – at least in part due to the rise of ridehailing services.

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3 UNDERSTANDING INTEREST IN PERSONAL OWNERSHIP AND USE OF AUTONOMOUS VEHICLES FOR RUNNING ERRANDS: A JOINT MODEL EXPLORATION

ABSTRACT

Transportation has been experiencing disruptive forces in recent years. One key disruption is the development of autonomous vehicles (AVs) that will be capable of navigating roadways on their own without the need for human presence in the vehicle. In a utopian scenario, AVs may enter the transportation landscape and foster a more sustainable and livable ecosystem with shared automated electric vehicles (SAEV) serving mobility needs and eliminating the need for private ownership. In a more dystopian scenario, AVs would be personally owned by households – enabling people to live farther away from destinations, inducing additional travel, and roaming roadways with zero occupants. Concerned with the potential deleterious effects of having personal AVs running errands autonomously, this chapter aims to shed light on the level of interest in sending AVs to run errands and how that variable affects the intent to own an AV. Using data from a survey conducted in 2019 in four automobile-oriented metropolitan regions in the United States, the relationship is explored through a joint model system estimated using the Generalized Heterogeneous Data Model (GHDM) methodology. Results show that even after accounting for socio-economic and demographic variables as well as latent attitudinal constructs, the level of interest in having AVs run errands has a positive and significant effect on AV ownership intent. The findings point to the need for policies that would steer the entry and use of AVs in the marketplace in ways that avoid a dystopian future.

3.1 Introduction

Rapid developments in the autonomous vehicle (AV) industry, coupled with technological advances in hardware, software, automation, and sensor systems, would enable vehicles of the future to navigate roadways without the need for human intervention (Sarker et al., 2019). Although many of the early prognostications regarding the development, adoption, market penetration, and availability of AVs have not materialized due to the complexities involved in AV development (Litman et al., 2017), it is expected that transportation futures will increasingly be characterized by AVs (Bansal and Kockelman, 2017).

There is considerable discussion on the manner in which AVs may enter the marketplace and be deployed in metropolitan areas and local communities (e.g., Litman, 2017; Fraedrich et al., 2019). On the one hand, a utopian future may be envisioned – one in which electric AVs are deployed by mobility service providers such that individuals can summon vehicles and share AV rides at an affordable cost. In such a scenario, the need for households to personally own vehicles would drop dramatically, the need for parking reduces substantially thus enabling land to be put to enhanced uses that improve quality of life, and land use patterns would densify and diversify as individuals seek to position themselves such that trip lengths (and hence ride costs) are modest. On the other hand, a dystopian future may be envisioned – one in which households choose to purchase and own an AV for every household member, individuals send zero-occupant AVs to go park themselves in faraway places where parking is cheap or free, land use patterns become sprawled as households and businesses no longer feel the need to be in close proximity of one another, and households deploy their personally owned AVs (with zero occupants) to run errands on their own. A number of modeling exercises have suggested that the adoption of AVs will lead to increases in vehicle miles of travel (VMT) and associated adverse impacts on the transportation system (e.g., Auld et al., 2017; Zhang et al., 2018). In addition, some studies have demonstrated through a variety of simulations that a future of shared autonomous electric vehicles (SAEV) would lead to considerable reductions in traffic volumes, congestion, air pollution, and parking needs (e.g., Zhang and Guhathakurta, 2017; Gurumurthy et al., 2019; Jones and Leibowicz, 2019).

In an effort to better understand how people may adopt and use AVs in the future, this study explores the relationship between the level of interest in using AVs to run personal errands (without vehicle occupants) and the level of interest in owning AVs. Although there is some survey-based research and evidence in the literature on the level of interest in purchasing AVs, there is little evidence on the level of interest in using AVs to run personal errands (autonomously). It may be hypothesized that households interested in sending AVs to run errands on their own are likely to be more inclined to personally own AVs. Thus, if technological capabilities allow AVs to be deployed autonomously to run errands, then that may spur greater levels of AV ownership – creating a dystopian future in which zero-occupant AVs roam the streets and households own AVs much like they own vehicles today.

This study aims to assess the level of interest in sending AVs to run errands on their own and the extent to which this level of interest affects potential household ownership of personal AVs. The study utilizes data from an in-depth survey of a sample of households located in four metropolitan regions of the United States, namely, Phoenix, Austin, Atlanta, and Tampa. Households were asked detailed questions about their attitudes towards, and potential adoption and use of, AVs in the future. To account for the possibility that the two behavioral phenomena considered in this chapter may constitute an activity-travel-lifestyle choice bundle, a simultaneous equations model system is estimated. The system jointly models the levels of interest in using AVs to run errands and personally owning AVs while accounting for common unobserved attributes that may affect both endogenous variables. In addition, the modeling framework incorporates latent attitudinal factors that may affect how individuals use and adopt AVs. The model system is estimated using the framework of the Generalized Heterogeneous Data Model (GHDM) developed by Bhat (2015); the methodology enables the computation of all model parameters in a single step while accounting for error correlation structures that capture the jointness of the phenomena under investigation.

The literature has identified the importance of these choice dimensions (i.e., using AVs to run errands autonomously and personally owning AVs) as key determinants of the sustainability of future transportation systems in which AVs are widely prevalent (e.g., Lavieri et al., 2017; Haboucha et al., 2017; Nazari et al., 2018; Harb et al., 2018; Moore et al., 2020). If individuals wish to deploy AVs independently to run errands and consequently own AVs personally, then it is more likely that a dystopian future will be realized. An understanding of the factors that contribute to levels of interest in deploying AVs to run errands and personally owning AVs, and of the extent to which the desire to have AVs run errands might influence the choice of personal AV ownership, is critical to designing an AV future that is sustainable and devoid of unintended consequences.

3.2 Data

This subsection provides a brief description of the survey and the data set used in this study. First, the survey and the sample characteristics are described. Second, a more in-depth descriptive analysis of endogenous variables and attitudinal indicators is provided.

3.2.1 Characteristics of the Sample

The data used in this study were collected through a survey conducted in the Fall of 2019 in four automobile-centric US metropolitan areas. The areas include Phoenix (Arizona), Austin (Texas), Atlanta (Georgia), and Tampa (Florida). The survey gathered rich information about people's attitudes towards and perceptions of new and emerging transportation technologies including ridehailing services, micromobility, and autonomous vehicles. The survey also gathered data on socio-economic and demographic characteristics, current mobility choices, and general lifestyle attitudes and preferences. Across the four regions, data were collected from 3,465 respondents. The same survey instrument was administered in all regions; however, the sampling methodology differed to a modest degree between metropolitan areas as customized attempts were made to enhance response rates and obtain a robust respondent sample size. Respondents were largely recruited through invitations sent to a random set of e-mail and mail addresses purchased from a commercial vendor. All respondents who furnished complete responses on a core set of questions received a $10 gift card as a post-completion incentive. After some filtering and cleaning of the survey data for obviously erroneous and missing data, the final data set comprised 3,358 records. Complete details about the survey and respondent sample may be obtained from the comprehensive survey reports (Khoeini et al., 2021). Table 4 presents the socio-economic, demographic, and endogenous variable characteristics for the sample used in this study.

Table 4 Socio-Economic and Demographic Characteristics of the Sample

Individual characteristics (N = 3,358)		*Household characteristics (N = 3,358)*	
Variable	**%**	**Variable**	**%**
Gender		**Household annual income**	
Female	58.3	Less than $25,000	11.2
Male	41.7	$25,000 to $49,999	15.6
Age category		$50,000 to $74,999	18.9
18-30 years	26.3	$75,000 to $99,999	15.1
31-40 years	11.5	$100,000 to $149,999	20.4
41-50 years	14.8	$150,000 to $249,999	12.6
51-60 years	16.6	$250,000 or more	6.2
61-70 years	16.1	**Household size**	
71+ years	14.7	One	21.3
Driver's license possession		Two	38.5
Yes	93.4	Three or more	40.2
No	6.6	**Housing unit type**	
Employment status		Stand-alone home	70.2
Student (part-time or full-time)	10.2	Condo/apartment	20.6
Worker (part-time or full-time)	52.1	Other	9.1
Both worker and student	11.1	**Homeownership**	
Neither worker nor student	26.6	Own	68.3
Education attainment		Rent	26.0
High school or less	9.4	Other	5.7
Some college or technical school	29.4	**Vehicle ownership**	
Bachelor's degree(s)	36.7	Zero	3.9
Graduate degree(s)	24.5	One	23.8
Race		Two	40.0
Asian or Pacific Islander	9.6	Three or more	32.3
Black or African American	7.9	**Location**	
Multi race	3.9	Atlanta, GA	29.5
Native American	0.6	Austin, TX	32.3
Other	1.8	Phoenix, AZ	30.7
White or Caucasian	76.3	Tampa, FL	7.5
Endogenous Variables			
Interest in having AVs run errands		**Interest in owning an AV**	
Strongly agree	15.7	Will be one of the first to buy	3.4
Somewhat agree	33.8	Will eventually buy	60.2
Neutral	20.5	Will never buy	36.4
Somewhat disagree	15.8	—	—
Strongly disagree	14.2	—	—

Overall, the sample characteristics are reasonable, consistent with expectations, and exhibit the desired level of variability to support an econometric simultaneous equations model estimation effort of the type undertaken in this study. The sample is slightly skewed in favor of females and the younger age group. While 58.3 percent of respondents are female, just over one-quarter of respondents are in the 18-30-year age group. There is however a good representation of all age groups in the sample. Just over 93 percent of respondents report having a driver's license. Over one-half of the sample reported being a worker (full or part-time), while over 26 percent reported being neither a worker nor a student. With respect to educational attainment, 36.7 percent report having a Bachelor's degree and 24.5 percent report having a graduate degree, suggesting that the respondent sample is skewed towards a higher level of educational attainment relative to the general population. All races are represented with over three-quarters White, just under 10 percent Asian or Pacific Islander, and nearly eight percent of African-American descent.

The income distribution of the sample represents a rich variation and representativeness of all income segments of the population. About 20 percent report incomes in the $100,000 to $149,999 range; about 27 percent report incomes less than $50,000; and nearly 19 percent report incomes greater than $150,000. It is found that 40 percent of respondents reside in households with three or more persons and 21 percent constitute single-person households. Just about 70 percent of individuals reside in stand-alone homes while another 20 percent reside in condo/apartment communities. Consistent with the residential dwelling unit type distribution, it is found that 68 percent own their home. Forty percent of respondents reside in two-vehicle households, and 32.3 percent reside in households with three or more vehicles. The sample is evenly split between Phoenix, Atlanta, and Austin; Tampa accounts for a smaller fraction of the sample.

The interest in having AVs run errands is measured on a five-point likert scale from strongly disagree to strongly agree. Nearly one-half of the respondents strongly agree or somewhat agree that they would like to send AVs to run errands. Thirty percent are not inclined to use AVs to run errands and 20 percent are neutral towards such usage. Interest in buying an AV for personal ownership is captured in three categories. Only 3.4 percent indicate that they will be the first to buy; about 60 percent indicate that they will eventually purchase an AV, while another 36.4 percent of respondents indicate that they will never buy an AV (it is uncertain whether that is because they do not wish to adopt the technology at all or simply wish to adopt the technology in a pure sharing mode as opposed to an ownership mode).

3.3 Endogenous Variables and Attitudinal Indicators

One of the key features of the survey dataset is that it includes a battery of attitudinal statements that can be used to develop latent attitudinal constructs which can, in turn, be incorporated into the modeling framework. By controlling for attitudes, it will be possible to obtain a deeper understanding of the extent to which interest in having AVs run errands would influence personal AV ownership. Three latent attitudinal constructs are considered in this study. They are depicted in Figure 4, together with the set of indicators that define them.

The latent attitudinal construct representing "driving enjoyment" is encapsulated by three indicators, the construct representing "technology savviness" is captured using three indicators, and the latent construct of "environmental consciousness" is comprised of two indicators. The attitudinal indicators are measured on a five-point likert scale ranging from strongly disagree to strongly agree. All of the indicators depict plausible distributions; in the interest of brevity, each and every statement is not described in detail. Only a few noteworthy patterns are highlighted here.

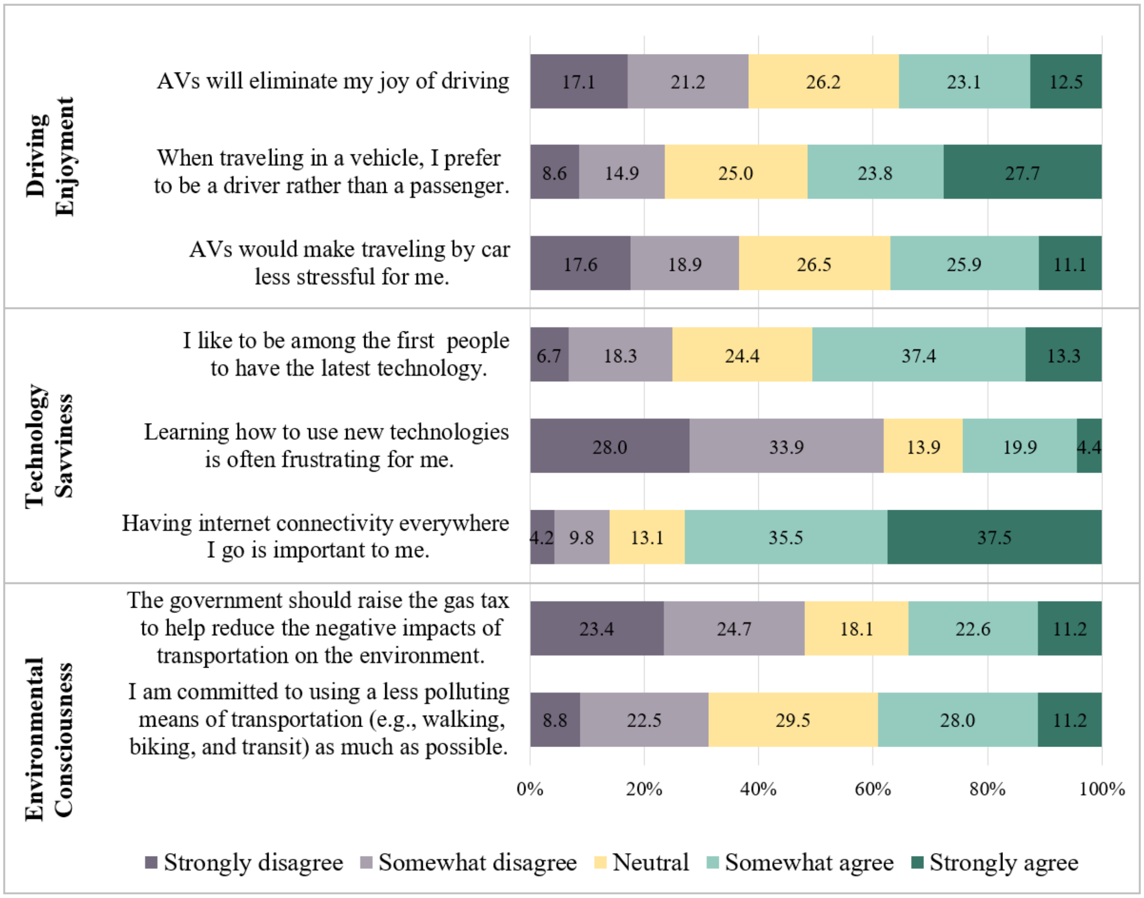

Figure 4 Distribution of Attitudinal Indicators Defining Latent Constructs (N = 3,358)

It is found that 50 percent of individuals prefer being a driver rather than a passenger when traveling in a vehicle. Nearly 37 percent somewhat or strongly disagree that AVs would make traveling by car less stressful for the individual, suggesting that many individuals do not necessarily see AVs as eliminating the stress of travel. Most of the respondents appear comfortable learning how to use new technologies; about 62 percent disagree that learning new technologies is frustrating. About 48 percent of the respondents are not in favor of the government raising the gas tax to combat pollution. Just about 39 percent are committed to using a less polluting means of transportation, while 30 percent indicate that they are neutral towards this statement.

Figure 5 shows the pattern of relationship between the two endogenous variables. A reasonably clear inverse relationship is discernible. Among those who intend to never buy an AV, 30 percent strongly disagree that they will send an AV to run errands and only six percent strongly agree that they would. At the other end of the spectrum, among those who intend to be one of the first to buy an AV (an arguably small number), only four percent strongly disagree that they would deploy AVs to run errands autonomously and a much larger 39 percent indicate strong interest in sending AVs to run errands on their own. The figure suggests that there is a relationship between the level of interest in having AVs run errands and the intended acquisition of AVs for personal ownership. A joint equations model system would help illuminate the nature of this relationship while controlling for other influential variables.

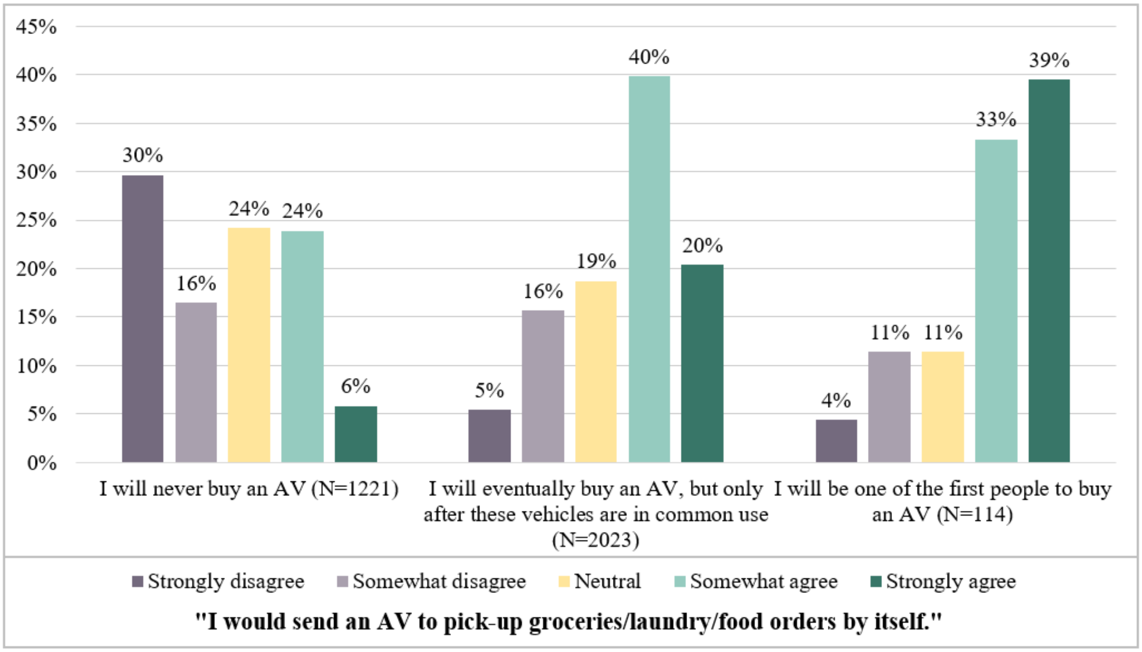

Figure 5 AV Ownership Intent by Interest in Sending AVs to Run Errands (N = 3,358)

3.4 Modeling Approach

This subsection presents the modeling framework adopted in this research effort. Recognizing the presence of multiple endogenous variables, and the desire to explicitly control for latent attitudinal constructs which are endogenous variables themselves, the study adopts a joint equations modeling framework capable of reflecting error correlations across latent constructs and endogenous variables.

3.4.1 Model Structure

The model framework is depicted in Figure 6. Exogenous variables include individual and household-level socio-economic and demographic attributes and a host of other travel-related variables that characterize the established and routine mobility patterns of the individual (and hence may be considered exogenous). The three latent attitudinal constructs constitute the intermediate layer of the model structure. They are influenced by exogenous variables and, in turn, influence the endogenous variables of interest. The exogenous variables can influence the endogenous variables directly or indirectly through the latent attitudinal constructs. The latent attitudinal constructs are not directly observable, but considered unobserved stochastic variables revealed through individuals' responses to a set of attitudinal statements or indicators. Finally, the endogenous variables are related to one another with the level of interest in sending AVs to run errands directly influencing the propensity to purchase an AV for personal ownership. Error correlations across the stochastic latent constructs are explicitly incorporated, and the latent construct errors engender an implied error correlation between the endogenous variables themselves. Thus, the framework accounts for the presence of correlated unobserved attributes simultaneously affecting latent constructs and the endogenous variables themselves. For purposes of parameter efficiency and to fully account for the endogeneity and error correlations embedded in the model structure, it is desirable to estimate all parameters in the model system in a single step. The Generalized Heterogeneous Data Model (GHDM) approach developed by Bhat (2015) offers a rigorous methodology for estimating the model system. The methodology is presented in the next subsection.

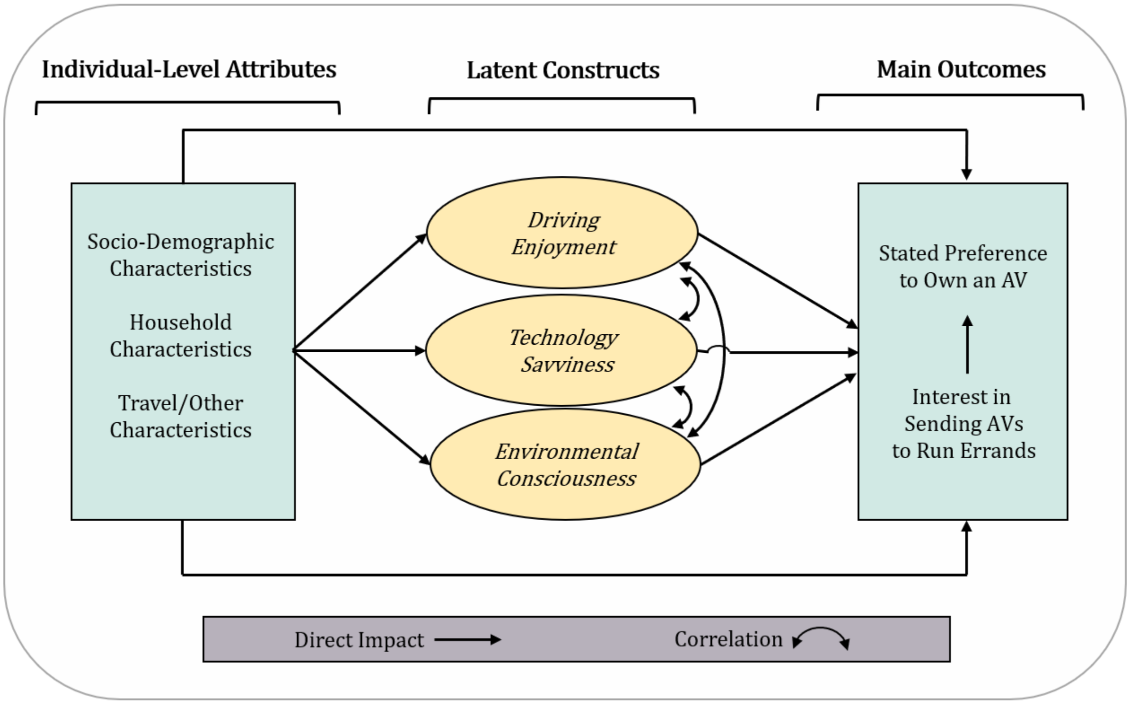

Figure 6 Simultaneous Equations Model Framework

3.4.2 Model Estimation Methodology

As all of the outcomes and indicators are ordinal in nature, the GHDM for this study is formulated for exclusively ordinal outcomes. Consider the case of an individual $q \in \{1, 2, ..., Q\}$. Let $l \in \{1, 2, ..., L\}$ be the index of the latent constructs and let z_{ql}^* be the value of the latent variable l for the individual q. z_{ql}^* is expressed as a function of its explanatory variables as,

$$z_{ql}^* = \boldsymbol{w}_{ql}^{\mathrm{T}} \boldsymbol{\alpha} + \eta_{ql} , \tag{10}$$

where $\boldsymbol{w}_{ql}$ $(D \times 1)$ is a column vector of the explanatory variables of latent variable l and $\boldsymbol{\alpha}$ $(D \times 1)$ is a vector of its coefficients. η_{ql} is the unexplained error term and is assumed to follow a standard normal distribution. Equation (1) can be expressed in the matrix form as,

$$\boldsymbol{z}_q^* = \boldsymbol{w}_q \boldsymbol{\alpha} + \boldsymbol{\eta}_q , \tag{11}$$

where $\boldsymbol{z}_{\boldsymbol{q}}^{*}$ $(L \times 1)$ is a column vector of all the latent variables, $\boldsymbol{w}_{\boldsymbol{q}}$ $(L \times D)$ is a matrix formed by vertically stacking the vectors $(\boldsymbol{w}_{\boldsymbol{q1}}^{\mathrm{T}}, \boldsymbol{w}_{\boldsymbol{q2}}^{\mathrm{T}}, ..., \boldsymbol{w}_{\boldsymbol{qL}}^{\mathrm{T}})$ and $\boldsymbol{\eta}_{\boldsymbol{q}}$ $(D \times 1)$ is formed by vertically stacking $(\eta_{q1}, \eta_{q2}, ..., \eta_{qL})$. $\boldsymbol{\eta}_{\boldsymbol{q}}$ follows a multivariate normal distribution centered at the origin and having a correlation matrix of $\boldsymbol{\Gamma}$ $(L \times L)$, i.e., $\boldsymbol{\eta}_{\boldsymbol{q}} \sim MVN_L(\boldsymbol{0}_{\boldsymbol{L}}, \boldsymbol{\Gamma})$, where $\boldsymbol{0}_{\boldsymbol{L}}$ is a vector of zeros. The variance of all elements in $\boldsymbol{\eta}_{\boldsymbol{q}}$ is fixed as unity because it is not possible to uniquely identify a scale for the latent variables. Equation (2) constitutes the structural component of the framework.

Let $j \in \{1, 2, ..., J\}$ denote the index of the outcome variables (including the indicator variables). Let y_{qj}^{*} be the underlying continuous measure associated with the outcome variable y_{qj}. Then,

$$y_{qj} = k \text{ if } t_{jk} < y_{qj}^{*} \leq t_{j(k+1)}, \tag{12}$$

where $k \in \{1, 2, ..., K_j\}$ denotes the ordinal category assumed by y_{qj} and t_{jk} denotes the lower boundary of the k^{th} discrete interval of the continous measure associated with the j^{th} outcome. $t_{jk} < t_{j(k+1)}$ for all j and all k. Since y_j^{*} may take any value in $(-\infty, \infty)$, we fix the value of $t_{j1} = -\infty$ and $t_{j(K_j+1)} = \infty$ for all j. Since the location of the thresholds on the real line is not uniquely identifiable, we also set $t_{j2} = 0$. y_j^{*} is expressed as a function of its explanatory variables and other observed dummy variable endogenous outcomes (only in a recursive fashion, if specified),

$$y_{qj}^{*} = \boldsymbol{x}_{\boldsymbol{qj}}^{\mathrm{T}} \boldsymbol{\beta} + \boldsymbol{z}_{\boldsymbol{q}}^{*\mathrm{T}} \boldsymbol{d}_{\boldsymbol{j}} + \xi_{qj}, \tag{13}$$

where $\boldsymbol{x_{qj}}$ is an $(E \times 1)$ vector of size of explanatory variables including a constant as well as including the possibility of other dummy variable endogenous outcome variables. $\boldsymbol{\beta}$ $(E \times 1)$ is a column vector of the coefficients associated with $\boldsymbol{x_{qj}}$ and $\boldsymbol{d_j}$ $(L \times 1)$ is the vector of coefficients of the latent variables for outcome *j*. ξ_{qj} is a stochastic error term that captures the effect of unobserved variables on y_{qj}^*. ξ_{qj} is assumed to follow a standard normal distribution. Jointly, the continuous measures of the *J* outcome variables may be expressed as,

$$\boldsymbol{y_q^*} = \boldsymbol{x_q \beta} + \boldsymbol{d z_q^*} + \boldsymbol{\xi_q}, \tag{14}$$

where $\boldsymbol{y_q^*}$ $(J \times 1)$ and $\boldsymbol{\xi_q}$ $(J \times 1)$ are the vectors formed by vertically stacking y_{qj}^* and ξ_{qj}, respectively, of the *J* dependent variables. $\boldsymbol{x_q}$ $(J \times E)$ is a matrix formed by vertically stacking the vectors $\left(\boldsymbol{x}_{\boldsymbol{q}1}^{\mathrm{T}}, \boldsymbol{x}_{\boldsymbol{q}2}^{\mathrm{T}}, \ldots, \boldsymbol{x}_{\boldsymbol{q}J}^{\mathrm{T}}\right)$ and $\boldsymbol{d}$ $(J \times L)$ is a matrix formed by vertically stacking $\left(\boldsymbol{d}_1^{\mathrm{T}}, \boldsymbol{d}_2^{\mathrm{T}}, \ldots, \boldsymbol{d}_J^{\mathrm{T}}\right)$. $\boldsymbol{\xi_q}$ follows a multivariate normal distribution centered at the origin with an identity matrix as the covariance matrix (independent error terms). $\boldsymbol{\xi_q} \sim MVN_J(\boldsymbol{0_J}, \mathbf{I}_J)$. The terms in $\boldsymbol{\xi_q}$ are assumed to be independent because it is not possible to uniquely identify all correlations between the elements in $\boldsymbol{\eta_q}$ and all correlations between the elements in $\boldsymbol{\xi_q}$. Further, because of the ordinal nature of the outcome variables, the scale of $\boldsymbol{y_q^*}$ cannot be uniquely identified. Therefore, the variances of all elements in $\boldsymbol{\xi_q}$ are fixed to one. The reader is referred to Bhat (2015) for further nuances regarding the identification of coefficients in the GHDM framework.

Substituting Equation (2) in Equation (5), $\boldsymbol{y}_q^*$ can be expressed in the reduced form as

$$\boldsymbol{y}_q^* = \boldsymbol{x}_q\boldsymbol{\beta} + \boldsymbol{d}\left(\boldsymbol{w}_q\boldsymbol{\alpha} + \boldsymbol{\eta}_q\right) + \boldsymbol{\xi}_q\,, \tag{15}$$

$$\boldsymbol{y}_q^* = \boldsymbol{x}_q\boldsymbol{\beta} + \boldsymbol{d}\boldsymbol{w}_q\boldsymbol{\alpha} + \boldsymbol{d}\boldsymbol{\eta}_q + \boldsymbol{\xi}_q\,. \tag{16}$$

On the right side of Equation (7), $\boldsymbol{\eta}_q$ and $\boldsymbol{\xi}_q$ are random vectors that follow the multivariate normal distribution and the other variables are non-random. Therefore, $\boldsymbol{y}_q^*$ also follows the multivariate normal distribution with a mean of $\boldsymbol{b} = \boldsymbol{x}_q\boldsymbol{\beta} + \boldsymbol{d}\boldsymbol{w}_q\boldsymbol{\alpha}$ (all elements of $\boldsymbol{\eta}_q$ and $\boldsymbol{\xi}_q$ have a mean of zero) and a covariance matrix of $\boldsymbol{\Sigma} = \boldsymbol{d}\boldsymbol{\Gamma}\boldsymbol{d}^{\mathrm{T}} + \mathbf{I}_J$.

$$\boldsymbol{y}_q^* \sim MVN_J(\boldsymbol{b}, \boldsymbol{\Sigma})\,. \tag{17}$$

The parameters to be estimated are the elements of $\boldsymbol{\alpha}$, strictly upper triangular elements of $\boldsymbol{\Gamma}$, elements of $\boldsymbol{\beta}$, elements of $\boldsymbol{d}$ and t_{jk} for all j and $k \in \{3, 4, ..., K_j\}$. Let $\boldsymbol{\theta}$ be a vector of all parameters to be estimated. The maximum likelihood approach can be used for estimating these parameters. The likelihood of the q^{th} observation is,

$$L_q(\boldsymbol{\theta}) = \int_{v_1 = t_{1y_{q1}} - b_1}^{v_1 = t_{1(y_{q1}+1)} - b_1} \int_{v_2 = t_{2y_{q2}} - b_2}^{v_2 = t_{2(y_{q2}+1)} - b_2} \cdots \int_{v_J = t_{Jy_{qJ}} - b_J}^{v_J = t_{J(y_{qJ}+1)} - b_J} \phi_J(v_1, v_2, \ldots, v_J \mid \boldsymbol{\Sigma})\, dv_1 dv_2 \ldots dv_J\,, \tag{18}$$

where, $\phi_J\left(v_1, v_2, \ldots, v_J \mid \boldsymbol{\Sigma}\right)$ denotes the probability density of a J dimensional multivariate normal distribution centered at the origin with a covariance matrix $\boldsymbol{\Sigma}$ at the point $(v_1, v_2, \ldots, v_J)$. Since a closed form expression does not exist for this integral and evaluation using simulation techniques can be time consuming, the One-variate Univariate Screening technique proposed by Bhat (2018) was used to approximate this integral.

3.5 Model Estimation Results

This section presents a summary of the model estimation results. The entire model framework presented in the previous section was estimated in a single step using the GHDM methodology.

3.5.1 Latent Construct Model Components

Table 2 presents results of the latent variable model components. The table shows the factor loadings for each of the attitudinal indicators used to construct the latent variables. A number of different latent variable indicators were considered, and the set of indicators and latent constructs shown in Table 5 were adopted as the final set based on behavioral intuitiveness, past research, and statistical significance and goodness-of-fit metrics. The factor loadings are all intuitive and the latent constructs capture a range of proclivities that are likely to influence an individual's propensity to adopt and likely manner of usage of new transportation technologies such as autonomous vehicles.

The latent factors are influenced by a host of socio-economic variables as expected. There is a significant gender effect with women less likely to be tech-savvy and less inclined to enjoy driving. These findings mirror those in the literature, with Asmussen et al. (2020) reporting similar gender effects for tech-savviness and Rahimi et al. (2020) reporting similar effects for driving enjoyment. On the other hand, gender is not significant for environmental consciousness, a finding also reported by Blazanin et al. (2021) and Rahimi et al. (2020). As expected, younger individuals appear to be more comfortable with technology, confirming earlier findings reported by Kang et al. (2021). Older individuals exhibit a greater likelihood to enjoy driving, which is also consistent with recent literature which suggests that younger generations are eschewing driving in favor of alternative modes of transportation (Polzin et al., 2014; McDonald, 2015). The middle age group of 31-65 years is less likely to be environmentally conscious relative to other age groups. Although there are some mixed findings reported in the literature regarding the connection between age and environmental consciousness, this finding is supported by Lavieri et al. (2017) and Otto and Kaiser (2014). In general, it appears that environmental consciousness diminishes during the peak travel years in an individual's life cycle.

Table 5 Determinants of Latent Variables and Loadings on Indicators (N = 3,358)

Explanatory Variables (base category)	**Structural Equations Model Component**					
	Driving Enjoyment		Technology Savviness		Environmental Consciousness	
	Coef	t-stat	Coef	t-stat	Coef	t-stat
Individual characteristics						
Gender (not female)						
Female	-0.13	-10.97	-0.32	-22.07	—	—
Age (*)						
18-30 years	—	—	0.85	41.17	—	—
31-40 years	—	—	0.73	29.05	—	—
31-65 years	—	—	—	—	-0.33	-19.24
61-70 years	0.43	26.97	—	—	—	—
71 years or older	0.53	31.09	—	—	—	—
Education (*)						
Some college or technical school	—	—	—	—	-0.22	-11.40
Bachelor's or graduate degree(s)	-0.23	-19.72	—	—	—	—
Graduate degree(s)	—	—	—	—	0.31	15.20
Household characteristics						
Household income (*)						
Up to $50,000	—	—	—	—	0.15	7.94
$150,000 or more	—	—	0.33	17.79	—	—
Correlations between latent constructs						
Driving enjoyment	1	—	-0.08	-1.25	-0.45	-6.53
Technology savviness			1	—	-0.17	-3.26
Environmental consciousness					1	—

Attitudinal Indicators	Loadings of Latent Variables on Indicators (Measurement Equations Model Component)					
AVs will eliminate my joy of driving.	1.07	38.97				
When traveling in a vehicle, I prefer to be a driver rather than a passenger.	0.58	34.84				
AVs would make traveling by car less stressful for me.	-0.73	-37.94				
I like to be among the first people to have the latest technology.			0.54	30.46		
Learning how to use new technologies is often frustrating for me.			-1.04	-25.98		
Having internet connectivity everywhere I go is important to me.			0.28	20.56		
The government should raise the gas tax to help reduce the negative impacts of transportation on the environment.					0.87	20.66
I am committed to using a less polluting means of transportation (e.g., walking, biking, and public transit) as much as possible.					0.48	22.71

Note: Base categories for attributes (*) are not identical across the model equations and correspond to all omitted categories.

Education is a significant determinant of the latent constructs. Higher education is associated with a greater level of environmental consciousness, a finding also reported by Lavieri et al. (2017), and a lower level of desire for driving control, a finding similar to that reported by Asmussen et al. (2021). On the other hand, education is not a significant determinant of tech-savviness, suggesting that educational attainment is not necessarily a barrier to technology adoption. This is similar to findings reported in Lavieri and Bhat (2019) and Moore et al. (2020). There is, however, a significant income effect associated with tech-savviness. Those in the highest annual income group of $150,000+ appear to be more tech-savvy than lower income groups, suggesting that higher income households are more comfortable with being early adopters of new technology, a finding also reported by Dannemiller (2021). Individuals in lower income households reported a greater level of environmental consciousness, confirming findings reported in Lavieri et al. (2019). As lower income communities have historically been disproportionately affected adversely when it comes to environmental impacts (e.g., Bullard and Wright, 1993), this finding is not entirely unexpected.

3.5.2 Bivariate Model of Behavioral Outcomes

Table 6 shows the estimation results for the model components corresponding to the behavioral outcomes of interest, namely, level of interest in sending AVs to run errands and intention to own an AV. The key finding of this study is that there is a clear and significant positive impact of the level of interest in using AVs to run errands on the intention to own an AV, even after controlling for all other socio-economic, demographic, and latent attitudinal variables. This means that, if AVs are able to run errands on their own, then individuals who have an interest in engaging vehicles in such a manner will be significantly more inclined to own AVs personally (note that this effect of the desire to have AVs run errands on AV ownership may be considered a “true” causal effect, after accommodating the spurious unobserved correlation between the two variables engendered by the stochastic latent construct effects).

All other findings reported in the table are consistent with expectations and behaviorally intuitive. Latent variables significantly influence behavioral dimensions in this study. The latent variable representing driving enjoyment reduces the propensity to send AVs to run errands and reduces the propensity to own an AV. This is consistent with the notion that those who enjoy driving would prefer to continue driving (manually) traditional vehicles rather than transition to AVs (Haboucha et al., 2017; Sener et al., 2019). Those who are tech-savvy, on the other hand, are more likely to send AVs to run errands and more likely to purchase and own AVs. Clearly, tech-savvy individuals are more likely to embrace new technology and use it to the fullest extent (Lavieri et al., 2017). Finally, environmental consciousness is associated with a reduced proclivity to own an AV, although the effect appears to be small as evidenced by the magnitude of the coefficient. Overall, latent attitudinal traits significantly influence an individual's proclivities towards embracing and using new and emerging transportation technologies.

Socio-economic and demographic characteristics affect the behavioral outcomes of interest along expected lines. Women are less inclined to own an AV, consistent with findings reported by Asmussen et al. (2020) and Sener et al. (2019). However, there is no gender effect on the level of interest in sending AVs to run errands. The youngest age group of 18-30 years is most inclined to own AVs while those in the next age group of 31-40 years exhibit the greatest proclivity to send AVs to run errands. The youngest group is inclined to embrace the technology by virtue of their tech-savviness and those in the 31-40-year age group are inclined to use AVs to run errands to take care of household obligations associated with this stage of the life cycle.

Table 6 Estimation Results of AV Errands and AV Ownership Model Components (N = 3,358)

Explanatory Variables (base category) Note: Base categories for attributes (*) are not identical across the model equations and correspond to all omitted categories.	**Main Outcome Variables**			
	AV Errands (5-level: strongly disagree to strongly agree)		AV Ownership (2-level: buy or never buy)	
	Coef	t-stat	Coef	t-stat
Endogenous variable				
Interest in sending AVs to run errands	—	—	0.39	48.99
Latent constructs				
Driving enjoyment	-0.37	-24.90	-0.54	-19.52
Technology savviness	0.20	13.20	0.24	8.95
Environmental consciousness	—	—	-0.06	-2.14
Individual characteristics				
Gender (not female)				
Female	—	—	-0.36	-15.68
Age (*)				
18-30 years	—	—	0.36	11.95
31-40 years	0.26	11.55	—	—
Race (*)				
Asian or Pacific Islander	—	—	0.41	11.23

White or Caucasian	0.08	5.21	—	—
Employment (not a worker)				
Worker	0.11	7.37	—	—
Household characteristics				
Household income (*)				
$150,000 to $250,000	0.19	8.96	—	—
$100,000 or more	—	—	0.33	16.60
Household structure (not a nuclear family)				
Nuclear family	—	—	0.15	6.24
Household vehicles (less than three)				
Three or more	-0.16	-10.93	—	—
Other characteristics				
Weekly VMT (less than 1 or over 25 mi)				
1 to 25 mi	—	—	-0.14	-6.02
Location (Austin, Phoenix, Tampa)				
Atlanta	0.05	3.62	—	—
Online shopping (zero delivery)				
At least one online delivery in last month	0.32	14.89	—	—
Thresholds				
1|2	-0.72	-28.22	0.90	30.30
2|3	-0.11	-4.40	—	—
3|4	0.49	19.29	—	—
4|5	1.61	58.95	—	—
Correlation				
AV errands	—	—	0.21	—

Data Fit Measures	**Joint (GHDM) Model**	**Independent (IOP) Model**
Log-likelihood at convergence	-6966.52	-6990.25
Log-likelihood at constants	-7408.59	
Number of parameters	79	32
Likelihood ratio test	0.0597	0.0565
Average probability of correct prediction	0.153	0.152

Contrary to previous studies that have largely reported no differences among racial groups with respect to AV adoption (e.g., Lavieri and Bhat, 2017; Wang and Zhao, 2019; Rahimi et al., 2020), the analysis in this study reveals significant race effects with Asians more inclined to own an AV and Whites exhibiting a greater proclivity towards sending AVs to run errands. Although the underlying reasons for these racial differences are not immediately apparent, recognizing their presence is critical to advancing equity in AV deployment. Not surprisingly, workers – who are likely to be more time-stressed – exhibit a greater proclivity to send AVs to run errands, but do not necessarily show a greater tendency to own AVs (finding also reported by Asmussen et al., 2020).

In general, higher income is associated with a higher probability of sending AVs to run errands and a greater proclivity towards purchasing AVs; these income effects are consistent with expectations and similar to those reported in prior studies (e.g., Moody et al., 2020). A nuclear family household (household with multiple adults and children) is more likely to purchase an AV, presumably due to the convenience that personal vehicle ownership affords in meeting the varied mobility needs of such a household. Households with three or more vehicles are less inclined to send AVs to run errands, presumably because there is a reduced need to share vehicles among household members in such households. Among the survey respondents, Atlanta residents indicated a higher propensity to send AVs to run errands; given that Atlanta suffers from some of the worst traffic congestion in the nation (Pirani, 2019), this finding is not surprising. Other intuitive findings include the result that those who travel limited miles on a weekly basis (1-25 miles) are less inclined to own an AV and those who received at least one online delivery in the previous month are more likely to send AVs to run errands. Both results are consistent with expectations; those who do not travel much are naturally inclined to feel a lower need for personal ownership of an AV, while those who engage in online shopping are likely to use an AV to run errands (pick up goods and deliver to the home).

From a goodness-of-fit standpoint, the joint model is found to offer a modest but statistically significant better fit than a corresponding independent model system in which error correlations engendered through the endogenous treatment of latent attitudinal constructs are ignored (restricted to zero by virtue of treating attitudinal variables as exogenous variables, similar to socio-economic and demographic variables). This shows that modeling latent attitudinal constructs and behavioral outcomes of interest in an integrated framework that recognizes endogeneity is critical to capturing the jointness in attitudes and behaviors.

3.6 Study Implications and Conclusions

Transportation is experiencing revolutionary transformations and disruptions in recent years. One key disruption is related to the development of automated (also referred to as autonomous) vehicles capable of navigating roadways on their own without the need for any human intervention or presence in the vehicle. Automated vehicles, when fully deployed in Level 5 (SAE, 2021), will be capable of traveling in completely autonomous mode. The implications of such an AV future are of much interest to the profession. AVs may enter the transportation landscape and foster a more sustainable and livable ecosystem with shared automated electric vehicles (SAEV) serving the mobility needs of society and eliminating the need for private ownership of vehicles. This constitutes a utopian AV scenario. A more dystopian AV scenario (which is what most travel demand forecasting models are prone to predict) is one in which households acquire and own AVs for themselves, AVs enable households and individuals to live farther away from destinations, AVs induce additional travel, and personally owned AVs roam highways and streets with zero occupants, running errands and parking themselves.

This work is particularly concerned with an aspect of the dystopian scenario in which households personally own AVs and use them to run errands autonomously (with zero occupants). If households are interested in using AVs to autonomously run errands, then they may be more inclined to own AVs for themselves (rather than depend on a shared fleet for mobility services). Using data from a survey conducted in 2019 in four large automobile-oriented metropolitan regions in the United States, this chapter aims to shed light on the relationship between level of interest in sending AVs to run errands and the intent to purchase and own an AV personally. The respondent sample is drawn from the Phoenix, Austin, Atlanta, and Tampa Bay metropolitan areas. All four of these regions are automobile-centric and characterized by dispersed land use patterns (and rather poor transit service).

The relationship between interest in sending AVs to run errands and acquiring AVs for private ownership is explored through the specification and estimation of a joint simultaneous equations model system. In addition, the model structure adopted in this study explicitly accounts for the role of attitudinal factors in shaping the nature of the relationship between the two endogenous variables. The study considers three latent attitudinal factors that are endogenous variables themselves. The model structure accounts for possible error correlations that may arise from the presence of correlated unobserved attributes that simultaneously affect multiple endogenous variables, thus capturing jointness in the behavioral dimensions of interest. The entire model system is estimated in a single step using the Generalized Heterogeneous Data Model (GHDM) methodology.

Model estimation results show that, even after accounting for all socio-economic and demographic variables as well as latent attitudinal constructs, the level of interest in having AVs run errands has a positive and significant effect on AV ownership. In other words, those who have an interest in sending AVs to run errands are more likely to purchase and own AVs privately. The three latent constructs considered in this study include measures of driving enjoyment, technology savviness, and environmental consciousness. These latent attitudinal factors influence both behavioral dimensions of interest and are themselves influenced by socio-economic and demographic characteristics. It is found that those who enjoy driving or are environmentally conscious are less likely to acquire AVs for personal ownership. Those who are technology-savvy are more likely to be interested in sending AVs to run errands and acquire AVs for private ownership.

The findings point to the need to prepare for the advent of this technology in the transportation landscape. If and when AVs become a reality, would it be desirable to have the technology capable of running errands autonomously? While such a feature may be of value to special market segments (such as those with mobility limitations), it is unclear if this capability is truly desirable on a widespread basis. Such technological capabilities may result in large numbers of AVs being used to run errands and roam the streets in zero-occupant mode. In addition, such capabilities will lead to private ownership of AVs on a larger scale as evidenced by the findings in this study. In order to have AVs enter the transportation landscape in a more sustainable manner, it may be advisable to ensure that AVs should limit their function in autonomous zero-occupant mode. This will limit the potential for induced travel and avoid a scenario where large numbers of zero-occupant vehicles are traveling on roadways.

If the technology is going to be capable of such zero-occupant travel (for running errands, parking itself, and picking up people at remote locations), then policies should be put in place to curtail the amount of such travel. Every zero-occupant vehicle trip could be assessed a fee to disincentivize the indiscriminate use of such technology. This would help ensure that only those zero-occupant trips that are truly necessary will be undertaken. In addition, the fee can vary by time of day, location, and size and fuel type of vehicle to advance a more sustainable approach to AV adoption and use. The other key finding is that environmental consciousness (latent factor) is associated with a lower proclivity towards AV ownership as well as a lower level of interest in sending AVs to run errands (relative to technology-savvy individuals). It may be helpful to organize information and awareness campaigns to raise environmental consciousness, especially surrounding the adoption and use of AVs. Through such campaigns, it may be possible to prevent a dystopian scenario characterized by the unbridled use of AVs to run errands in autonomous mode.

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4 A MULTIDIMENSIONAL ANALYSIS OF WILLINGNESS TO SHARE RIDES IN A FUTURE OF AUTONOMOUS VEHICLES

ABSTRACT

A sustainable transportation future is one in which people eschew personal car ownership in favor of using automated vehicle (AV) based ridehailing services in a shared mode. However, the traveling public has historically shown a disinclination towards sharing rides and carpooling with strangers. In a future of AV-based ridehailing services, it will be necessary for people to embrace both AVs as well as true ridesharing to fully realize the benefits of automated and shared mobility technologies. This study investigates the factors influencing willingness to use AV-based ridehailing services in the future in a shared (with strangers) mode. This is proposed by an estimation of a comprehensive behavioral model system on a comprehensive survey data set that includes rich information about attitudes, perceptions, and preferences regarding the adoption of automated vehicles and shared mobility modes.

4.1 Introduction

The transportation ecosystem has experienced a few key disruptions in the recent past. After several decades of little to no innovation and game changing technologies, the world of transportation has seen the emergence of new mobility options and technology disruptors within the span of 15 years. A key development in the transportation space is the rise of ridehailing services, also referred to as mobility-on-demand (MOD) services or mobility-as-a-service (MaaS), which enable individuals to summon a curb-to-curb ride using a convenient mobile application that integrates trip/vehicle tracking and payment.

Ridehailing services have grown rapidly in the past decade and are now offered in cities and countries around the world; companies that offer such services include Lyft in the US, Uber in many different countries, Didi in China, and Ola in India (along with several other Australasian nations). Ridehailing services now serve millions of trips worldwide on a daily basis. In a few markets, ridehailing services have introduced true rideshare services where complete strangers ride together in the same vehicle; such shared rides come at a lower cost, but a longer travel and wait time due to the circuity imposed by sharing. Due to the complexity of ride matching and the reluctance of consumers to accept a travel time penalty in exchange for lower cost, the rideshare feature has been implemented in only select markets (Malik et al., 2021). Many believe ridehailing services exhibit the potential to reduce private vehicle ownership (Tirachini, 2020; Sikder, 2019), as individuals increasingly embrace a service-based transportation system (thus reducing the need to rely on privately owned cars).

At the same time, rapid advances are being made in transportation automation with the development of automated vehicles offering the promise for driverless transport in the future (An et al., 2022; Zhang et al., 2022). In fact, such driverless rides are now being offered in a couple of markets (McAslan et al., 2021; Etminani-Ghasrodashti et al., 2022), ushering in a whole new era of mobility. The impediment to widespread adoption of ridehailing services is that the fare is rather prohibitive for regular/daily use of such services (Henao et al., 2019). If, however, the driver is removed from the equation, then the price of such services may potentially drop significantly (Gurumurthy et al., 2019; Hyland and Mahmassani, 2020; Zafar et al., 2022), although there is some continued uncertainty of the extent to which fares could drop even in an automated vehicle-based ridehailing service future (Irannezhad and Mahadevan, 2022). Because of the potential game changing nature of automated vehicle technology, many have touted a utopian future vision of transportation characterized by shared automated vehicles (SAV) providing mobility-as-a-service at scale roaming around the streets of a city, providing low-cost on-demand shared rides. If the vehicles are electric, that would further advance a utopian transportation future in which vehicular travel leaves behind a much smaller operational carbon footprint. And if the vehicles are connected, enabling vehicle-to-vehicle and vehicle-to-infrastructure communication, additional efficiencies can be gained in a future of automated, connected, electric, shared (ACES) vehicles providing rides on-demand.

The utopian vision of a safe, sustainable, affordable, and automated transportation future will only be realized only if people *share* rides in large numbers (Batur et al., 2022; Merlin, 2019). Although travel demand may decrease in a scenario where individuals pay by the trip, substantial gains (in terms of reduced number of vehicle trips) can only happen if people are willing to, and actually do, share rides on a consistent basis. However, the history of ridesharing in the United States is not particularly encouraging. Average vehicle occupancies have continuously decreased over time in the US and carpool mode share has exhibited a consistent decline over the past several decades, despite many efforts to promote carpooling through the construction of high occupancy vehicle (HOV) lanes, managed lanes, and rideshare programs and incentives (Olsson et al., 2019). With millions of driverless automated vehicles available to service rides on-demand, shared rides could potentially be offered with minimal inconvenience at low cost. In such an automated vehicle service future, to what extent would individuals be willing to *share* rides with strangers? Who would be early adopters of such *shared* automated vehicle services, and who would be reluctant to participate in such a mobility future? Does current experience with private or shared ridehailing services affect the willingness to share rides in an automated vehicle future? These are the questions that this study seeks to answer through a rigorous behavioral modeling exercise. It is envisaged that insights to these questions will help in the identification and recruitment of early adopters; these early successes can then be marketed and communicated to the reluctant market segments with a view to influence their attitudes and perceptions and bring them on-board as well. If current experience with private or shared ridehailing services has a positive effect on willingness to share rides in an automated vehicle future, then efforts and campaigns may be directed towards enabling individuals to gain such experiences in the current ecosystem.

The literature dedicated to understanding willingness to share in an automated vehicle mobility-as-a-service future is rather limited (Lavieri and Bhat, 2019a; Gurumurthy and Kockelman, 2020). There is a vast body of literature that has examined the adoption of ridehailing services and the characteristics of those who are more or less likely to use such services (Dias et al., 2017). In general, it is found that younger age, highly educated, technology-savvy, urban dwellers are more likely to embrace ridehailing services. A number of studies have also explored the willingness of individuals to adopt and ride in automated vehicles. Studies have explored factors affecting willingness to ride alone (Lavieri et al., 2017) and in a shared modality (Stopher et al., 2021; Gurumurthy et al., 2019; Hyland and Mahmassani, 2020). In general, it is found adopters of shared automated vehicle services would include low income individuals (Sener and Zmud, 2019), and those with higher levels of education (Gurumurthy and Kockelman, 2020). Although these studies present excellent insights, there is very limited knowledge of the role of current ridehailing experience in shaping willingness to ride automated vehicles in the future in different modalities (alone, with friends and family, or with strangers). In addition, even if a prior study purported to study this particular linkage, the influence of attitudinal factors was rarely incorporated.

One exception is the study by Lavieri and Bhat (2019a), which considered the influence of attitudinal factors in examining the relationship between current experiences and future intentions to use shared/private ridehailing services for commute and leisure trips. The study was based on survey data collected from commuters in Dallas, TX, and it employs a stated choice experiment to elicit information about future intentions. This experiment involved presenting respondents with AV-based ridehailing options for hypothetical trips that varied in time, cost, and other factors, and asking them to choose between solo and pooled options. Given the experiment's focus on individual trips, the study incorporated attitudinal factors that may have the most significant influence on shaping decisions in this context, including privacy sensitivity, time sensitivity, and interest in the productive use of travel time. Despite its valuable contributions to the body of literature, this study is limited in a number of ways, as indicated by its conceptualization and objectives. While the study focuses on hypothetical individual trips with varying trip characteristics, its findings may not necessarily indicate general tendencies toward the willingness to use AV-based ridehailing services, whether in private or shared mode. Additionally, the selected attitudinal constructs are limited in that they largely apply to trip-specific decision-making processes. Thus, they do not provide much information about the general attitudes, personality, and lifestyle preferences of the respondents, which may be useful in developing policies to incentivize such services. Finally, the findings of the study may not be generalizable or transferable to other population groups or geographical areas, since it is based on a sample of commuters from Dallas, TX.

The current study further explores how current experiences with ridehailing services influence people's willingness to ride in AV-based ridehailing services in the future by addressing the challenges and limitations identified in previous research. It involves the specification and estimation of a simultaneous equations model system in which current ridehailing experience and future willingness to share rides in an autonomous vehicle future are modeled jointly. The model is estimated on a data set derived from a detailed survey conducted in 2019 in four automobile-oriented metropolitan areas in the United States, namely, Phoenix, Austin, Atlanta, and Tampa, offering a nuanced understanding of the potential geographic disparities that may impact the phenomena under investigation. The respondent sample included individuals aged 18 years and above, thereby enabling generalizations to be drawn about entire population groups. The survey includes detailed information about current ridehailing experience and stated willingness to ride in automated vehicles in alternative configurations in the future (ride alone, ride with family and friends, ride with strangers). Thus, the study aims to measure overall tendencies towards using AV-based ridehailing services, rather than focusing on choices for individual trips. The proposed model system is strengthened by the inclusion of a number of latent attitudinal constructs to account for their influence in shaping mobility choices and willingness to share rides with strangers. A host of socio-economic and demographic variables serve as exogenous explanatory variables. The entire model system is estimated in a single step through the use of the Generalized Heterogenous Data Model (GHDM) methodology developed by Bhat (2015).

The remainder of the chapter is organized as follows. The next section presents a detailed description of the data and the endogenous variables of interest. The third section presents the modeling framework and methodology, and the fourth section that presents detailed model estimation results. Finally, the fifth section offers a discussion of the study implications and concluding thoughts.

4.2 Data

This subsection presents an overview of the survey data set used in this study. First, an overview of the survey and the sample description is provided, and second, deeper insights on the endogenous variables and attitudinal indicators used in the modeling effort are furnished.

4.2.1 Characteristics of the Sample

The data set used in this study is derived from a comprehensive survey conducted in 2019 in four automobile-oriented metropolitan areas in the US, namely, Phoenix (Arizona), Austin (Texas), Atlanta (Georgia), and Tampa (Florida). The survey was specifically aimed at gathering very detailed information about attitudes and perceptions towards emerging transportation technologies such as ridehailing services, micromobility technologies, and autonomous vehicles. The survey also gathered detailed socio-economic, demographic, and mobility behavior data so that the responses of individuals to questions about ridehailing services and automated vehicles could be placed in appropriate context. Full details about the survey instrument, questions/content, sampling strategies, response rates, and weighting methods are documented in Khoeini et al. (2021).

A total of 3,465 responses were collected. After removing records with missing data and filtering obviously erroneous records, the clean data set included 3,377 respondents. All respondents are adults (18+ years of age) residing in the specific four metropolitan areas of the United States. Table 7 provides an overview of the sample characteristics. It is found that there is a slightly larger share of females (at 57 percent), and a somewhat larger share of young (18-30 years) individuals in the respondent sample. Only 6.6 percent of respondents report not having a driver's license. Just over one-half of the sample is employed with 26.8 percent of the respondents indicating that they are neither a worker nor a student. Educational attainment distribution shows that the sample is fairly well-educated overall, with 36.5 percent having a Bachelor's degree and 24.5 percent having a graduate degree. Just over seventy percent of the respondents are White and 7.6 percent are Black. The income distribution shows that 34 percent fall in the middle household income range of $50,000 to $99,999 per year. The sample shows a good variation across the different income groups. About 40 percent of the respondents reside in households with three or more members, 70 percent reside in a stand-alone home, and 68 percent own the home in which they reside. Vehicle ownership profile shows that only four percent reside in households with no vehicles, which is not surprising given the very automobile-oriented nature of the transportation systems in the four metropolitan areas where data was collected. A smaller percent of respondents (just 7.6 percent) are based in Tampa, with the remainder of the sample quite evenly spread across the other three metro areas.

Table 7 Sample Socio-economic and Demographic Characteristics

Individual Characteristics (N = 3,377)		Household Characteristics (N = 3,377)	
Variable	%	Variable	%
Gender		**Household annual income**	
Female	56.9	Less than $25,000	10.7
Male	43.1	$25,000 to $49,999	15.8
Age category		$50,000 to $99,999	34.1
18-30 years	26.0	$100,000 to $149,999	21.0
31-40 years	11.4	$150,000 to $249,999	12.4
41-50 years	14.9	$250,000 or more	6.0
51-60 years	16.7	**Household size**	
61-70 years	16.1	One	21.2
71+ years	14.9	Two	38.7
Driver's license possesion		Three or more	40.1
Yes	93.4	**Housing unit type**	
No	6.6	Stand-alone home	70.2
Employment status		Condo/apartment	20.6
A student (part-time or full-time)	10.1	Other	9.3
A worker (part-time or full-time)	52.1	**Home ownership**	
Both a worker and a student	11.0	Own	68.0
Neither a worker nor a student	26.8	Rent	26.0
Education attainment		Other	6.0
Completed high school or less	9.3	**Vehicle ownership**	
Some college or technical school	29.7	Zero	3.9
Bachelor's degree(s) or some grad. School	36.5	One	24.0
Completed graduate degree(s)	24.5	Two	39.9
Race		Three or more	32.2
Asian or Pacific Islander	8.8	**Location**	
Black or African American	7.6	Atlanta, GA	29.6
Native American	0.5	Austin, TX	32.1
White or Caucasian	71.0	Phoenix, AZ	30.7
Other	12.2	Tampa, FL	7.6
Endogenous Variables	%		%
Willingness to Use AV Ridehailing Service: Private (Alone or Family/Friends)		**Willingness to Use AV Ridehailing Service: Pooled with Strangers**	
Strongly disagree	18.4	Strongly disagree	30.7
Somewhat disagree	11.7	Somewhat disagree	27.5
Neutral	22.1	Neutral	21.4
Somewhat agree	34.9	Somewhat agree	16.4
Strongly agree	12.9	Strongly agree	4.0

4.3 Endogenous Variables and Attitudinal Indicators

This study aims to understand user willingness to ride in a future automated vehicle (AV) based ridehailing service in different modes – *private mode* (riding alone or with friends and family) and *shared mode* (riding with strangers). The survey included questions asking respondents to indicate the degree to which they agree that they are willing to ride in AV-based ridehailing services (in the future) in each of these modes (bottom of Table 7). As expected, individuals are more agreeable to riding in an AV-based ridehailing service in a private mode, either alone or with friends and family.

The objective of this chapter is to examine the potential influence of experiences with using *current* ridehailing services on the degree to which individuals are willing to use *future* AV-based ridehailing services in a private or shared mode. Respondents were asked to indicate the frequency with which they currently use ridehailing services. Although pooled ridehailing services (such as UberPool and LyftShare) are not offered in all four metropolitan area markets, these services are available in select markets. As such, some respondents reported having experience with pooled ridehailing services. Based on the responses to current ridehailing experience questions, respondents were grouped into three categories:

- <u>No experience</u>: if a respondent has not used (or is unfamiliar with) *both* private and pooled ridehailing service options;
- <u>Private ridehailing experience only</u>: if a participant has used private ridehailing services (ride alone or with friends and family only) but has no experience with the shared option; and

- Pooled (shared) experience: if a participant reported using shared ridehailing services, involving strangers as fellow passengers (note that individuals in this group may have also used ridehailing services in a private mode).

As expected, among individuals who fall into the third group (experienced shared ridehailing services), the vast majority of respondents have also experienced private ridehailing services. Figure 7 depicts the bivariate relationship between the intention to use AV ridehailing services in the future and current ridehailing experience.

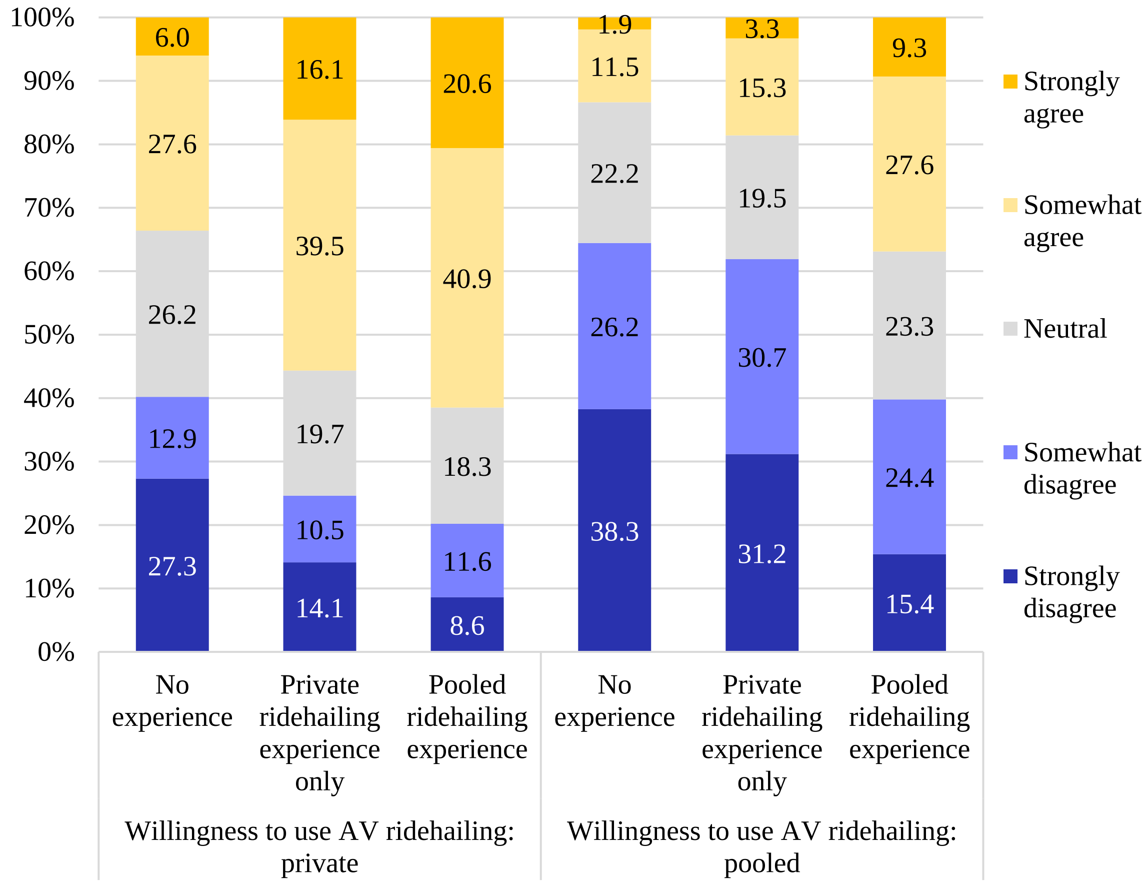

Figure 7 Willingness to Use AV Ridehailing Services by Current Ridehailing Experience (N= 3,377)

The bivariate chart depicts a discernible pattern, suggesting that there is an association between current experience with using ridehailing services and the future intentions of using AV-based services in different modes. The percent that is not inclined to use AV-based ridehailing services in the future declines as the current experience with ridehailing services is richer. In general, the graphic shows that the percent willing to ride privately in AV-based ridehailing services exceeds the percent willing to *share* rides with *strangers* in an AV-based ridehailing future. This bivariate relationship and the overall socio-economic profile of the sample renders the data set suitable for the type of modeling effort undertaken in this chapter.

An important set of determinants of the adoption of new technologies and mobility options is attitudes, values, perceptions, and preferences. These traits are often not captured in survey data sets, and simply assumed to be part of the unobserved random error term in statistical and econometric choice models. To overcome this limitation and capture the relationship between current and future ridehailing service use more accurately, this study incorporates the influence of attitudinal variables within the overall modeling exercise. The survey included a large number of attitudinal statements, many of which are correlated with one another; these statements were intended to elicit information about the degree to which individuals embrace new technologies, are environmentally oriented, enjoy social interactions, and would like to reside in urban environments of different types (besides a host of other attitudes related to lifestyle and mobility preferences). Based on an extensive review of the literature, a series of trials of alternative model specifications, and behavioral intuitiveness considerations, three attitudinal constructs are specified and utilized in this study. They may be termed as *AV Technology Trust*, *Discomfort Around Strangers*, and *Transit-oriented Lifestyle*.

The latent constructs used in this study are not uncommon, as similar psycho-social factors have been used in previous literature to analyze mobility choices in the context of emerging transportation technologies. For instance, Batur et al. (2022) included driving enjoyment, technology savviness, and environmental consciousness in their study to examine the interest in personal ownership and the use of autonomous vehicles for running errands. Similarly, Lavieri et al. (2019b) considered the effects of privacy-sensitivity, tech-savviness, variety-seeking lifestyle propensity, and green lifestyle propensity latent constructs when analyzing ridehailing adoption and use frequency, residential location choices, and vehicle availability patterns. In a study more relevant to the current study, Lavieri et al. (2019a) examine current ridehailing choices and future intentions to use shared rides and estimate individuals' willingness to share, as well as their values of travel time for different trip purposes. As the authors analyzed choices between solo and pooled AV-based ridehailing options for hypothetical trips, their chosen latent constructs (i.e., privacy-sensitivity, time sensitivity, and interest in the productive use of travel time) were reflective of the ones that are more relevant to shaping mobility choices in trip-specific contexts.

With this background, this study posits that the three latent constructs chosen in this study are important determinants of current ridehailing behaviors and the general willingness to use AV-based ridehailing services in the future. The *AV Technology Trust* latent construct is intended to capture the respondents' willingness to use AV-based ridehailing services compared to conventional ridehailing services. As prior experience with AVs significantly shapes people’s perceptions of the technology's safety (Stopher et al., 2021), it is reasonable to assume that this latent construct, which is formed by attitudinal statements related to various safety aspects of AV technology, also captures to some extent the respondents' any prior experience with AVs. In addition, the *Discomfort Around Strangers* latent construct aims to measure the extent to which respondents are concerned about their safety and security when sharing a ride or public space with strangers, as well as their desire for privacy or personal space. This discomfort may lead to a preference for traveling alone or with familiar people, which can ultimately result in a reduced willingness to use both AV-based and traditional ridehailing services in a pooled mode. Finally, the *Transit-oriented Lifestyle* latent construct reflects a lifestyle choice that many people adopt for various reasons, such as environmental concerns, shared-mobility preferences, cost savings, and convenience. This lifestyle choice is important for ridehailing usage as people who regularly use public transit may be more likely to use ridehailing services as a complementary mode of transportation to travel to destinations that are not easily accessible or during off-hours of transit. By including this latent construct in the modeling framework, the aim is to disentangle the impacts of this lifestyle preference on both current ridehailing usage and the willingness to use AV-based ridehailing services in the future.

Three attitudinal indicators were used to define each of the latent constructs. Figure 8 shows the latent factors and the respective attitudinal statement indicators that define them. For each attitudinal statement, the figure shows the distribution of responses ranging from *strongly disagree* to *strongly agree*. The distributions are intuitive and consistent with expectations. For the sake of brevity and given that the distributions and latent constructs are largely self-explanatory, a further in-depth description of the latent constructs is suppressed.

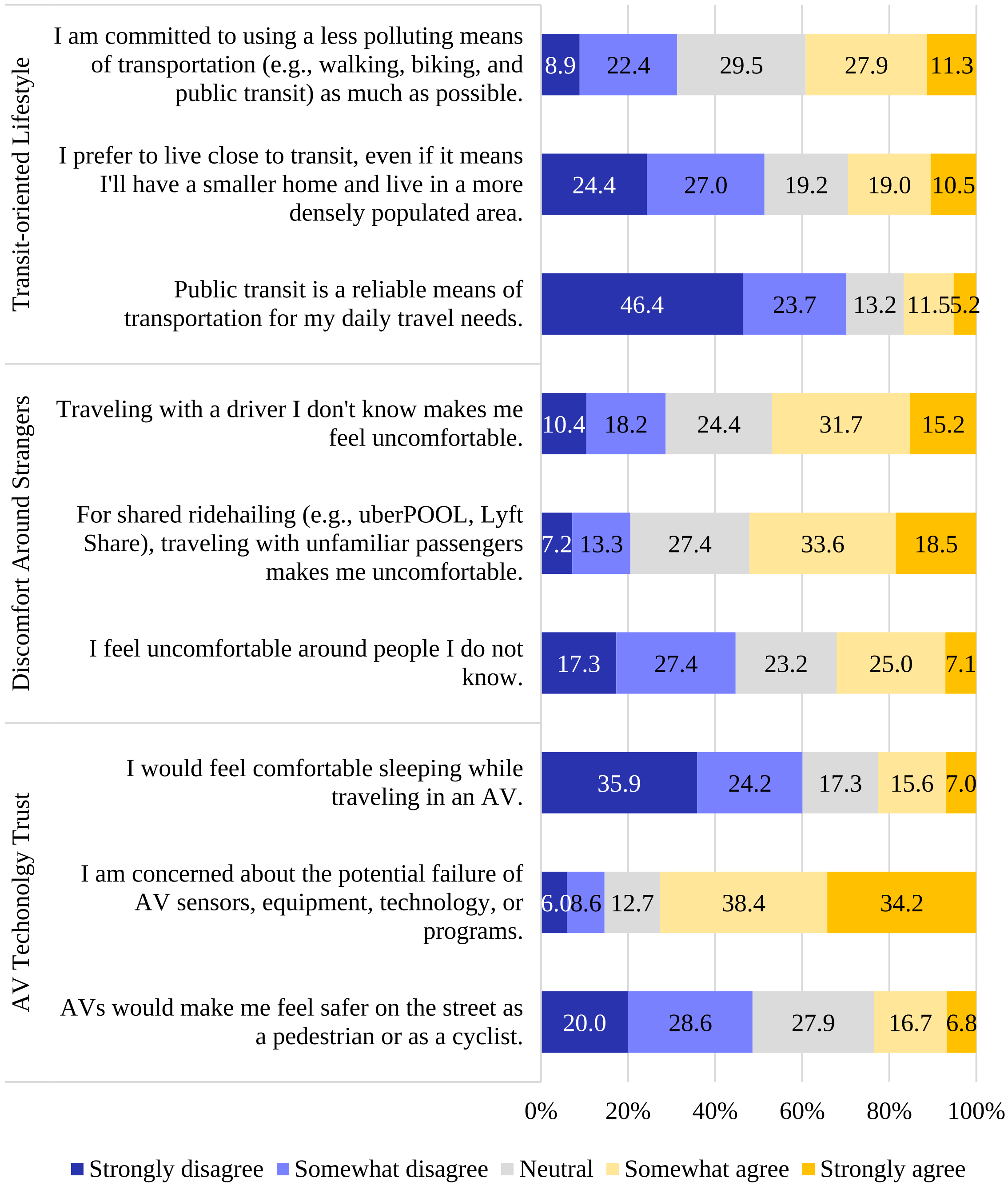

Figure 8 Distribution of Attitudinal Indicators of Latent Constructs (N= 3,377)

4.4 Modeling Approach

This section presents a brief overview of the model structure and formulation. In the interest of brevity, only a qualitative description of the modeling methodology is provided in this manuscript. A detailed exposition of the model formulation and estimation methodology is provided in the appendix and is not critical for understanding the empirical results presented later. The formulation is quite long and notation-intensive, and interested readers should refer to Bhat (2015) for details.

4.4.1 Model Structure

This subsection presents the behavioral modeling framework adopted in this study. A simplified representation of the model structure is shown in Figure 9. The model system is intended to connect two key endogenous variables, namely, the *current ridehailing experience* and the future *stated intention to use AV-based ridehailing services in different modalities* (private versus shared). Thus, the right hand side of the figure shows the dependent variables with current ridehailing experience influencing the willingness to ride future AV-based ridehailing services in a private or shared mode. It is hypothesized that current ridehailing experience would play a role in shaping people's willingness to ride in future AV-based services, and the bivariate relationship depicted in Figure 7 supports this hypothesis. A host of socio-economic, demographic, household, and other travel and built environment attributes are treated as exogenous variables. They are assumed to influence both the latent constructs as well as the main outcomes (endogenous variables). The three latent constructs serve as mediating variables; they are both influenced by the exogenous variables, and in turn, they influence the main outcome variables of interest. Correlations between the attitudinal constructs are accommodated to reflect the possible presence of correlated unobserved factors simultaneously affecting multiple behavioral measures and latent attitudinal variables. This is possible because the latent attitudinal constructs are treated as stochastic variables with a random error term. Because error correlations between the latent constructs are explicitly accommodated in the model formulation, it is not necessary to separately specify error correlations between the main outcome variables. The error correlations between the latent constructs engender error correlations between the main outcome variables by virtue of the joint model specification in which all parameters and relationships are estimated simultaneously in a single step using the Generalized Heterogeneous Data Model (GHDM) methodology (Bhat, 2015). Thus, the model structure accounts for endogeneity, the stochastic nature of latent constructs, and error correlations between latent constructs and between the main endogenous variables of interest. The full model estimation methodology is provided in the Appendix. Further details about the error structures may be found in Bhat (2015).

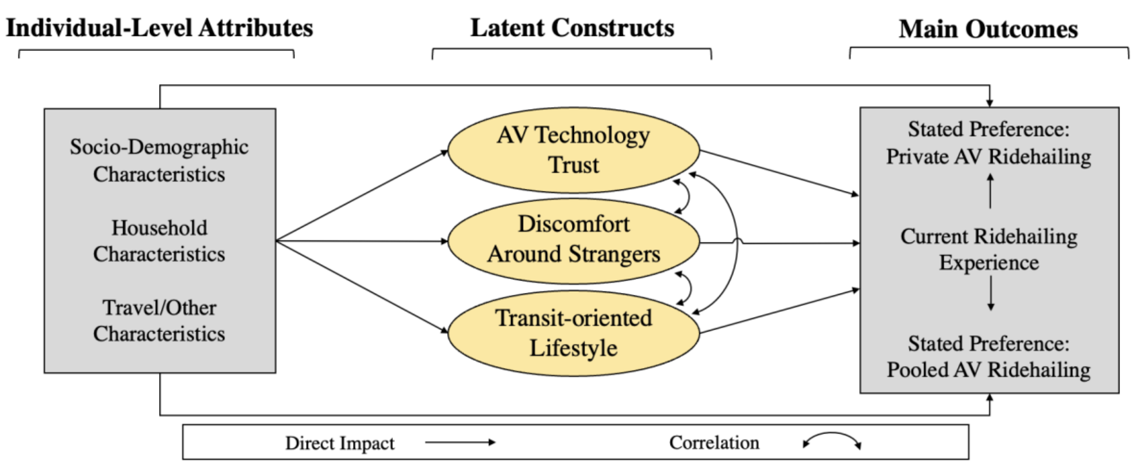

Figure 9 Model Structure and Behavioral Framework

4.4.2 Model Estimation Methodology

The modeling methodology adopted in this study is a special case of the Generalized Heterogeneous Data Model (GHDM) developed by Bhat (2015). The model is adapted to accommodate one multinomial (nominal) choice variable (corresponding to current ridehailing experience) and two ordinal choice variables (corresponding to degree of willingness to ride in an AV-based ridehailing service in the future in a private or shared mode). The private AV-ridehailing and shared AV-ridehailing measures constitute two ordinal dependent variables that are influenced by the nominal choice variable of current ridehailing experience. A direct relationship between the outcome variables may be incorporated because of the behaviorally intuitive and logical nature of the influence. As mentioned earlier, unobserved stochastic psychosocial constructs serve as latent factors that provide a structure to the dependence among the endogenous variables of interest, while the latent constructs themselves are explained by exogenous variables and may be correlated with one another in a structural relationship.

There are two components to the latent factors component of the GHDM model. The first is the latent variable structural equation model (SEM) and the second is the measurement equation model (MEM) relating latent factors to their attitudinal measures. The SEM component defines stochastic latent constructs as a function of exogenous variables and unobserved error components that may be correlated with one another. The joint model of endogenous outcomes captures the influence of latent factors and socio-economic variables on the dependent variables of interest. No separate error correlations are estimated because the error terms of the SEM equations (which define the latent variables) permeate into the endogenous choice model component (which describes the outcome variables), resulting in an efficient and compact dependence structure among all endogenous variables. The error terms are assumed to be drawn from multivariate normal distributions (with the dimension equivalent to the number of latent variables).

The formulation depends on the types of dependent variables comprising the model, following the usual ordered response formulation with standard normal error terms for the ordinal indicator variables, and the typical random utility-maximization model with a probit kernel for the nominal and ordinal outcomes of primary interest. The latent constructs are estimated at the person level (as a stochastic function of individual socio-economic attributes). These latent constructs influence the current ridehailing experience endogenous variable in a cross-sectional setting (one observation per respondent) as well as both AV ridehailing interest (private and pooled) endogenous variables. In doing so, the model structure simultaneously captures not only unobserved factors impacting the indicator and endogenous outcomes of interest, but also accounts for covariations among the three endogenous variables of the same individual. Thus, the stochastic latent factors help to efficiently incorporate observed and unobserved individual heterogeneity in variables of interest through interactions of the latent factors with exogenous variables. The GHDM was estimated according to methods described in Bhat (2015) and Bhat (2018) and further details are available in the Appendix.

4.5 Model Estimation Results

Detailed model estimation results are furnished in this section. As the GHDM comprises two components, they are presented and discussed in sequence.

4.5.1 Latent Construct Model Components

The results for the latent construct model component are presented in Table 8. The table has two parts to it. The first part shows the influence of various exogenous variables on the three latent constructs. The second part shows the factor loadings of latent variables on the various attitudinal indicators that define them. The top half of the table shows that the latent attitudinal constructs are influenced by a host of socio-economic and demographic variables.

Table 8 Determinants of Latent Variables and Loadings on Indicators (N=3,377)

	Latent construct model					
	AV technology trust		Discomfort around strangers		Transit-oriented lifestyle	
Explanatory variables (base category)	Coef	t-Stat	Coef	t-Stat	Coef	t-Stat
Age (*)						
18-40 years	0.28	7.26	na	na	0.30	5.43
65 years or older	na	na	0.13	2.78	na	na
Gender (male)						
Female	-0.46	-12.81	0.44	12.19	na	na
Race (not Black or African American)						
Black or African American	-0.26	-3.76	na	na	na	na
Employment (*)						
Worker	na	na	-0.14	-3.67	na	na
Student	na	na	na	na	0.59	8.53
Both worker and student	0.16	2.66	na	na	na	na
Education (less than Bachelor's degree)						
Bachelor's or graduate degree	na	na	-0.12	-3.28	0.16	3.46
Household structure (not in a nuclear family)						
Nuclear family	na	na	na	na	-0.15	-2.73
Household annual income (*)						
Less than $50,000	na	na	na	na	0.30	5.76
$100,000 or more	0.16	4.59	–	–	na	na
Correlations between latent constructs						
AV technology trust	1.00	na	-0.27	-8.32	0.21	4.44
Discomfort around strangers	na	na	1.00	na	-0.18	-3.32
Transit-oriented lifestyle	na	na	na	na	1.00	na
Attitudinal indicators	Loadings of latent variables on indicators (measurement equation model component)					
AVs would make me feel safer on the street as a pedestrian or as a cyclist.	0.97	50.62	na	na	na	na
I am concerned about the potential failure of AV sensors, equipment, technology, or programs.	-1.15	-55.64	na	na	na	na
I would feel comfortable sleeping while traveling in an AV.	1.25	58.46	na	na	na	na
I feel uncomfortable around people I do not know.	na	na	0.29	15.95	na	na
For shared ridehailing (e.g., uberPOOL, Lyft Share), traveling with unfamiliar passengers makes me uncomfortable.	na	na	1.09	27.76	na	na
Traveling with a driver I don't know makes me feel uncomfortable.	na	na	1.61	18.41	na	na
Public transit is a reliable means of transportation for my daily travel needs.	na	na	na	na	0.66	27.55
I prefer to live close to transit, even if it means I'll have a smaller home and live in a more densely populated area.	na	na	na	na	0.51	21.72
I am committed to using a less polluting means of transportation (e.g., walking, biking, and public transit) as much as possible.	na	na	na	na	0.28	13.56

Note: Coef = coefficient; "–" = not statistically significantly different from zero at the 90% level of confidence;
"na" = not applicable; *Base category is all other complementary categories for the corresponding variable.

As expected, younger individuals depict a higher level of trust in technology and embrace a transit-oriented lifestyle more than older age groups; these findings are consistent with expectations and prior literature (Hulse et al., 2018; Nielsen et al., 2018). Older individuals are less comfortable around strangers, reflecting a more cautious attitude that comes with age. Females trust technology less and are more uncomfortable around strangers due to privacy and security concerns (also reported by Sener et al., 2019). Blacks depict a lower trust in AV technology, presumably due to the digital divide, as documented in the literature that Blacks and other minority groups do not enjoy the same level of technology access as majority groups (Wu et al., 2021). Students are more likely to embrace a transit-oriented lifestyle (consistent with expectations and findings reported by Brown et al., 2016), while individuals who are both workers and students trust AV technology more so than others. This is likely a reflection of the greater exposure to technology experienced by individuals who are both workers and students. Households that constitute a nuclear family are less likely to be transit-oriented; households with children likely reside in lower density suburban neighborhoods and are therefore more car-oriented than other types of households that may reside in urban contexts (Magassy et al., 2022a). Lower income individuals are more transit-oriented while high-income individuals depict a higher level of trust in AV technology. The error correlations show a negative relationship between AV technology trust and discomfort around strangers. This makes sense in that unobserved factors that enhance AV technology trust (e.g., like to be more adventurous and risk-taking) are likely to contribute to lower discomfort of being around strangers. On the other hand, there is a positive error correlation between AV technology trust and transit-oriented lifestyle, while there is a negative correlation between discomfort around strangers and transit-oriented lifestyle. Those who value privacy (uncomfortable around strangers) are likely to eschew a transit-oriented lifestyle in favor of an automobile-oriented lifestyle. These findings are consistent with expectations, justifying the adoption of a joint simultaneous equations model.

The bottom half of the table shows the equivalent of factor loadings of latent variables on the attitudinal indicators. AV technology trust is positively associated with feeling safe on the streets with AVs present and feeling comfortable sleeping in an AV, but negatively associated with concern about potential technology failure. These are behaviorally intuitive and statistically significant loadings. For discomfort around strangers, all three loadings are positive; the attitudinal statements correspond to indicators that measure the degree of discomfort around unknown people, discomfort traveling with unfamiliar passengers, and discomfort traveling with a driver who is not known, and hence the positive loadings are behaviorally intuitive. Finally, the transit-oriented lifestyle construct is associated positively with attitudinal indicators measuring the extent to which individuals feel that public transit is a reliable means of travel, prefer living close to transit even at the expense of home size, and are committed to using less polluting means of transportation. Once again, all loadings have behaviorally intuitive signs and are statistically significant. These three latent constructs are used in the measurement equation model component to explain the relationship between current ridehailing experience and willingness to ride in a future AV-based ridehailing service in a private or shared mode.

4.5.2 Bivariate Model of Behavioral Outcomes

Table 3 presents estimation results for the measurement equation model component. This component corresponds to the behavioral outcomes of interest, namely ridehailing experience and willingness to use future AV-based ridehailing services in a private (alone or with friends/family) and shared/pooled (with strangers) mode.

Table 9 Estimation Results of the Joint Model of Intention to Use AV Ridehailing Services and Current Ridehailing Experience (N=3,377)

	Main outcome variables							
	Current ridehailing experience (base: no experience)				Private AV ridehailing (ordered, 5-level)		Pooled AV ridehailing (ordered, 5-level)	
Explanatory variables	Private only experience		Pooled experience					
(base category)	Coef	t-Stat	Coef	t-Stat	Coef	t-Stat	Coef	t-Stat
Current ridehailing experience (no experience)								
Private only experience	na	na	na	na	0.49	11.23	na	na
Pooled experience	na	na	na	na	0.63	11.15	0.60	10.14
Latent constructs								
AV technology trust	na	na	na	na	0.85	44.39	0.58	29.75
Discomfort around strangers	-0.32	-13.29	-0.42	-12.42	na	na	-0.33	-16.99
Transit-oriented lifestyle	na	na	0.94	24.86	na	na	0.16	6.37
Age (*)								
18-30 years	0.43	6.41	na	na	na	na	na	na
31-40 years	0.45	6.59	na	na	na	na	na	na
51-60 years	na	na	na	na	-0.22	-4.04	na	na
65 years or older	na	na	-0.29	-3.10	-0.34	-6.87	na	na
Gender (male)								
Female	0.28	5.71	0.25	3.75	0.10	2.53	na	na
Race (*)								
White	0.24	4.68	na	na	na	na	na	na
Non-Hispanic White	na	na	na	na	0.20	3.46	na	na
Asian or Pacific Islander	na	na	0.48	5.35	na	na	na	na
Employment (*)								
Worker	0.31	6.03	0.49	6.39	na	na	na	na
Student	na	na	-0.37	-4.07	na	na	na	na
Education (less than Bachelor's degree)								
Bachelor's or grad. degree	0.36	6.89	0.28	3.96	0.19	4.79	na	na
Household size (*)								
1	na	na	0.21	2.92	na	na	na	na
2	na	na	na	na	na	na	-0.16	-4.14
Vehicles available in household (zero)								
1 or more	na	na	-0.91	-7.67	na	na	na	na
Household annual income (*)								
\$50,000 to \$99,999	na	na	na	na	na	na	0.09	2.38
\$100,000 or more	0.61	11.74	0.69	9.84	na	na	na	na
Online shopping (no online deliveries in last month)								
At least one online delivery in last month	na	na	na	na	0.42	6.67	0.21	2.95

Estimation Results of the Joint Model of Intentions to Use AV Ridehailing Services and Current Ridehailing Experience (N=3,377) (continued)

Explanatory variables (base category)	Main outcome variables: Current ridehailing experience (base: no experience): Private only experience Coef	t-Stat	Pooled experience Coef	t-Stat	Private AV ridehailing (ordered, 5-level) Coef	t-Stat	Pooled AV ridehailing (ordered, 5-level) Coef	t-Stat
Location (*)								
Atlanta, GA	na	na	na	na	–	–	na	na
Austin, TX	0.10	1.82	0.63	8.30	na	na	na	na
Phoenix, AZ	na	na	na	na	0.14	2.75	0.16	3.71
Commute distance (*)								
Between 20-40 miles	na	na	na	na	na	na	–	–
Population density (high population density area)								
Low population density area (< 2900 persons/sq. mi.)	-0.21	-4.41	-0.27	-4.31	na	na	na	na
Constant	-1.07	-13.81	-1.20	-7.19	na	na	na	na
Thresholds								
1|2	na	na	na	na	-0.53	-6.32	0.33	3.96
2|3	na	na	na	na	0.01	0.10	-0.63	-7.70
3|4	na	na	na	na	0.82	10.08	-1.46	-17.40
4|5	na	na	na	na	2.33	26.85	-2.72	-28.33

Correlations	Private only experience	Pooled experience	Private AV ridehailing	Pooled AV ridehailing
Private only experience	1.00	0.44	0.05	0.12
Pooled experience	na	1.00	0.14	0.28
Private AV ridehailing	na	na	1.00	0.36
Pooled AV ridehailing	na	na	na	1.00

Data fit measures	GHDM	Independent model
Log-likelihood at convergence	-12090.58	-3710.01
Log-likelihood at constants	-13842.57	
Number of parameters	116	79
Likelihood ratio test	0.127	0.103
Avg. prob. Of correct prediction	0.039	0.035

Note: Coef = coefficient; "–" = not statistically significantly different from zero at the 90% level of confidence;
"na" = not applicable; *Base category is all other complementary categories for the correspondent variable.

The key findings of interest are related to the endogenous variable and latent construct effects. It can be seen that the current ridehailing experience has a significant impact on the willingness to use AV-based ridehailing services in the future. Individuals having only a private ridehailing experience thus far (currently) are, as expected, more likely to be willing to engage in private AV-based ridehailing services in the future. However they are *not* more likely to engage in shared AV-based ridehailing services. On the other hand, individuals who have experienced pooled ridehailing services (currently) are more likely to be willing to ride future AV-based ridehailing services in *both* a private mode and a shared mode. In other words, people need to have the experience of shared rides (for themselves) to overcome the hesitation to ride future AV-based services with strangers. This is a key finding that has important implications for the types of strategies that need to be deployed to enhance a shared mobility future.

Latent attitudinal factors also play a key role in shaping the endogenous outcomes of interest. As expected, AV technology trust positively influences the willingness to ride AVs in a private or shared mode. Those who are uncomfortable around strangers are less likely to use current ridehailing services (either in a private or pooled mode), which is not surprising, given that even riding privately in current ridehailing services entails being in the same vehicle with an unknown driver. Likewise, discomfort around strangers negatively influences the likelihood of being willing to ride future AV-based services in a shared mode. A transit-oriented lifestyle proclivity is, however, associated with a greater likelihood of being willing to ride future AV-based ridehailing services in a shared mode, presumably because such individuals are more open to using shared modes of transportation where fellow passengers are strangers. This is another set of key findings that has important implications for the types of awareness campaigns and messaging that is needed to overcome attitudinal barriers to adoption of a shared mobility future. The rest of the table shows exogenous variable effects and a detailed exposition is not offered here in the interest of brevity. In general, it is found that young individuals are more likely to embrace ridehailing while older adults are less likely to do so, similar to those reported in the literature. Interestingly, age has no significant direct effect on willingness to ride AV-services in a shared/pooled mode; however, the indirect effects are mediated through the latent constructs. Although females trust technology less and are more uncomfortable around strangers (Table 2), they are more likely to use ridehailing services currently and future AV-based services in a private mode. As women have more complex travel patterns and may have lower access to a private vehicle (de Oña and de Oña, 2022), it is likely that they take advantage of the flexibility and convenience of ridehailing services despite issues related to technology trust and discomfort with strangers (Wu et al., 2021). Racial differences are found, with Asians more likely to use shared ridehailing services currently and Whites expressing a greater willingness to use future AV-based ridehailing services in a private mode. As expected, employment and education are both positively influencing ridesharing mode usage, but have no direct effect on willingness to ride future AVs in a shared mode. Single adults are more likely to use pooled ridehailing services currently, while individuals in two-person households are less likely to embrace a future shared AV-ride service; the underlying reasons for this latter finding are not clear and warrant further investigation.

Middle income individuals are more likely to embrace pooled AV ridehailing services, while those in the higher income group are more likely to be current users of ridehailing services. Individuals in the middle income age group are likely to be comfortable using technology and have a desire to enjoy cost savings that come with sharing rides in an AV future. Those who engage in more online shopping (essentially more prone to using technology for fulfilling activities) are more likely to embrace technology in the future; they are more likely to ride AV-based services in the future in both private and shared modes (although the coefficient for the *shared* option is only about one-half of the coefficient for the *private* option). Residents of Austin exhibit a greater proclivity towards using ridehailing services currently (in both private and pooled mode), which is consistent with the high-tech nature of the metropolitan area. On the other hand, residents of Phoenix express a greater likelihood of being willing to try future AV-based ridehailing services in both a private and shared mode. This is likely due to the familiarity with AV technologies that Phoenix residents enjoy, stemming from the current availability of AV-based ridehailing services in the metropolitan area (and people are able to see and experience AVs firsthand). Residents of low population density areas are less likely to use ridehailing services, presumably because such residents have access to their own private automobiles (Zhang and Zhang, 2018).

4.6 Study Implications and Conclusions

The utopian vision of a sustainable mobility future is often described as one in which automated, connected, electric, and shared (ACES) vehicles serve the mobility needs of the public. While considerable strides are being made on the technological front to advance automated, connected, and electric vehicles, the transportation ecosystem continues to struggle with advancing a *shared* mobility paradigm – one in which *strangers* share the same vehicle at the same time to travel between origin and destination pairs that are reasonably aligned with one another. Past trends suggest that it is challenging to get people to share rides, as evidenced by the decline in carpool mode shares and average vehicle occupancies over the past several decades.

In an effort to better understand the factors that influence the willingness to share rides in an automated vehicle (AV)-based future, this study presents a behavioral choice model of the willingness to ride in future AV-based ridehailing services in a *private* or *shared* mode. The private mode entails riding in such vehicles alone or with friends and family, while the shared mode entails riding with strangers. The model estimation utilizes a comprehensive survey data set that includes detailed information about attitudes and perceptions towards automated vehicles and ridehailing services, and willingness to ride future AV-based services in private and shared modes. The model is a comprehensive econometric model system that accounts for the influence of current ridehailing experience on the willingness to ride AVs in the future in different modes, which is also treated as an endogenous variable in the model formulation. The model structure incorporates a battery of attitudinal statements represented by three latent attitudinal constructs (capturing lifestyle and mobility preferences) along with the usual host of exogenous socio-economic and demographic variables that typically influence mobility choices. The data set comprises more than 3,000 adults drawn from the Phoenix, Atlanta, Austin, and Tampa areas of the United States.

The model estimation results reveal the following key findings of this study. Firstly, current ridehailing experiences (whether an individual has experienced private or pooled ridehailing services that currently exist in the market) significantly influence the likelihood of being willing to ride in AV-based services in the future. Secondly, mere *private* ridehailing experiences, however, are not sufficient to bring about a higher proclivity towards embracing *shared* AV-based ridehailing services in the future. Lastly, experience riding current ridehailing services in a pooled mode does significantly enhance the likelihood of being willing to ride future AV-based services in a *shared* mode.

The bottom line is that experience matters; it outweights any amount of literature, brochures, publicity campaigns, and media coverage when it comes to overcoming the barriers and hesitation to sharing rides with strangers. Whether it be the discomfort of being in close proximity of strangers, the inconvenience of increased wait and travel time due to trip circuity, or a desire for privacy, there are numerous barriers to widespread adoption of AV-based ridehailing services in a shared/pooled mode. To overcome these barriers, people need to experience such services firsthand, and become comfortable with the logistics and social aspects of a shared ride with a stranger. With traditional transit under threat in a post-COVID era, public transit agencies may be able to play a key role in advancing and implementing such flexible shared ride services, as has been done recently (De La Canal, 2022). This also speaks to the need to reimagine future automated vehicle designs, where individual passengers enjoy greater privacy, security, and comfort without feeling that other passengers are intruding in their personal space.

This is not to say that educational awareness campaigns, demonstrations, and media coverage are not useful. In fact, in this study, residents of Pheonix indicate a higher proclivity towards embracing an AV-based mobility future in *both* private and shared modes. This finding is very likely due to the rather significant presence of AVs and AV-based ridehailing services in the Phoenix metropolitan area. The presence of such services engenders a sense of familiarity and comfort with the technology, that in turn advance a greater degree of willingness to embrace the technology. The study results show that attitudes, perceptions, and preferences strongly influence the willingness to ride AVs in different modalities. Trust in technology is critical as it positively impacts the proclivity to ride AVs in *both* modes. However, discomfort with strangers remains a barrier. Educational awareness campaigns should be aimed at making public aware of the reliability and performance of the technology to enhance trust in such automated vehicle systems. Unfortunately, media coverage tends to highlight technology failures, thus raising questions about the trustworthiness of these systems. Public and private entities should band together to provide accurate information about technology performance and safety, conduct demonstrations and trials, and run educational awareness campaigns. In addition, public and private entities involved in providing mobility services should continue to put appropriate safety systems in place to help individuals overcome discomfort with strangers. It may be necessary to provide special incentives to motivate individuals to try shared AV-based ridehailing services to accelerate the pace of adoption and convert the unwilling to the willing. The results provide key insights into likely early adopters of such shared AV-based ridehailing services (young, middle income, technology savvy individuals); start with these market segments, demonstrate and achieve success, and then other population subgroups are likely to follow as (negative) attitudes and perceptions are overcome.

One limitation of this study is that it uses survey data collected prior to the COVID-19 pandemic, so the results may not necessarily reflect individuals' current attitudes and behaviors. After the pandemic, the attitude statements reflecting a transit-oriented lifestyle and discomfort around strangers are likely to have altered significantly. Future research is needed to explore the stability of attitudes and behaviors in a post-pandemic world, particularly in the context of emerging transportation technologies and their potential implications on the transportation system (Rostami et al., 2022; da Silva et al., 2021;

Javadinasr et al., 2022; Magassy et al., 2023; Dirks et al., 2022). On a related subject, one can question the relevance of the latent constructs considered in this study, given that we only investigated three latent variables from a wide range of alternatives. Hence, future research should investigate the influence of additional latent factors on ridehailing experiences that were not taken into account in this study, such as positive ridehailing experience, positive transit experience, transit dependency, technology savviness, and environmental friendliness. Furthermore, for private ridehailing trips, this study made no distinction between solo rides and shared rides with family and friends. Because riding with friends/family allows them to spend time together, future study might establish this distinction between private ridehailing trips. Finally, in investigating the factors influencing the potential use of AV-based ridehailing services, this study focused on the respondent's overall tendency and willingness to use these services, without taking into account the possible influence of trip-level attributes. Addressing this limitation may allow for a more nuanced understanding of the behavioral phenomena studied in this chapter.

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5 AUTONOMOUS VEHICLES (AVS) IN THE REAL WORLD: A TALE OF TWO AV PILOT DEPLOYMENTS IN ARIZONA

ABSTRACT

Emerging technologies such as ridehailing services, e-scooters, and electric and autonomous vehicles have been increasingly part of the transportation system throughout the world. In recent years, autonomous vehicle (AV) technologies have been expeditiously advancing and promising transportation benefits in terms of safety, mobility, economy, environment, and efficiency. Exploring whether, and to what extent, someone will or will not use AVs is very challenging and encompasses several factors, such as psychosocial, technological, temporal, financial, and legal. In the past couple of years, two pilot projects launched in the Arizona Valley gained attention: the Waymo/Valley Metro Partnership and Peoria's RoboRide Autonomous Shuttle. The Waymo/Valley Metro Partnership pilot was an on-demand, private, autonomous vehicle shuttle service. RoboRide was a public low-speed shuttle vehicle operating on a fixed route around a medical district. These two AV pilot projects, while different in their nature and purpose, provided valuable lessons regarding public acceptance of automated technology as well as insights on willingness to use AVs in the future, perceptions of safety and convenience, and mobility needs. In both experiences, participants were subject to surveys in which they could state their opinions, preferences, and attitudes regarding AV and their travel patterns. This study uses both datasets to investigate how AV opinions and perceptions may vary depending on the nature of the project, as well as to explore mobility patterns and general AV concerns and preferences. In addition, this research effort will summarize major lessons learned from these two experiences in Arizona and provides key insights on the future of automated

mobility. The results will directly benefit service providers, that want to meet people's travel needs, and stakeholders, that are constantly developing strategies to ensure the AV technology will be properly accommodated by our transportation system.

5.1 Introduction

The transportation industry has been rapidly evolving in the past decades. The advent of emerging technologies such as ridehailing services, e-scooters, and electric and autonomous vehicles have been increasingly part of the transportation system and quickly gained adoption. Ridehailing services, also referred to as mobility-on-demand (MOD) services or mobility-as-a-service (MaaS), are currently an important piece of most transportation systems throughout the world, with convenient and efficient mobile applications that are appealing to users providing user-friendly interfaces that allow users to request rides with ease and reliability.

However, ridehailing services have not reached widespread adoption in terms of frequency of use. They are usually used in specific situations, rather than on a daily basis. Scholars have shown that service pricing is a crucial factor that, among others, prevents many individuals from strongly adopting ridehailing services. Ideally, when the driver is removed from the equation, the price is expected to drop significantly. As a result, due to the lower cost of operations, services tend to be more affordable (Gurumurthy et al., 2019; Hyland and Mahmassani, 2020). Given their potential financial benefits, in parallel to the growth of ridehailing services, automated driving technologies have been increasingly gaining attention and awareness.

Considered one of the most significant changes in the future of transportation, AV technologies have been vastly explored, and their potential benefits in terms of safety, mobility, economy, environment, and efficiency are appealing (NHTSA, 2021). Although AVs could be owned for private use, major advantages from automated mobility are expected to occur from shared services: either as ridehailing, on demand service, or as a transit option, in which a bus or shuttle could serve big groups given a fixed route. In fact, driverless rides are being offered in various settings across the US (McAslan et al., 2021). The success of AVs will be heavily determined by the number of people using the services. Unfortunately, not everyone will adopt the technology at the same levels and at the same time. Given the novelty of AV technology, there are segments of society who are eager to embrace the technology; those who are still uncertain and skeptical; and some who dislike the idea of having vehicles with no driver on the roads.

Scholars have found that proper knowledge about the technology, especially through firsthand experiences, has potential to increase acceptance, trust, and willingness to use AVs. As the first AV pilot programs and experiences start to be available to the public and people have the chance to try these services, there is a great opportunity to explore travel behaviors, attitudes, and opinions from these novice users.

The state of Arizona has been welcoming AV developers to test their driverless technologies across the state (ADOT, 2022). In 2019, Waymo's autonomous vehicles (AVs) served Valley Metro's RideChoice program—a subsidized curb-to-curb individual mobility service (via taxi or ride-hailing services) for paratransit-certified people under the Americans with Disabilities Act (ADA) and for seniors aged 65 and over living in Greater Phoenix. Project partners designed the pilot to understand the potential for AVs to meet the daily needs of otherwise mobility-disadvantaged citizens. The project engaged current RideChoice participants and catered to their mobility needs. The results provided an evidence base for further exploration into how transit services might facilitate and subsidize point-to-point mobility through AVs for mobility-disadvantaged residents, particularly if the operating costs decrease sufficiently to facilitate much broader use of AVs, making the service budget-friendly (affordable) for low-income households.

A couple of years later, in 2021, the Maricopa Association of Governments (MAG) funded the deployment of RoboRide, a low-speed autonomous vehicle (LSAV) shuttle service operated on a pre-designated route within a medical district in Peoria, Arizona. This project aimed to assess how individuals perceive and embrace autonomous vehicle (AV) technology. Feedback was collected on how the technology could be enhanced to serve mobility needs better for all. Performance characteristics of the shuttle were obtained to provide insight into areas for improvement of the technology.

Although both projects were AV pilots, they were different in nature and purpose. However, lessons obtained from both were valuable. Surveys were collected from participants in both experiences, resulting in rich datasets that include participants' opinions and attitudes regarding AVs, their travel patterns, and sociodemographic information. Using both datasets, this study will highlight the major lessons learned from both AV deployments, explore how different users, nature of project, type of service, timeline, and additional attributes may impact AV perceptions and mobility patterns. As a result, this study will provide key takeaways regarding the future of automated mobility and inform service providers, by understanding the current state of AV adoption and public perception; stakeholders, who are working on raising AV awareness and preparing the current infrastructure and legislation to accommodate the technology; and the body of literature, by providing empirical data, recent insights on users' opinions about the novel AV technology from two recent AV experiences in Arizona.

5.2 WAYMO/VALLEY METRO DEMONSTRATION PROJECT

5.2.1 Project Description

The Waymo/Valley Metro Demonstration Project was launched in 2019 and funded by the Federal Transit Administration (FTA) Mobility on Demand (MOD) Sandbox program. Through the grant, Valley Metro, Waymo, and Arizona State University (ASU) partnered to pilot the use of Waymo autonomous vehicles (AVs) as certified vehicles for Valley Metro's RideChoice program—a subsidized curb-to-curb individual mobility service (via taxi or ride-hailing services) for paratransit-certified people under the Americans with Disabilities Act (ADA) and for seniors aged 65 and over living in Greater Phoenix region.

The project goal was to explore how AVs can those considered mobility-disadvantaged citizens and explore the integration between transit services and first- and last-mile connections through AVs, especially if net operating costs can be reduced with widespread adoption of AV services in these scenarios for low-income households and those with mobility limitations.

During the six-month demonstration project (September 15, 2019 – March 15, 2020), this project aimed to understanding the potential behavioral impacts of AV MOD services, including the perceptions and attitudes of users (and non-users) towards such new technologies and services.

The data was collected through surveys (before, during, and after the demonstration was over) and focus groups, as well as analyzed trip data, to understand how experiencing AVs might affect perceptions of safety, rider experience and satisfaction, and travel behavior. Before the first of these surveys, an Expression of Interest survey was conducted to recruit the sample that would participate in the pilot. It was hoped that those who expressed interest and otherwise met criteria to participate in the study would respond to all three of the subsequent surveys. A total of 72 individuals expressed interest and met all other criteria for participating in the pilot. The Prior Survey was deployed in September 2019 and 51 valid responses were collected. The During Survey was deployed in March-April 2020 (at about the time that the Waymo AV MOD service was suspended due to COVID-19) and 35 valid responses were recorded. Finally, the Post Survey (conducted in May-June 2020, two months after the Waymo pilot ended), with 39 valid responses, was intended to assess the extent to which respondents may have changed their attitudes towards AVs, travel behavior, and mobility patterns, following the pause in Waymo operations (beginning March 15, 2020) due to COVID-19. In addition, the Post Survey was intended to gather information on the extent to which patrons wish the service was still in place, would like to see it restored, and are interested in continuing to use it for their travel. For this demonstration study, the cost of a Waymo AV ride was capped at $3 per trip for all study participants, regardless of trip length.

In addition to conducting surveys and gathering trip data, the project team believed that additional insights could be obtained through focus groups, where in-depth discussions centered on key questions that could further illuminate underlying motivations, attitudes, and perceptions that could drive the future of AV MOD services. While the surveys and data collection activities described in the previous paragraphs provide critical and detailed information about what happened in the context of the specific AV MOD experiment conducted in this project, they might not offer sufficient insights about the future of such services as they become increasingly pervasive in the transportation landscape. The purpose of the focus groups was to understand better how, why, and under what conditions the public may embrace AV MOD services on a large scale and what that might mean for the future of public transit as it exists today. In addition, the project team was interested in learning about the perceptions of city officials and agency stakeholders, and how they plan to prepare for the advent of AV MOD services in their jurisdictions. Therefore, the project team conducted two focus groups and a policy maker roundtable.

One focus group involved the participants in the AV MOD experiment. This focus group included about a dozen individuals, and moderators with expertise in facilitating discussions were tasked with conducting the focus group event. The project team worked with Valley Metro and Waymo to identify key topics to be covered at the focus group, the key questions that needed to be addressed, and the extent to which participants would be allowed to digress and share perspectives on a variety of issues related to the future of AV-based MOD services. The second focus group was composed of subject matter experts, with 27 urban and transportation planners providing an overview from a planning standpoint, helping to understand how such projects involving AVs may impact the Phoenix metropolitan area. The discussion focused on how such AV pilot project experiences may affect Valley Metro transit users, especially in terms of potential long-term benefits, allowing local cities to learn and adapt to this emerging technology together.

The focus group sessions were recorded for subsequent analysis and extraction of key insights.

The policy maker roundtable involved local planning and transit agency stakeholders, primarily from jurisdictions in the Phoenix metropolitan area. This roundtable engaged about a dozen stakeholders, with discussions largely centered on how cities and jurisdictions are preparing for a future of AV and MOD services. With the increasing adoption and market penetration of these technologies and services, there are a number of considerations – including, but not limited to, the need for parking as it exists today, street design, safety of pedestrians and bicyclists, meeting mobility needs of the transportation disadvantaged, concerns about induced travel demand, increased traffic congestion due to zero-occupant vehicles[1] (ZOVs), and the role of public transportation in an AV- and MOD-based mobility future. Concerns about equity and environmental quality were also discussed, and participants in the focus group were asked to share their ideas on how they plan to welcome this technology into their jurisdictions in a manner that enhances mobility while minimizing any unintended consequences. In other words, the discussion addressed the theme of "anticipatory governance" as related to an automated mobility future. For more details about the Waymo/Valley Metro demonstration project, please refer to Stopher et al. (2021).

[1] When zero-occupant vehicles have to reposition themselves for the next use, they generate deadhead travel that can add considerably to existing traffic congestion.

5.2.2 Data

In this section, the three surveys administered throughout the pilot study and the respondent samples are described briefly. The survey forms are shown in the Appendix. The respondent demographics are summarized in this section, offering a comparison of survey samples and showing statistical significance of any differences between the samples. It is important to note that the samples are self-selected and that results cannot be generalized to the broader population. The results apply to RideChoice customers who, prior to the demonstration project, were willing and interested to take part in this pilot study, met certain criteria, and indicated a willingness to respond to surveys and share trip data.

5.2.2.1 Prior Survey

The Prior Survey was deployed in September 2019. The survey was conducted through the Qualtrics online platform, in which participants could complete the form either on a phone or computer. To boost the response rate, two rounds of reminders were sent, one in each week after the survey was deployed. In addition, $100 gift cards were offered to all respondents who provided a complete Prior Survey, as a form of incentive for their participation. On average, it took 30 minutes for participants to complete the Prior Survey. Of the 72 individuals who expressed interest and met criteria to participate in the study, 52 participants provided valid responses to this survey. However, one respondent provided contradictory responses about the use of RideChoice between this survey and the Post Survey and was subsequently removed from analysis.

Prior to the Waymo onboarding phase, the Prior Survey was administered to all recruited participants (72 individuals). The Prior Survey comprised three sections:

- *Section A – Current RideChoice Service Use Patterns*: This section gathered detailed information about the most recent RideChoice trip including day of week and time of day, origin-destination locations, travel time, waiting time, trip start and end times, service cost, travel companion presence, trip purpose, and availability of alternative travel modes. This section also gathered information about the general frequency of use of RideChoice service and perceptions of and attitudes towards the current RideChoice service.

- *Section B – Thoughts About Self-driving and On-demand Mobility Services*: This section gathered information on level of familiarity with automated vehicles, willingness to adopt or ride in autonomous vehicles, attitudes and perceptions about the operation of autonomous vehicles, expected changes in travel behavior with the advent of mobility-on-demand autonomous vehicles, and expectations around autonomous vehicle on-demand mobility services.

- *Section C – Background Information*: This section gathered sociodemographic information, including age, gender, education attained, employment/student status, work/school locations, vehicle ownership, household location, household size, type of housing, income, and residential and work locations. The goal of this survey section was to understand the socioeconomic profiles of respondents better, so that the influence of socioeconomic and demographic variables on attitudes towards and use of mobility-on-demand autonomous vehicle services could be quantified in subsequent analyses.

5.2.2.2 During Survey

The During Survey was sent to 46 study participants. The reduction in sample size occurred because five of the original 51 respondents to the Prior Survey never enrolled in the RideChoice program and were hence ineligible to take rides under the RideChoice program. The survey was deployed in the early part of March 2020 and responses were collected between March 4 and April 5, 2020. The During Survey was also conducted through the Qualtrics online platform. The same reminders and incentives were used as in the Prior Survey. On average, it took 20 minutes for participants to complete the During Survey. It proved challenging to obtain a strong response rate for the During Survey despite the reminder and incentive protocols. Because of the onset of the pandemic and the beginning of the shutdown of the state on March 15, 2020, it is likely that study participants were distracted by pandemic-related concerns. The responses to the During Survey may be somewhat affected by the reduced amount of travel in the wake of the pandemic. A total of 35 responses were obtained (out of the 46 individuals who received the survey).

The During Survey was intended to be conducted during the experimental phase, in which participants were onboarded and had Waymo as an option for their RideChoice rides. The During Survey was intended to understand how automated vehicle mobility-on-demand services were being used by study participants, and to compare data collected in the During Survey with data collected in the Prior Survey. The During Survey comprised three sections:

- *Section A – Transportation Choices*: This section gathered detailed information about recent transportation choices of participants, including opinions about Waymo and non-Waymo RideChoice services. In addition, details about the most recent ride taken by both types of services were collected, including month and year of ride, day of week and time of day, origin-destination locations, travel time, waiting time, travel companion presence, trip purpose, availability of alternative travel modes, ride satisfaction levels, and use of time during the reported ride.

- *Section B – Thoughts About Self-driving and On-demand Mobility Services*: This section gathered information on level of familiarity with self-driving cars, willingness to adopt or ride in autonomous vehicles, attitudes and perceptions towards the operation of autonomous vehicles, expected changes in travel behavior with the advent of mobility-on-demand autonomous vehicles, expectations around autonomous vehicle on-demand mobility services, as well as comparative ratings on attributes of regular taxi, Uber/Lyft, and Waymo.

- *Section C – Background Information*: This section gathered sociodemographic information, specifically employment/student status, work/school locations, vehicle ownership, household location, household size, and income. The goal of this survey section was to understand the socioeconomic profiles of respondents so that the influence of socioeconomic and demographic variables on attitudes towards and use of mobility-on-demand autonomous vehicle services could be quantified in subsequent analyses. Collecting these data also enabled a comparison of respondent profiles across surveys, thus making it possible to see if difference in socio-economic profiles of respondent samples may have contributed to any observed differences in attitudes and travel behavior between surveys.

5.2.2.3 Post Survey

Participants in the Valley Metro/Waymo Demonstration Project were invited to answer the Post Survey. The survey was deployed in May 2020 to the same 46 participants who received the During Survey and responses were collected from May 27 to June 17, 2020. Because the project worked with the same population since the beginning, each of the During Survey and Post Survey samples are a sub-sample of respondents who responded to the Prior Survey. The Post Survey was administered through the Qualtrics online platform, in which respondents could complete the forms either on a phone or computer. Again, the same reminders and incentives were used as in the Prior and During Surveys. On average, respondents took about 10 minutes to complete the Post Survey. At the time of this survey, the shutdown of many businesses and reduction in travel due to the COVID-19 pandemic were in full effect. The results of this survey, therefore, reflect much of the reduction in travel arising from the pandemic-related shutdown. A total of 40 responses were received to the Post Survey, all but one of which were deemed valid responses, giving a final Post Survey sample of 39 responses.

The Post Survey was administered about one month after respondents no longer had Waymo as an option for their RideChoice rides. This enabled an understanding of how travel patterns and behaviors had changed over time, including COVID-19 impacts on transportation. The Post Survey comprised three sections:

- *Section A – Travel Choices and Experiences*: This section gathered general information about the recent transportation choices of respondents, including their Waymo experiences. In addition, data were collected regarding basic travel patterns before the COVID-19 pandemic and potential changes that might occur after the pandemic to analyze how it might affect the travel behaviors of participants and their RideChoice usage.

- *Section B – Thoughts About Self-driving and On-demand Mobility Services*: This section gathered respondent perceptions of, and expectations related to, new mobility services and technologies, considering transportation needs and experiences in general and not necessarily focused exclusively about RideChoice or Waymo vehicles and services. In this section, respondents were asked to indicate their preferences and behaviors under the assumption that the COVID-19 pandemic is over.

- *Section C – Employment Status and Incentive*: This short and final section had only two questions: one regarding their employment status, which allowed comparisons to the During Survey and Prior Survey (particularly in the wake of employment disruptions that occurred due to the pandemic), and another question regarding the $100 gift cards they were to receive as an incentive.

5.2.3 Characteristics of Survey Samples

In general, the study sample exhibited heterogeneity in demographic characteristics with individuals in all demographic categories (Table 1). On most of the demographics collected in the Prior Survey, there were few significant differences among the surveys, with most of the few differences occurring between the During Survey and either or both of the Prior and Post Surveys. The biggest differences appeared in employment status, student status, and occupation. For these three variables, there were clear differences between respondents and non-respondents that led to some impact on the results obtained from the During and Post Surveys. These differences should be borne in mind when looking at comparisons of experiences, preferences, and other attributes that are discussed in the balance of this study. The main conclusion to be drawn is that the During and Post Surveys have a considerably smaller proportion of employed people and particularly a smaller proportion of people in the Professional, Managerial, and Technical occupations.

Table 10 Summary Demographics of the Three Survey Samples

Demographic	Prior Survey (N=51)	During Survey (N=35)	Post Survey (N=37)
Age			
18-30	21%	20%	22%
31-40	16%	11%	11%
41-50	10%	6%	8%
51-60	21%	23%	24%
61-70	16%	20%	19%
71 and older	16%	20%	16%
Gender			
Male	59%	48.5%	51%
Female	41%	51.5%	49%
Household Size			
1	20%	21%	16%
2	31%	27%	30%
3	31%	24%	35%
4 or more	18%	29%	19%
Type of Home			
Stand-alone	67%	68%	70%
Attached home/townhome	6%	3%	3%
Condo/Apt	23%	26%	24%
Mobile Home	2%	3%	3%
Other	2%	0%	0%
Vehicle Ownership			
0	26%	27%	24%
1	33%	32%	38%
2	29%	27%	24%
3 or more	12%	15%	14%
Household Income			
Less than $25,000	28%	29%	32%
$25,000 to $49,999	29%	34%	32%
$50,000 to $74,999	14%	11%	16%
$75,000 to $99,999	16%	14%	5%
$100,000 to $149,999	14%	9%	14%
$150,000 and over	0%	3%	0%
Employment Status			
Employed Full Time	29%	14%	13%
Employed Part Time	8%	14%	8%
Self-Employed	4%	3%	5%
Retired	22%	31%	28%
Homemaker	0%	3%	2%
Unable to Work	25%	17%	26%
Looking for Work	6%	6%	2%
Not Looking for Work	0%	0%	3%
Other	6%	12%	13%
Occupation			
Sales or Service	24%	36%	25%
Clerical/Admin Support	10%	9%	17%
Manufacturing, Construction, Maintenance, or Farming	19%	18%	17%
Professional, Managerial, or Technical	33%	0%	33%

Demographic	Prior Survey (N=51)	During Survey (N=35)	Post Survey (N=37)
Education, Training, or Library	5%	18%	0%
Other	10%	18%	8%
Educational Attainment			
Completed High School, GED, or Less	16%	15%	16%
Some College/Tech. School	49%	47%	51%
Bachelor's Degree/Some Grad School	20%	21%	16%
Completed Grad Degree(s)	16%	18%	16%

5.2.4 Mobility Choices: Past, Present, and Future

Figure 10 shows the changes in respondent use of RideChoice services over the three surveys. It must be noted that the question in the Prior Survey was different from that in the During and Post Surveys, with the Prior Survey asking about RideChoice usage in general and including a category of Never. However, the During and Post Surveys asked about RideChoice usage in the prior 30 days. If someone indicated they had not used RideChoice in the past 30 days, they were categorized as "Less than monthly". Categories in the Prior Survey were recoded to match those of the Post Survey as closely as possible, for comparison purposes.

The effect of the COVID-19 pandemic on respondent RideChoice usage is quite noticeable in Figure 10; the frequency of RideChoice service usage decreased dramatically in the Post Survey when compared to the Prior and During Surveys. In the Prior and During Surveys, about one third of respondents (31 to 35 percent) did not use RideChoice in the past 30 days (combining Never Used and Less Than Monthly in the Prior Survey), whereas during the pandemic (the past 30 days from when the survey was administered in mid-May), nearly three-quarters of respondents (73 percent) did not use the service. In the Prior and During Surveys, 23 to 26 percent used RideChoice less than one day a week, compared to 17 percent in the Post Survey. Similarly, weekly or more frequent use was reported by 42 percent of respondents in the Prior Survey and 43 percent in the During Survey compared to just 10 percent in the Post Survey. It is evident that the COVID-19 pandemic substantially restricted travel and hence the use of RideChoice services. Statistical tests show that the Prior Survey results are not significantly different from the During Survey results, but that the Post Survey statistics are very significantly different (at 99 percent confidence) from both the Prior and During Surveys.

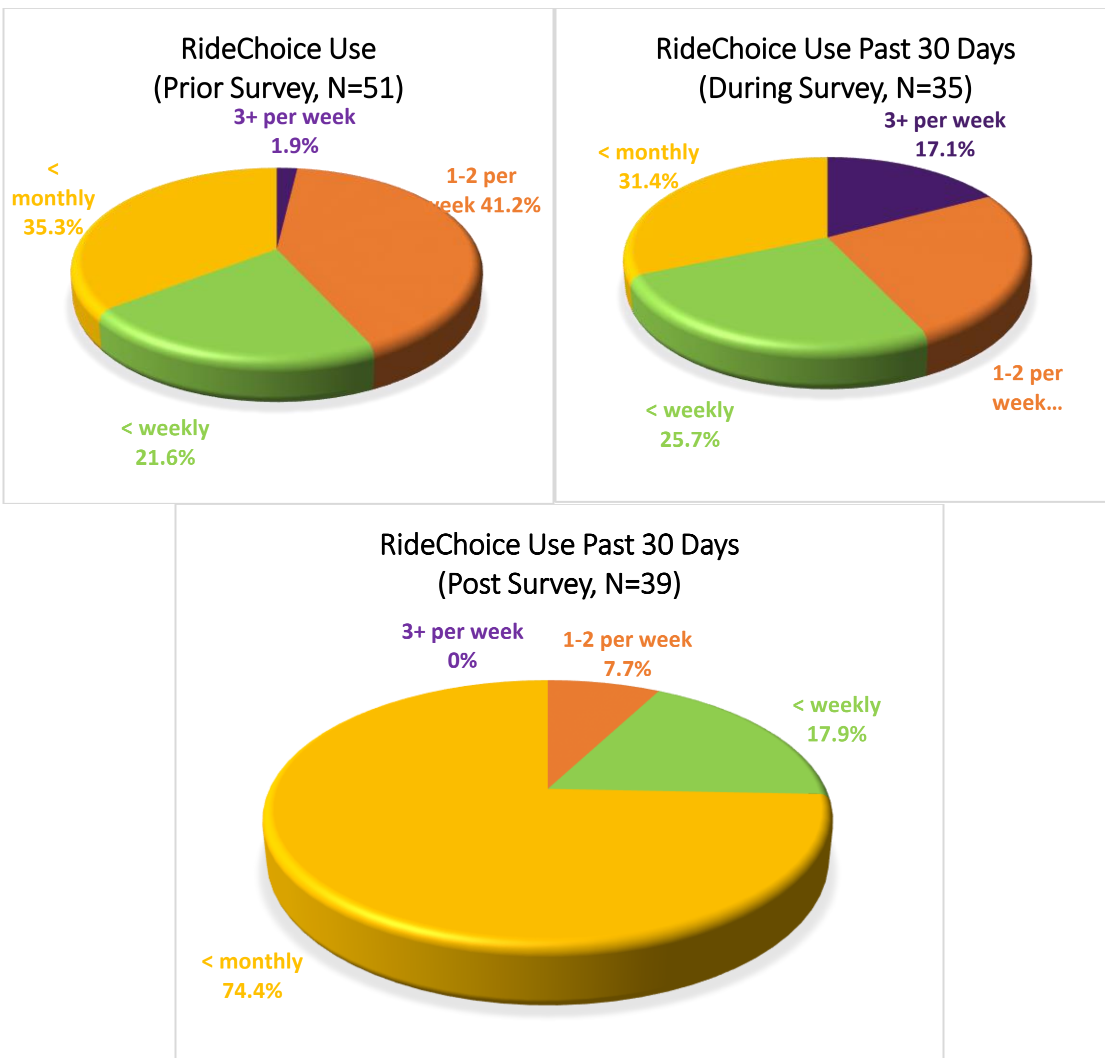

Figure 10 Changes in non-Waymo RideChoice Usage

As expected, the use of other modes of transportation seemed to be impacted throughout the demonstration pilot. Figure 11 shows that before the pilot started, about 27 percent of respondents used to ride as a passenger in a car; this number dropped slightly to 24 percent in the During Survey but went up to 30 percent in the Post Survey. In the Prior Survey, around six percent of respondents were also driving, either alone or with passengers. It is seen that over 20 percent and 18 percent of respondents were driving in the During and Post Surveys, respectively, suggesting that the pandemic led to a considerable uptick in the level of driving among this subpopulation.

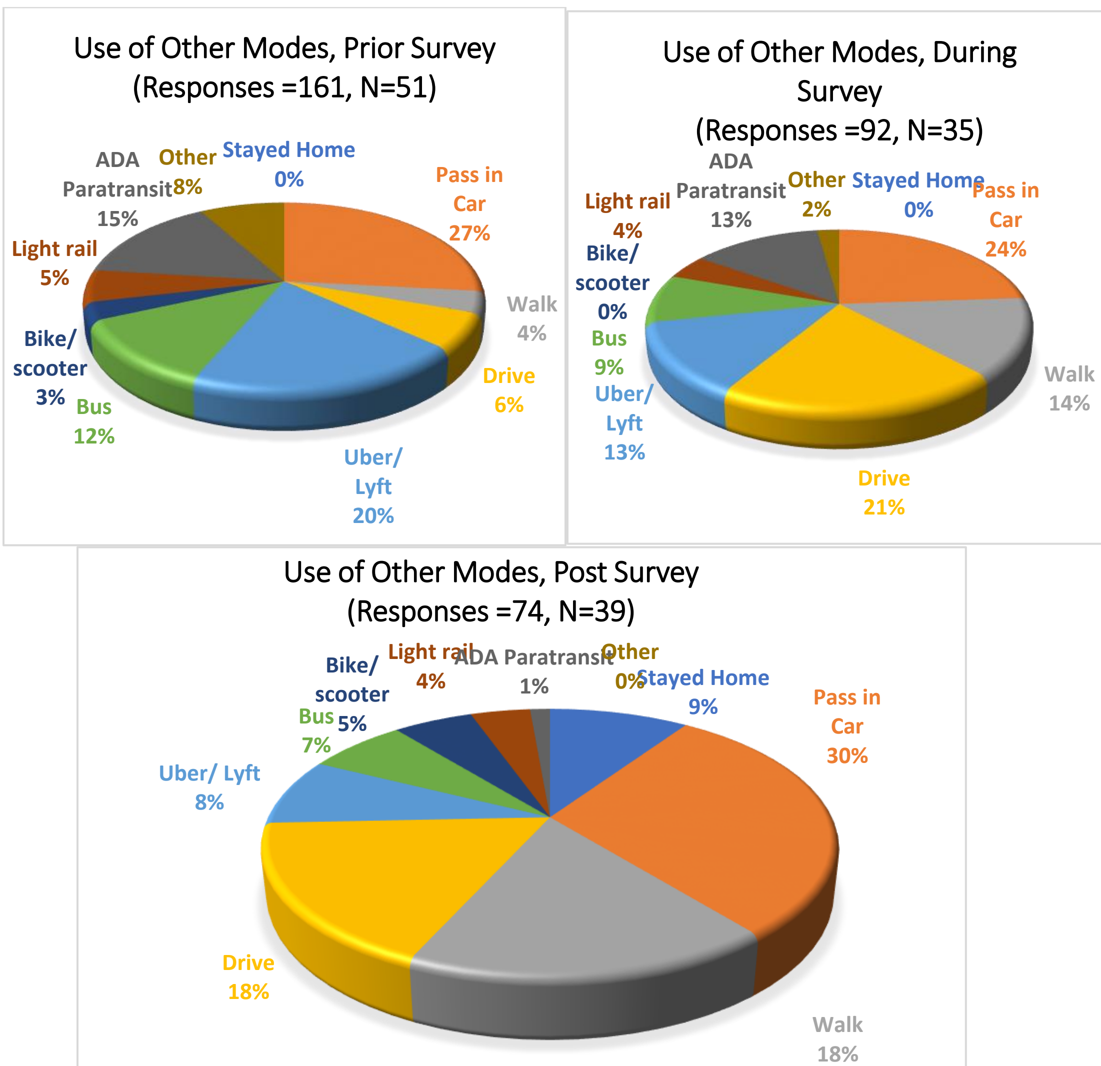

Figure 11 Changes in Use of Other Modes of Transportation

Interestingly, there was a decrease in Uber/Lyft use (from 19.8 percent in the Prior Survey to 13 percent in the During Survey), possibly due to Waymo availability, which may have contributed to a lower use of ride-hailing services outside of the RideChoice program. A decrease in ride-hailing usage during the COVID-19 pandemic was also observed in the Post Survey, where only eight percent of respondents reported using such services in the most recent 30 days, most of which fell in the time period of the pandemic. The same effect of a decrease in use was captured for ADA paratransit services, which decreased from 14.9 percent in the Prior Survey to 13 percent in the During Survey, and finally to 1.3 percent in the Post Survey.

Use of the walk mode increased from 3.7 percent in the Prior Survey to 14.1 percent in the During Survey and 17.3 percent in the Post Survey. As there is no evidence in the dataset that would suggest usage of Waymo contributed to switching to more active modes of transportation, the likely explanation for that change might be due to weather conditions and the onset of the pandemic. The Prior Survey was conducted in September 2019, when it is very hot in the Phoenix metropolitan area, whereas the During Survey was deployed in March 2020, when the temperature was cooler and more walk friendly.

In the During Survey, respondents were asked to indicate if their use of non-Waymo modes had increased, decreased, or stayed about the same since the introduction of the Waymo option within the RideChoice program. No comparable question was asked in the Post Survey. Figure 12 summarizes the results from the During Survey and shows that more than half the respondents indicated no change in their use of driving alone, driving with passengers, riding in a car with others, light rail, bike sharing or e-scooters, walking, and riding a bicycle or scooter. At the same time, more than half of the respondents showed a decrease in the use of bus, traditional taxi, and Uber/Lyft. Almost none of the respondents indicated an increase in use of any of these modes in absolute terms.

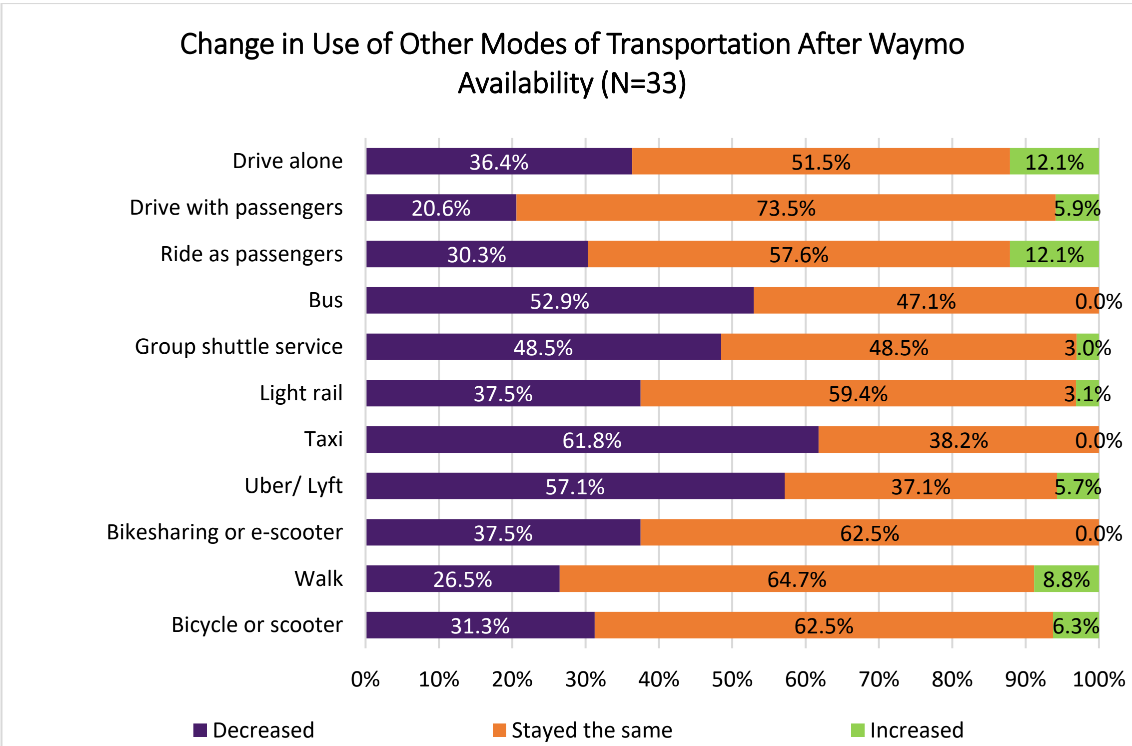

Figure 12 Change in Use of Other Modes (During Survey)

5.2.5 Perceptions of Waymo

During the demonstration, Waymo rides appeared to have spiked in the first half of the program, especially in November and December 2020, followed by a decline in use during the subsequent months (Figure 13). The reason for such different patterns in use is possibly the initial excitement to use Waymo, which might have made participants use Waymo more frequently.

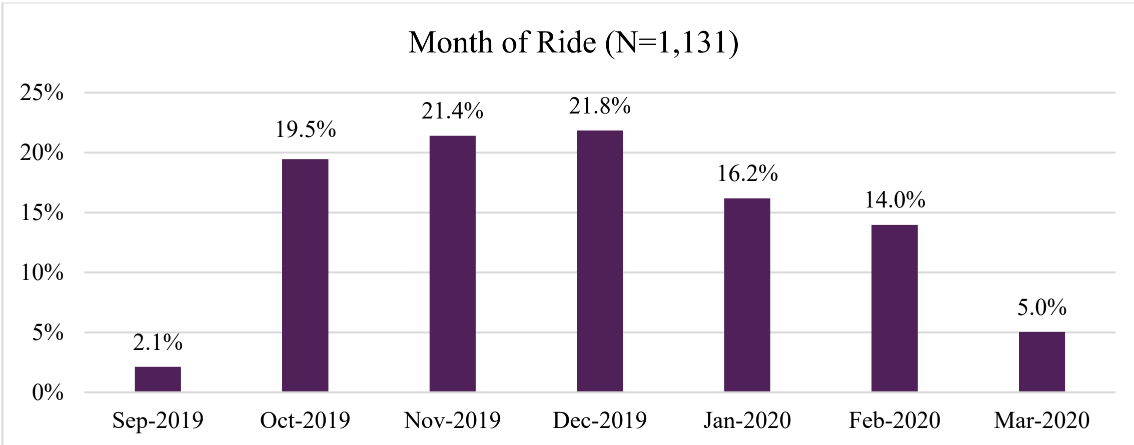

Figure 13 Waymo Rides by Month

Figure 14 shows the frequency distribution of Waymo rides of participants in the experiment. The During Survey was administered over a 33-day period, starting on March 4, 2020 and ending on April 5, 2020. However, Waymo suspended service on March 15, 2020 due to the COVID-19 pandemic. Hence, participants had the ability to use the Waymo service for only 12 of the 33 days. Overall, it can be seen that 23 percent of all survey respondents did not take a single Waymo ride throughout the AV MOD experiment.

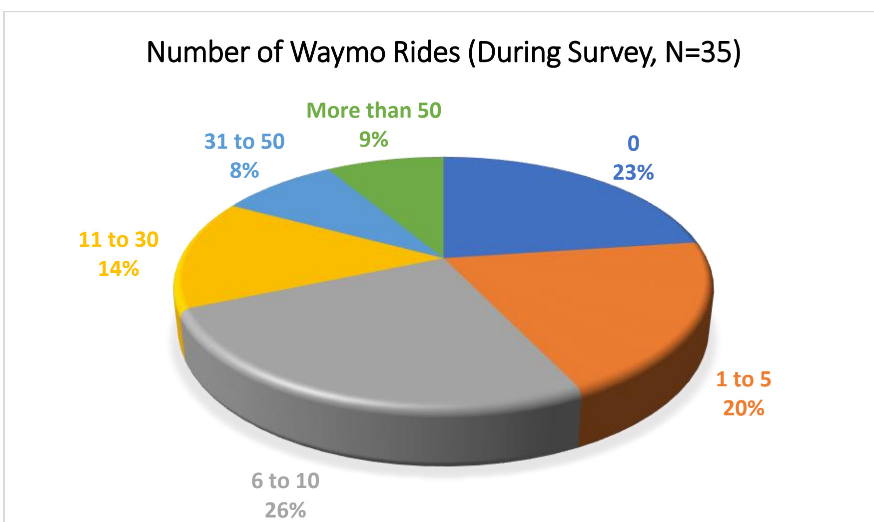

Figure 14 Number of Waymo Rides Taken Since Beginning of Demonstration Project (September 2019)

In the Post Survey that had 39 responses, the question was asked as to whether or not the respondent had taken any rides with Waymo during the demonstration. Of the 39 respondents, 30 indicated having taken rides and nine indicated never having taken a ride. This is consistent with the During Survey, which showed that 23 percent of respondents had not taken a ride with the Waymo service. Waymo users were asked in the During Survey if they were making new trips on RideChoice as a result of having Waymo available as a service option. As shown Figure 15, almost 60 percent of Waymo riders agreed or strongly agreed with this statement; only eight percent strongly disagreed. The remainder were either neutral or didn't know.

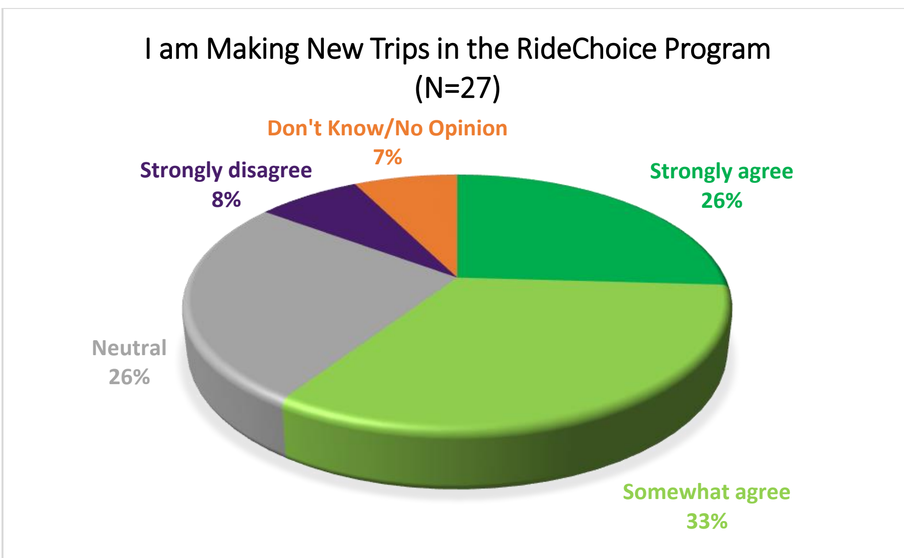

Figure 15 Making New Trips as a Result of Waymo Option in RideChoice Services (During Survey)

When asked in the During Survey if they liked riding in Waymo autonomous vehicles more than in a traditional RideChoice Vehicle, the answers showed that 67 percent either agreed or strongly agreed and just seven percent strongly disagreed, as shown in Figure 16. Just over one quarter of respondents were neutral.

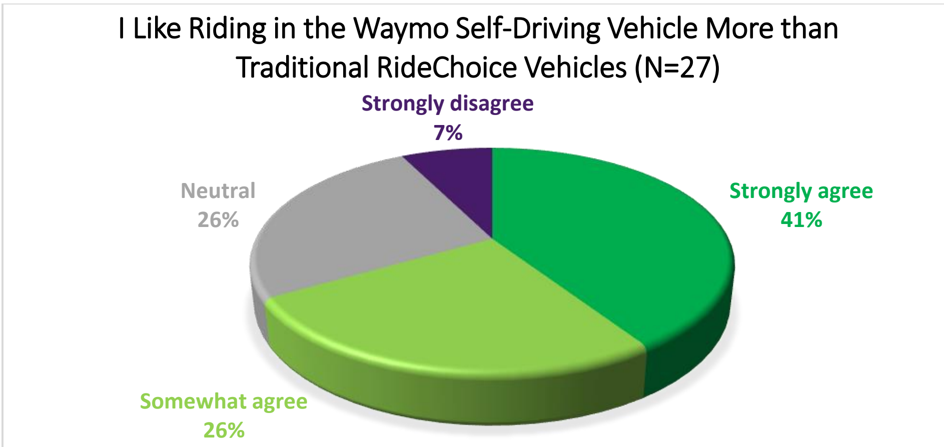

Figure 16 Riding in Waymo Vehicles Preferred to Traditional RideChoice Vehicles (During Survey)

In the During Survey, participants were asked to generally evaluate different mobility services with respect to various attributes (not focusing specifically on the most recent trip by each service). The three services presented to respondents included Regular Taxi, Uber/Lyft and Waymo. Seven different aspects were rated by the respondents (Figure 17). In terms of average rating scores, Waymo dominates the other vehicular services with respect to waiting time, ride comfort, cleanliness, ease of getting into and out of the vehicle, and ease of requesting the ride. Uber/Lyft is slightly better with respect to travel time and drop-off/pick-up locations, possibly due to the ability of the human driver to optimize execution of the journey. Moreover, the social aspect associated with riding a human-driven vehicle may have helped riders perceive a lower burden of travel time when compared to riding in a self-driving vehicle. As for drop-off/pick-up locations, Waymo vehicles are programmed to follow safety protocols that many human drivers may not follow precisely. Unlike human-driven vehicles, Waymo vehicles target a specific safe location for drop-off and pick-up, which may not necessarily be at the exact location where riders may wish to board and alight. Hence, Waymo scores are slightly lower than Uber/Lyft scores in the drop-off/pick-up location domain. Generally, regular Taxi is consistently rated last on every aspect when comparing all three entities.

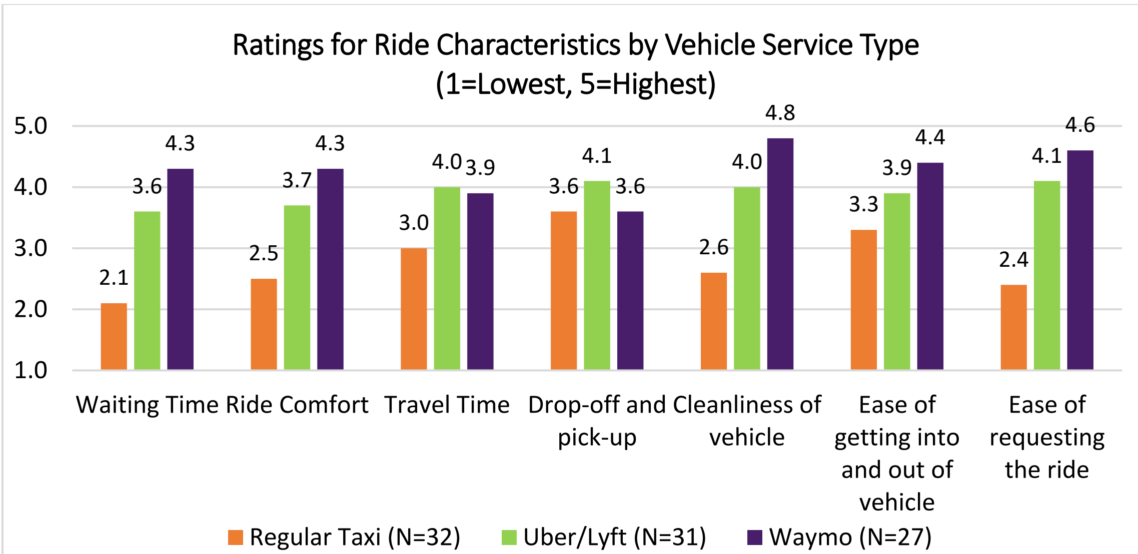

Figure 17 Average Ratings for Ride Attributes by Vehicle Service Type (During Survey)

5.2.6 Perceptions Towards Self-Driving Vehicles

In the previous section, it was found that Waymo RideChoice services were seen as providing good accessibility, convenience, comfort, and convenience, although users did recognize the limited geographical reach of the Waymo service within the designated service territory. To capture a broader set of attitudes and perceptions towards emerging transportation technologies, all three surveys also included questions and statements to better understand general attitudes and perceptions towards self-driving vehicles and mobility-on-demand services. This section provides a summary of results for this set of survey questions.

In the Prior Survey, respondents were also asked whether they had experienced riding in a self-driving vehicle. For all respondents to that survey, just 27.5 percent had previously ridden in a self-driving vehicle. Among Waymo riders, this was only 20 percent, while among non-Waymo riders it was none. Therefore, while the previous question showed a fairly high level of familiarity with self-driving vehicles, only a few respondents actually had experience of riding in such a vehicle.

When asked about riding in a fully self-driving vehicle with no human safety operator, the survey design was slightly different in the Prior Survey, which asked about their willingness to ride in a self-driving car with no backup driver/operator present in the vehicle, whereas in the During and Post Survey they were simply asked if they would ride in a fully self-driving vehicle. Although the effect being captured is virtually the same, it is important to distinguish the survey designs before drawing conclusions. These attitudes were measured in the three surveys for the same three scenarios: riding alone, riding with a known passenger such as a family member or friend, or riding with strangers.

Reactions to the first scenario are shown in Figure 18 their willingness to take such a ride, as expressed in the Prior Survey, did not change when asked in the During and Post Survey if they would ride in a fully self-driving vehicle alone. Over 12 percent of respondents, although familiar with such technologies, are still hesitant to engage in this experience alone. Waymo riders showed about the same level of unwillingness through the three surveys. Apparently, the experience of using Waymo did not change this attitude, which is probably not surprising because they did not experience a self-driving vehicle with no safety operator on board. Non-Waymo users showed an inconsistent attitude over the three surveys but ended up seemingly more willing to use a self-driving vehicle alone by the Post Survey than in either of the previous surveys. None of these differences is statistically significant, however.

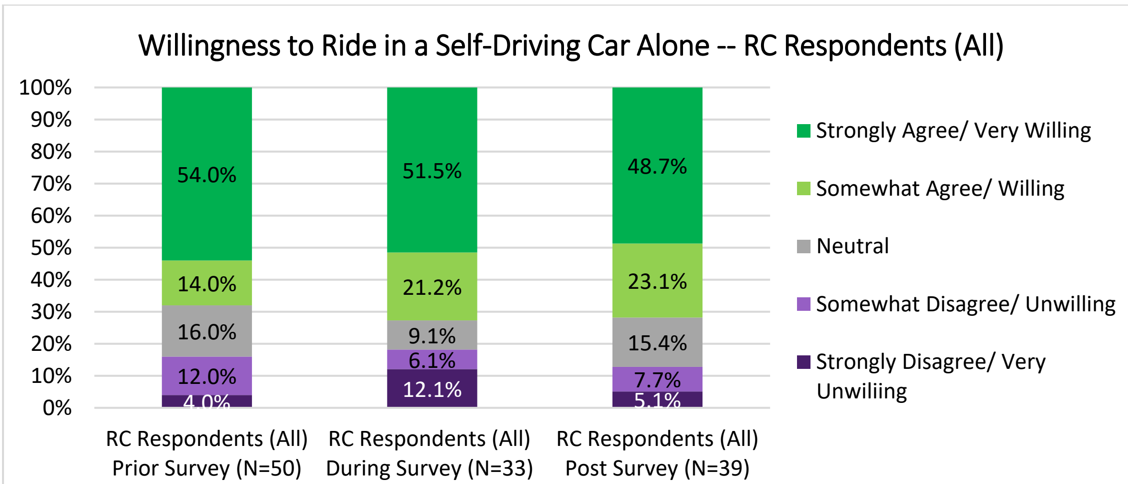

Figure 18 Willingness to Ride in a Fully Self-Driving Vehicle Alone (All Surveys)

Sharing a ride in a fully self-driving vehicle with friends and family was the most agreeable scenario in all three surveys. Over time, respondents are increasingly comfortable with the idea of sharing a ride in a self-driving vehicle with a family member or a friend. The results went from 78.4 percent of respondents willing to ride in such a scenario in the Prior Survey, to 82.3 percent in the During Survey, and finally to 92.3 percent in the Post Survey (Figure 19).

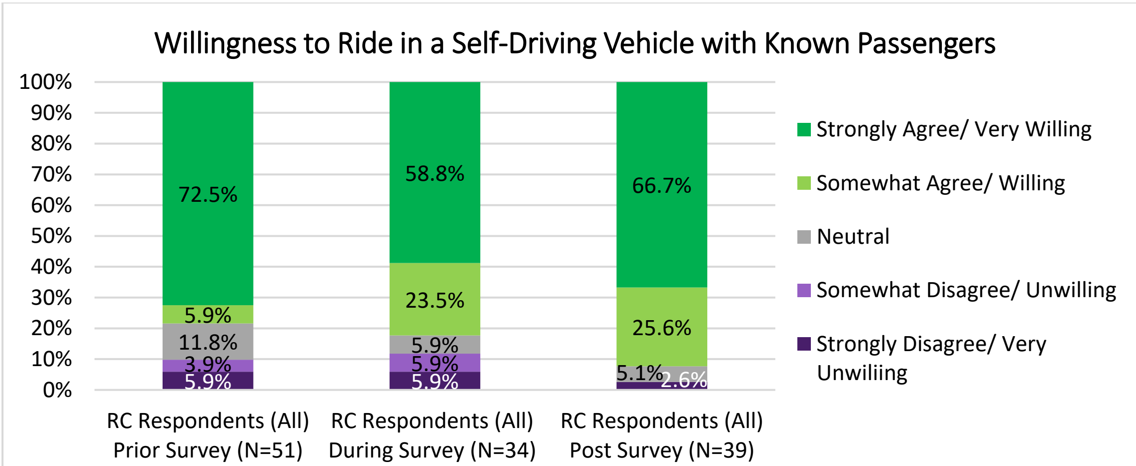

Figure 19 Willingness to Ride in a Fully Self-Driving Vehicle with Known Passengers (All Surveys)

Finally, the scenario of sharing a self-driving vehicle ride with strangers changed over time. The willingness to engage in such a ride shared with strangers went from 44 percent in the Prior Survey, to 42.5 percent in the During Survey, to 48.8 percent in Post Survey (Figure 20). Unwillingness to ride remained about the same across the three surveys, but those who were neutral increased in the During Survey and then decreased somewhat in the Post Survey. None of the differences is statistically significant.

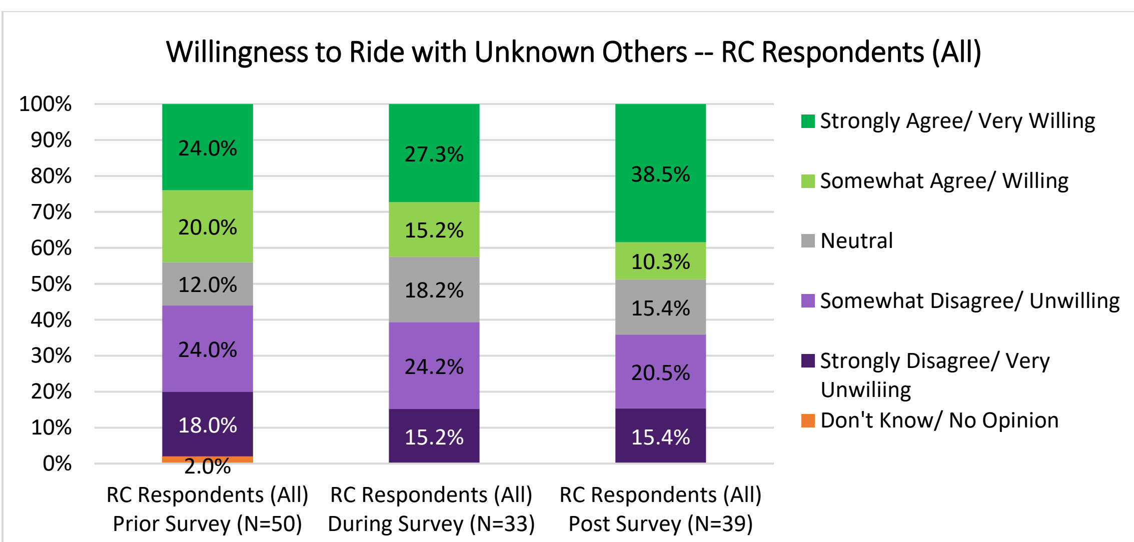

Figure 20 Willingness to Ride in a Fully Self-Driving Vehicle with Strangers (All Surveys)

In the Prior and During Surveys, respondents were asked questions about the safety that they would expect in a future when most vehicles would be self-driving. Respondents that offered no opinion disappeared in the During Survey. The strength of agreement with this idea increased significantly (95 percent confidence) from the Prior Survey to the During Survey for both all respondents and Waymo riders only. Among those indicating agreement, the proportion indicating strong agreement nearly doubled from the Prior to the During Survey. Based on these two questions, it appears that the experience of using Waymo has significantly influenced the survey respondents to look more favorably on the safety aspects of self-driving vehicles than they did before the experiment. This is reflected further in the focus group results described in the next section.

5.2.7 Focus Groups Results

This section summarizes the results of these focus groups and the policy roundtable event. The three subsections that follow include separate analyses for the rider focus groups, urban and transportation planners or subject matter expert (SME) focus groups, and the policy maker roundtable.

5.2.7.1 Rider Focus Groups

The rider focus groups provided a qualitative analysis of rider experiences with autonomous vehicles, their attitudes about this emerging technology, and how it changed their behavior. These focus groups supplement the surveys conducted throughout the pilot project (the Prior Survey, the During Survey, and the Post Survey), which are the subject of the preceding sections of this chapter. Like the rider surveys, the focus groups were asked questions to encourage study participants to detail their experiences using the Waymo MOD service, how their attitudes about AV technology have evolved during the pilot project period, and how the MOD service and AV technology affected their travel behavior during the pilot project. The focus groups provided qualitative data that could not be collected through surveys alone.

i. Background Information

The rider focus groups comprised two main groups of users. The first group consisted of those in the RideChoice program who had previously been selected as participants in the pilot program. Participants enrolled in the MOD pilot were able to use the Waymo service as they would any other RideChoice option available in the Chandler/Tempe/Mesa/Phoenix service area and paid a flat $3.00 fare[2]. The 46 RideChoice users were contacted in April 2020 to gauge interest in participating in a virtual focus group virtually via Zoom[3]. Twenty users expressed interest. In May 2020, these twenty participants were contacted again and invited to participate in one of two focus group sessions. The two focus groups were held on May 27 and May 29, 2020. A total of ten participants took part in the focus groups – six on May 27 and four on May 28. Each rider compensated with a gift card for their participation in the focus group. Of the ten participants, two were blind, one was partially blind, one had autism, and four had some sort of mobility limitation, including one who used a manual wheelchair and another who frequently used an electric wheelchair.

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[2] RideChoice is normally a base fare of $3.00 per ride and $2.00 per mile over eight miles, but given Waymo's service area, a majority of trips would naturally fall within the eight miles, so the pilot program used a flat fare for Waymo rides.

[3] The focus groups were initially intended to take place in person, but rather than delaying them during COVID-19, it was decided to hold them virtually.

The second group that participated in the rider focus groups were Valley Metro employees. An earlier phase of the partnership between Valley Metro and Waymo allowed employees of Valley Metro to use the Waymo MOD service to provide a first/last mile connection to public transit, which employees can utilize with their regular monthly transit pass[4]. This focus group explored the same general topics as the RideChoice focus group, only without the focus specifically on the RideChoice service component. A total of three Valley Metro employees participated in this focus group on May 20, 2020. They did not receive any incentive for their participation.

ii. Rider Focus Group Format

All of the focus groups were conducted via Zoom, which allowed participants to see and hear each other just as they would in an in-person setting. This format generally worked well for each focus group with no major issues. The focus groups were scheduled for 90minutes and consisted of three main sections and introduction and concluding sections. Each focus group session had three researchers present: two moderators who alternated between sections and one notetaker. The three main sections of the focus groups each covered how a different dimension of the Valley Metro Waymo MOD pilot affected riders and closely mirrored the questions asked in the surveys (full focus group protocol in Appendix VI):

[4] The first phase with Valley Metro employees served as a feasibility study before expanding to RideChoice riders, and as a result, all rides taken by Valley Metro employees were covered by Valley Metro, not the individual riders.

Section 1 – Technology, Attitudes and Perceptions: This section asked questions about users' thoughts, feelings and perceptions of autonomous vehicles, how these changed during the course of the pilot, what they liked and disliked about the technology based on their experiences, and their thoughts about riding a fully driverless car without a Waymo-trained human safety operator.

Section 2 – User Experience of the Waymo MOD Service: This section asked users about their experiences using the Waymo MOD service. Riders were asked to talk specifically about their experience with Waymo and how it compared to previously-used transportation options available through RideChoice and other transportation options more broadly. Riders were also asked what they liked the most and the least about the Waymo MOD service and what would make them take Waymo rides more frequently. In the introductory section, riders were asked about one of their most memorable Waymo trips, which offered more insight into their experiences using the Waymo MOD service.

Section 3 – Rider Choice and Travel Behavior: This section explored how the Waymo MOD service affected the riders' ability to travel and how their travel behavior changed during the pilot. Questions were asked about how well Waymo met their mobility needs, why they chose to use Waymo over other options available, and how they anticipate using autonomous vehicles in the future. In the conclusion, riders were also asked whether they would continue to use Waymo if it was or was not part of the Valley Metro RideChoice program.

iii.Key Takeaways

RideChoice riders experienced an increased sense of safety and independence

All riders felt that the autonomous vehicles were safer than other drivers, especially over those of other rideshare services. Riders felt safe knowing that they were dealing with a company's fleet and trained vehicle operators, as opposed to individuals with their own cars. RideChoice users by-and-large experienced an increased sense of independence with the Waymo MOD service stating they no longer needed to rely on family or friends to give them rides. This resulted in them using the Waymo MOD service more frequently and going places they might otherwise not have. Related to this sense of independence, riders liked the ability to hail a ride from the Waymo MOD service whenever they wanted it instead of needing to schedule rides hours or even days in advance.

Waymo MOD provides a better service than existing RideChoice options

There was general agreement among RideChoice riders that the Waymo MOD service provided a far better service than other modes of transportation that participants previously had available to them, including bus, paratransit, taxi, or other ride-hailing services. Wait times were shorter. Vehicles were cleaner. There was no need to book a vehicle hours or days in advance. Using Waymo's app, riders could see where the vehicle was and know exactly when it would arrive. Riders mentioned several recurring issues, such as with pick-up and drop-off locations, accessibility of the app and the Waymo vans, and inefficient routing. Despite these issues, riders were still very satisfied with the service and commented frequently that rider support was always available to address any problems they had, which added to the high quality of service.

Riders like ride-hailing, but not necessarily the idea of sharing a ride with strangers

A majority of riders from the RideChoice and Valley Metro employee groups preferred the ride-hailing model of transportation that the Waymo MOD service offers. Many riders liked the ability to hail a ride and the possibility that this type of service may allow them to give up personal car ownership or provide a service they can utilize if they are unable to drive due to age-related causes. With the Waymo MOD service, most riders liked not needing to interact with the driver and said that would be another benefit of the rides being fully driverless.

What is less strong is a preference to share a ride with a stranger, consistent with the findings from the surveys. Many riders had done this either with paratransit or with shared ride-hailing rides. In some cases, it made the service less convenient since they would pick up and drop off other passengers along the way, making a trip take longer. In other instances, it was simply a preference for not wanting to share a ride, which was related to the preference for not talking to other people, whether it be the driver or other passengers.

Riders are eager to use Waymo to go more places and to do so without a human safety operator

All the participants were eager for the Waymo MOD service to start up again after it paused its service in March 2020 due to an abundance of caution during the COVID-19 pandemic.

Many riders look forward to continuing to use the service and plan to use it more as the service area expands. Currently, this is one of the only limitations as to why riders were not using the service more frequently. Likewise, riders were in general agreement in their excitement to ride in a Waymo with no trained vehicle operator. Some hesitation was cited, but many felt that, just as they became comfortable with the autonomous vehicle technology with a trained vehicle operator who is only there as back-up, they felt that they would similarly adjust to riding in fully driverless vehicles and looked forward to the opportunity to do so.

5.2.7.2 Subject Matter Expert Focus Groups

Early in the development of the Valley Metro Waymo MOD pilot project, the project team decided that in addition to understanding how the MOD service and AV technology affected Valley Metro transit users, and what the potential long-term benefits of AV technology might be for Valley Metro, it would be useful to understand the implications of the MOD pilot project, and AV technology more broadly, in Phoenix area cities. In particular, the goal was to understand better how Phoenix area cities are able to learn from the Valley Metro pilot project and what insights they offer as the region plans for this emerging technology together. In order to do this, two focus groups were conducted with urban and transportation planners (subject matter experts or SMEs) in Phoenix area municipalities and a policy maker roundtable was also held (detailed in section 8.3).

i. Background Information

The research team conducted the SME focus groups on July 6 and 7, 2020. The research team contacted representatives in each of the cities and towns that are part of the Valley Metro service area (seventeen towns and cities plus Maricopa County). In total, between the two sessions, participants from twelve out of the eighteen jurisdictions joined, with a total of twenty-seven participants. On July 6, a total of twelve participants joined from the City of Mesa (four participants), the City of Chandler (one participant), the City of Glendale (one participant), the City of Tempe (two participants), the City of Peoria (two participants), and the City of Buckeye (two participants). On July 7, fifteen participants joined from the City of Phoenix (four participants), the City of Surprise (two participants), the City of Avondale (two participants), the City of Goodyear (three participants), the City of El Mirage (two participants), and Maricopa County (two participants).

ii. SME Focus Group Format

Each focus group lasted 90 minutes and took place virtually on Zoom. Like the rider focus groups, the SME focus groups were broken into three main sections and introductory and concluding sections. These sections were determined in collaboration between the ASU research team, Valley Metro and Waymo to understand how cities are planning for AVs, the benefits of pilot projects and mobility partnerships as tools for planning for AVs. The focus group protocol is provided in Appendix VII. The three sections were as follows:

> *Section 1 – Transportation, Mobility and Autonomous Vehicles:* This section asked participants to discuss how their local jurisdictions are planning for AVs and how

AVs fit broadly into their plans for public transportation and mobility. This section asked local jurisdictions to talk about what efforts they have taken to date (if any) to plan for AVs, about opportunities and challenges their communities face in planning for AVs, and how they have or might engage the public in regard to AVs.

Section 2 – Pilot Projects: This section dealt with how pilot projects might help local jurisdictions plan for AVs. This section was developed with the idea that priorities for and approaches to pilot projects may vary between local jurisdictions and regional agencies such as Valley Metro. Questions were asked specifically about the Valley Metro Waymo pilot project and about what elements of this pilot were most useful to local jurisdictions. Participants were then asked about other types of pilot projects that jurisdictions may be interested in seeing in the region or developing themselves and if any barriers to developing pilot projects exist in their communities.

Section 3 – Mobility Partnerships: The final section explored the role of partnerships in planning for AVs. This was included because the partnership between Valley Metro and Waymo was a key component of the current project and the project team felt it was useful to understand better how local jurisdictions were thinking about what their relationships with AV companies would be as the technology continues to be tested and deployed. Participants were asked what partnerships with AV companies might look like in local jurisdictions and what barriers, if any, exist in developing these partnerships.

The focus group concluded by asking each jurisdiction what types of information would be most useful to their community to advance their efforts in planning for AVs in the Phoenix region.

iii. Key Takeaways

Develop pilot projects that explore ways to enhance public transit service and identify infrastructure needs

Both SME focus groups discussed how to use AVs to enhance public transit service, recognizing that they faced numerous challenges in expanding current systems (both bus and light rail) as well as circulator systems that many Valley cities operate independent of Valley Metro. Participants were particularly interested in exploring how AVs may enable them to connect lower density areas of their cities, areas farther away from their downtowns, and other activity centers to the rest of the city. There was a lot of interest in the possibility of AV shuttles in possibly filling this need. They were also seen as a way to expand the availability of AVs beyond Waymo's existing service in the East Valley. There was equal interest in whether Waymo could expand to other areas of the Valley and expand its current MOD pilot project to other communities, either by expanding its current service area or leapfrogging to other areas of the Valley, such as the West Valley.

There was also a lot of interest in making sure that AV pilot projects helped communities understand better the infrastructure needs that would be required. This would help them think about the types of projects they could fund based on current and future levels of funding. Participants also discussed the benefits of using pilot projects to engage the public on AVs. A public meeting could only achieve so much but giving people the opportunity to experience the technology first-hand was of interest, as was finding more ways the AV industry and the public sector could share responsibility for engaging the public.

Address uncertainty at a regional level

One of the key barriers that emerged from these two roundtables for planning for AVs was that there remains a lot of uncertainty about the technology and deployment that needs to be addressed in a more robust and regional way. Barriers discussed included: uncertainty around how and when the technology would be deployed across the region; costs to cities related to conducting pilot projects, providing service, or investing in infrastructure; uncertainty about what the state or federal government might do in terms of regulation; and numerous obstacles around how local communities might work with industry partners to provide meaningful transportation improvements to their residents.

5.2.7.3 Policy Maker Roundtable

The final component of the work conducted by the ASU research team at the Center for Smart Cities and Regions was a policy maker roundtable. ASU researchers convened Valley Metro board members with two goals in mind. First, to share some of the preliminary findings of the MOD pilot program and second, to engage policy makers in a conversation about the implications of the Valley Metro Waymo pilot project and possible next steps that could be taken by Valley Metro, local jurisdictions, and industry partners. Participants for the roundtable were identified by Valley Metro and were all members of the Valley Metro Board of Directors. Seven board members participated, representing both large and small jurisdictions throughout the region. There were also numerous participants from ASU, Valley Metro and Waymo joining the roundtable as observers.

i. Roundtable Format and Agenda

The policy maker roundtable was held on July 8, 2020. The roundtable took place virtually on Zoom and lasted 90 minutes. The roundtable was divided into four parts: an introduction and overview of the MOD pilot project and the partnership between Valley Metro and Waymo; a presentation of results from the rider surveys and from the rider focus groups; a discussion about the Valley Metro Waymo MOD pilot project and AV planning more generally; and a closing comments section where questions were asked about possible next steps. The roundtable protocol is provided in Appendix VIII. The discussion component of the roundtable was broken into three sections:

> *Section 1 – Implications of the Valley Metro Waymo MOD pilot project:* This section asked participants to consider what the pilot project meant for Valley Metro and for transportation policy in the region more generally and some of the main issues it raises for them.

> *Section 2 – AVs in public transit:* This section asked participants to discuss how they envision AVs interacting with public transit in the future and what types of pilot projects they may be interested in seeing developed in the Phoenix region.

Section 3 – AVs in Phoenix area jurisdictions: This section asked participants to discuss their own jurisdiction's thinking about AVs and how local planning for AVs can align with regional efforts. They were also asked broadly about the types of transportation issues they would be interested in seeing AVs address.

The roundtable concluded by asking about possible next steps that Valley Metro and the region could take in their efforts to plan for AVs and what type of information would be most useful for them in their role as decision makers.

ii. Key Takeaways

Several key issues emerged from the roundtable discussion that are identified here that will help the region think in greater detail about how best to plan for autonomous vehicles. Generally, there was a lot of interest in the Valley Metro Waymo MOD pilot project and interest in seeing how it could be expanded. There was also a lot of interest in exploring other use cases for AVs and several important issues were raised.

Explore additional use cases

A key point of discussion in the roundtable discussion was a desire to explore other demonstration projects for autonomous vehicles in the Phoenix area. Participants were generally pleased with the Valley Metro Waymo MOD pilot program and wondered how easily this service could be expanded. It was pointed out that the on-demand transportation requires extensive mapping of a neighborhood before the service can start. It was discussed whether this was the right fit for every community in the near-term, although there was uncertainty around how quickly Waymo might expand its service area.

AV shuttles were brought up as a possible alternative due to their larger size. Several participants commented that for transit, a four-to-five-person autonomous vehicle might not make the most sense in a lot of places, but also recognized that a full-size bus might not make the most sense either in many parts of the Phoenix area. Medium-sized shuttles, similar to the circulator buses or trolleys that many cities currently operate, could be an alternative use for AVs. These types of vehicles offer a mid-sized vehicle that seats between eight and twelve passengers, which could make it a good option to explore in the future. One participant mentioned how their community is having conversations about their circulator system and that AV shuttles could be part of that conversation moving forward. There was a particular interest in these types of projects moving since they could be deployed on existing fixed route circulator routes and be less dependent on Waymo to expand its service area before deploying its autonomous vehicles for this use.

In general, the conversation was supportive of exploring a variety of other demonstration projects as long as they met two criteria. First, the goal should not be to replace existing transit, but to find ways to complement it with new uses. Second, within the context of transit, AV technology should enable first/last mile connections to existing transit, particularly to high-capacity transit corridors. It was pointed out that as the region continues to grow, improving the first/last mile connections will be a critical goal that will help ensure that transit remains a viable mode of transportation for the region. Also raised was the overall benefit of deploying AV technologies around the Valley as a way of getting people familiar with the technology and letting people experience it, which was identified as a critical component of these early planning efforts.

Who pays for AV projects?

A second key discussion point was on funding of AV projects. This was raised within the context of the next regional transportation plan and the potential need to allocate money for AV projects, and to identify corresponding projects, within that framework. Valley Metro staff echoed that funding was critical and that it would not take funds away from existing service to fund AV pilot projects. Valley Metro would instead pursue grant opportunities, either on their own or with local jurisdictions as opportunities to do so became available. Valley Metro has also been advocating with Maricopa Association of Governments (MAG) to explore opportunities to create a dedicated regional fund for local jurisdictions to conduct pilot projects – possibly as part of the next regional transportation plan funding.

Data-sharing

The issue of data-sharing came up within the context of discussing transportation issues and whether efforts were being made to develop an app that would essentially enable residents to access multiple modes (e.g., light rail, bus, Waymo, rideshare, e-scooters, etc.) in one platform, instead of needing to use multiple apps. While there is no regional effort to do this, the City of Phoenix is leading this effort and the technology will be used regionally. For Valley Metro's part, they make all their bus location data available and have an application programming interface (API) so that a third party can access and utilize those data. This then expanded into a discussion about ensuring that future pilot projects and partnerships develop data-sharing agreements that facilitate the collection, sharing, and use of data between Valley Metro, cities, AV service providers and other potential partners.

Collaboration and coordination between jurisdictions

The final key discussion point in the roundtable was around coordinating and collaborating on planning efforts for AVs throughout the region. Over the next few years, MAG is developing the next regional transportation plan and there is a need to engage with MAG to ensure that local issues and priorities for AVs are leveraged at the regional level. The need to engage with MAG was seen as beneficial in the future to address efforts around both project planning and as a possible funding source for AV pilot projects.

The need for collaboration and more regional conversations emerged out of an acknowledgement that current efforts are not highly coordinated and knowledge about different projects is not necessarily widely known. While efforts to do this are being made, such as through the Institute of Automated Mobility, a state-level initiative to advance planning for autonomous vehicles statewide, many different actors are working in this space. For example, at ASU numerous faculty members are working on different aspects of AVs, but there is no single person or entity to which go to learn about all these efforts. The need for a more effective platform of information sharing was made more apparent by the lack of knowledge by roundtable participants of the Peoria AV shuttle pilot that operated for about three weeks prior to being stopped early due to COVID-19 considerations.

One suggestion to advance further regional collaboration was to expand on the smart region efforts being led by ASU, by creating a smart region subgroup on transportation. Whatever the forum, it was agreed that conversations such as this roundtable were useful for participants in the public and private sectors and that it is important to have active and continuing dialogues so that the region can best advance its planning around autonomous vehicle mobility.

5.2.8 Lessons Learned

The following conclusions can be drawn from the data described in this chapter. Again, it must be kept in mind that the samples are not representative samples and so the findings apply only to those who participated in the various data collection efforts. Additionally, other limitations were observed in this demonstration, such as the small sample sizes in some analyses; the nature of self-selected participants, which could result in biases when answering some questions; the understanding that the study would last six months only, potentially impacting users' usual travel patterns; and the unprecedented COVID-19 pandemic impacts at the end of the study. For readability, the conclusions presented below are summarized by topic and presented in bullet-point format. For further details and additional discussions, including insights on research questions and supplemental materials, please refer to Stopher et al. (2021).

5.2.8.1 Demographics

- The samples that responded to the surveys tended to be younger than general participants in the Valley Metro RideChoice program.

- The respondents that answered the During and Post Surveys showed differences between respondents and nonrespondents based on the Prior Survey, particularly on employment status, student status, and occupation.
- Those who did not use Waymo during the demonstration project (RC Respondents (non-Waymo)) were generally older than the RC Respondents (Waymo), predominantly male, coming from larger households with more vehicles, were more likely to live in a stand-alone home, were more likely to live in a gated community, were not currently working, had a higher proportion of students, had a higher income level, and were better educated.
- It is not appropriate to compare the demographics of the samples in this study to the general population, because only those who were eligible to use the RideChoice program were affected and could be included in the samples.

5.2.8.2 Current and Recent Travel Behavior

- In the During and Post Surveys, 23 percent of respondents did not use Waymo RideChoice at all. The main reason for not using Waymo appeared to be the limits of its geographical service area.
- In the past 12 months (from May 2019 to May 2020), 80 percent of RC Respondents (Waymo) and 100 percent of RC Respondents (non-Waymo) had used non-Waymo RideChoice services. However, in the period since March 15, 2020 (COVID-19 restrictions), most respondents (51.3 percent) had not used any non-Waymo RideChoice services.

- Almost half of both RC Respondents (Waymo) and RC Respondents (non-Waymo) expected to use RideChoice services at least once or twice per week after the COVID-19 pandemic.
- The proportion of users (both Waymo and non-Waymo) using ride-hailing services outside of the RideChoice program dropped significantly after the introduction of the Waymo service.
- In rating the various ride characteristics of regular taxi, Uber and Lyft, and Waymo, Waymo was rated highest on all attributes except pick-up and drop-off locations and travel time. Regular taxi was rated the lowest on all attributes.

5.2.8.3 Comparison of Trip Characteristics

- Waymo was used significantly more for travel between midnight and 6 a.m. than other RideChoice services.
- Waymo riders also were accompanied by others significantly less frequently than other RideChoice services.
- Waymo riders were overwhelmingly satisfied with the wait time, travel time, cost, and comfort of their most recent Waymo ride.
- Most RC Respondents (Waymo) had taken between 6 and 30 rides on Waymo in the December through February period.

5.2.8.4 Perceptions of Waymo and Non-Waymo RideChoice Services

- In the Prior Survey, respondents indicated that they relied on the RideChoice program to go different places, found the program affordable, and a majority felt they would be unable to find a reasonable alternative to RideChoice.

- In evaluating safety and security of the RideChoice Waymo services, respondents who used Waymo were more satisfied with the safety and security of RideChoice Waymo services than of traditional RideChoice options.
- Respondents were generally more satisfied with the travel times and costs for RideChoice Waymo services than for traditional RideChoice services.
- Respondents were more satisfied with the ease of ordering RideChoice Waymo services than traditional RideChoice services but found little difference in the ease of getting in and out of the vehicles.
- Respondents were more satisfied with the reliability of RideChoice Waymo services than with traditional RideChoice services.

5.2.8.5 Attitudes and Perceptions Towards Self-Driving Vehicles and On-Demand Mobility Services

- Of three scenarios – riding alone, riding with friends or relatives, and riding with strangers, riding with friends or relatives was preferred to either of the other options.
- Waymo riders became more comfortable with riding with friends or relatives and riding with strangers after experiencing Waymo rides but became less comfortable with riding alone.
- Non-Waymo riders showed increasing comfort with all three scenarios, progressing from the Prior to the Post survey.

- All Survey participants felt that autonomous vehicles would improve safety on the roads, would meet the mobility needs of all people and also those with special needs, and agreed that it would be good to see more such vehicles on the roads.
- Most Survey participants agreed that they would switch to requesting self-driving vehicles when available as part of RideChoice, and also that they would like to be among the first to use such vehicles when they become widely available.

5.2.8.6 Focus Groups

- The rider focus groups tended to confirm the findings of the surveys.
- Waymo riders found the Waymo service to give them a greater sense of safety and independence.
- Waymo riders felt that Waymo service was better than other RideChoice options.
- Waymo riders liked the idea of a ride-hailing AV service, but were somewhat less comfortable with ridesharing with strangers.
- Waymo riders are eager to use Waymo to go more places and to do so without a vehicle operator.
- The Subject Matter Experts (SME) focus group was keen to see pilot projects that would point the way to enhancing transit service and identify infrastructure needs.
- The SME focus group also felt that there was a need to address the uncertainties of the technology at a regional level.
- The Policy-Maker Roundtable felt there was a need to explore more use cases within the region. They also raised the issue of who pays for such use cases; they raised the issue of data sharing, particularly with private companies that may be

offering the AV services; and they emphasized the need for collaboration and coordination among the various jurisdictions.

Overall, the demonstration project was successful in helping people to understand and perceive the benefits of AVs and to overcome some of their initial misgivings about such technology. The Waymo services were well received by the sampled RideChoice users and were rated as providing better service than other RideChoice options.

5.3 PEORIA'S ROBORIDE AUTONOMOUS SHUTTLE

5.3.1 Project Description

Funded by the Maricopa Association of Governments (MAG), the RoboRide was a low-speed autonomous vehicle (LSAV) shuttle service operated on a fixed route within a medical district in Peoria, Arizona. This project aimed to assess opinions and concerns regarding AV technologies, especially if used in that proposed scenario in a controlled region, and, from the technology standpoint, how AVs could be enhanced to serve mobility needs better for all.

RoboRide shuttle took place from January through April 2022 in a controlled area within a robust healthcare district in Peoria, AZ home to more than 100 medical facilities and more than 500 senior living residences. This service connected local residents from their point of origin to their destination within the service area. The 2.4-mile route had 13 stops and connected people living in assisted living facilities and multi-family residential housing with medical facilities and commercial establishments (Figure 21). During the four-month pilot (January – April 2022), the shuttle was scheduled to operate 6 hours a day, from Monday through Saturday, 8 am-2 pm. The shuttle was free of cost to the public and required no registration to utilize. When driving the loop, the shuttle stopped at each stop on the route to look for passengers, and if someone was waiting to ride, the operator opened the shuttle doors to permit entry.

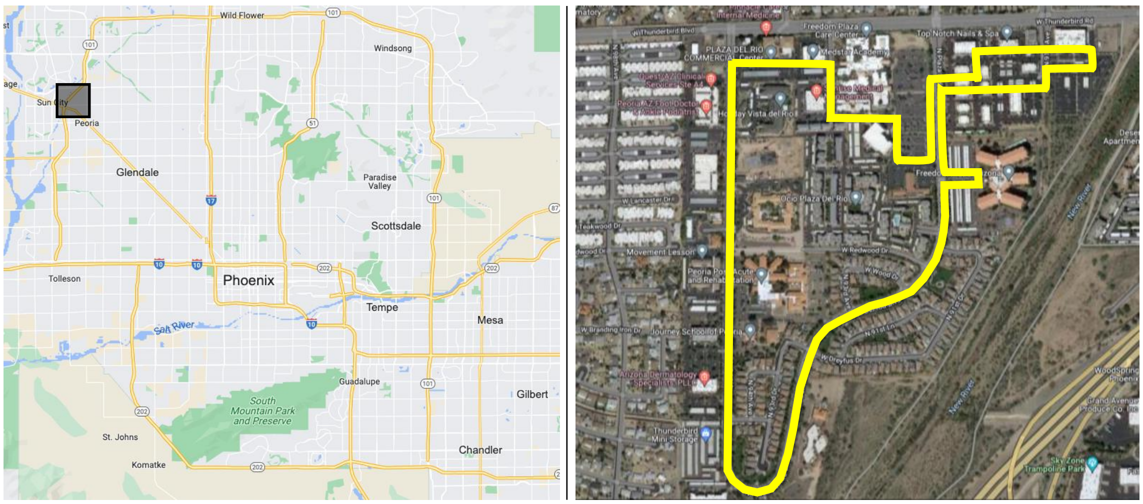

Figure 21 RoboRide Service Location and Route

It was expected that individuals living in these residential settings would take advantage of the service to access destinations in the commercial establishments and undertake activities. The roads on which the shuttle was operated were low-speed and low-traffic volume roads, which presented an opportunity to have the shuttle travel in mixed traffic. Although the roadway speed limit on N 94th Drive is 25 mph, regular vehicular traffic often travels at higher speeds. The City of Peoria, therefore, decided that separating the LSAV from regular vehicular traffic on this road was the best choice, both in terms of safety and maintenance of vehicular flow in the travel lane. The City of Peoria re-marked a separate lane for the LSAV to utilize. Separation of the shuttle from other traffic on the main road was possible due to the wide width of the roadway. However, the shuttle operated in mixed traffic in parking lots and on minor roads.

The LSAV shuttle with no steering wheel or pedals was operated by Beep. Although the vehicles were fully autonomous and did not require human intervention, a trained attendant was always onboard as a backup. A shuttle could fit eight seated passengers, and real-time location and schedule were available through the Beep app. The shuttle inauguration occurred in November 2021, but the shuttle was only operated a few days in November and December 2021. These days were excluded from the analysis presented in this study because operation during this period was considered a trial phase. Although the public was invited to ride, the primary reason for the operation of RoboRide during this time was to double-check minor details such as schedule, stop locations, vehicle speed, and other operational characteristics that would ensure safe and efficient shuttle performance.

Given this pilot's complexity, the evaluation of the service is multidimensional, encompassing both ridership and technology performance analysis. A comprehensive assessment of the RoboRide shuttle was completed by analyzing various aspects (e.g., shuttle operation, accessibility, and utility) and gathering insight from multiple methods (e.g., intercept surveys, mailed and emailed invitations, flyers, shuttle performance data, etc.). This evaluation was possible thanks to collaboration among the City of Peoria, MAG, ASU, and Rick Engineering.

In order to evaluate and provide meaningful insights into the pilot, critical data had to be collected and analyzed upfront. The data collected included but is not limited to public opinion (from both RoboRide users and non-users), ridership metrics (e.g., number of passengers; embark and disembark locations; miles covered), and vehicle performance (e.g., travel speed; battery efficiency; and disengagement instances).

In terms of public opinion and preferences, surveys were the main form of data collection. During the pilot, two surveys were deployed, the Intercept Survey and the Full Survey. In the Intercept Survey, an Arizona State University student intercepted people in the streets of Peoria's medical district for a quick (about five minutes long) interview. The Full Survey was a longer (about 25 minutes long) in-depth survey that was undertaken online. Recruitment for this online survey was deployed via multiple platforms. Both surveys aimed to capture respondents' perceptions and attitudes about self-driving technologies, usage of and awareness about RoboRide, current mobility patterns, future mobility choices, background information, and more. In this chapter, results and details regarding the Intercept Survey are omitted; however, it does not compromise by any means the evaluation and insights obtained from this project. The full project details and discussions will be published later in 2023 (Stopher et al., 2023). The survey instruments are available in the Appendix section.

In addition to descriptive analysis of survey results, statistical models were utilized to investigate the impacts of sociodemographic, attitudinal, and latent variables on crucial questions of interest (such as proclivity to use AV shuttle service in the future) after controlling for different factors. These models help explain travel patterns and choices while accounting for the influence of exogenous variables and unobserved factors. Model details and estimation results are included throughout this chapter under their appropriate sections.

During service operations, the service provider, Beep, collected ridership metrics and vehicle performance data. Beep provided the data to ASU for additional data exploration and analysis. Details about the dataset and variables are provided later in this chapter.

After extensive data analysis and model estimations, the final evaluation of the pilot project was performed by summarizing the main findings and conclusions by topic. This section is intended to provide insightful information for cities, agencies, and technology developers on how users perceive AV technology, how policymakers can prepare for similar projects in the future, and how transportation technology developers can enhance their services to serve peoples' travel needs better.

5.3.2 Data

This study uses RoboRide project's Full Survey data, roughly twenty-seven-question long online survey that took about twenty-five minutes to complete. Upon request, a telephone-based survey could also be accommodated. Although the survey was twenty-seven questions long, some questions involved and required multiple responses. Display logic was used to ensure that follow-up questions were only asked to relevant respondents (e.g., only RoboRide users were asked about the comfort of riding in the RoboRide vehicle). The survey questions asked about familiarity with RoboRide and AVs, opinions on safety and use of AVs, current travel patterns, future travel expectations and hypothetical future AV use, and background and demographic data.

Respondents for the survey were recruited in multiple ways. ASU students left flyer handouts with a QR code and URL link to the survey in the neighborhood's medical offices, restaurants, businesses, and assisted living facilities. In addition, 10,000 email addresses and 2,000 home addresses were purchased from Data Axle. All addresses and emails were from three zip codes surrounding the RoboRide service area (namely RoboRide Region). The zip codes mainly cover the City of Peoria and are 85345, 85351, and 85381. A map of these zip codes can be seen in Figure 22. Email invitations were sent to the 10,000 purchased email addresses explaining the project's purpose and providing multiple links to the survey. A cover letter and flyer handout with a QR code and URL link to the survey was delivered to the 2,000 purchased addresses. Finally, the City of Peoria posted the survey on its website with a public invitation to participate. In all the invitation forms, participants were offered an electronic $10 Amazon gift card as a token of appreciation for submitting a complete survey response. Responses were collected from late February through early June 2022. A total of 274 responses were gathered after data cleaning was complete.

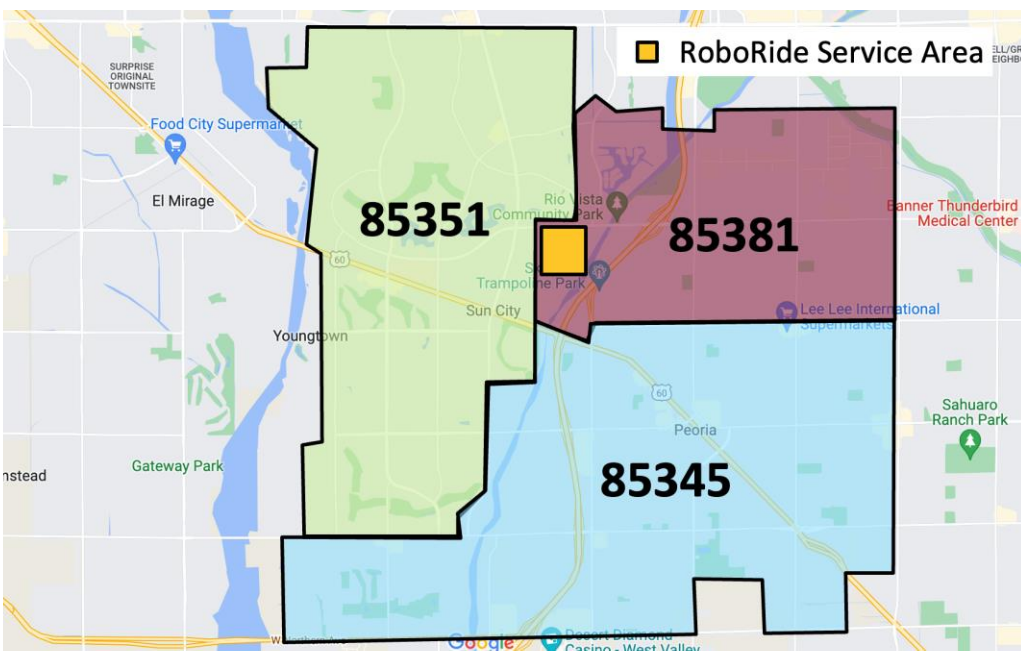

Figure 22 Zip Codes Surveyed Near Peoria's Medical District

Table 11 shows a comparison of the demographics from the Full Survey, those of the Peoria zip codes, and the US Census. As expected, given the nature of the RoboRide service area and the local population, the intercept survey exhibits a much higher proportion of elderly respondents (over 65) than the Full Survey or the Peoria area. The Full Survey y, as would also be expected, is a much closer match to the age distribution of the Peoria area. In terms of gender, the Full Survey has a higher proportion of female respondents. shows as being smaller for the Full Survey than for either Peoria, or the US Census, with a larger proportion of 2-person households than either Peoria or the US. The percentage of households with 4 or more people is similar to that for Peoria, but much smaller than the average for the US.

Table 11 Summary Demographics of the Two Survey Samples

Demographic	Full Survey (N=274)	Peoria, AZ (Zip Codes: 85345, 85381, 85351)	Adults in the United States (Census)
Age			
18-35	13%	18%	30%
36-45	9%	10%	16%
46-65	33%	28%	34%
66 and older	45%	44%	20%
Gender			
Male	42%	47%	49%
Female	58%	53%	51%
Household Size			
1	24%	36%	28%
2	47%	38%	34%
3	15%	11%	16%
4 or more	14%	15%	23%
Vehicle Ownership			
0	4%	5%	28%
1	36%	46%	34%
2	38%	33%	16%
3 or more	22%	16%	23%
Household Income			
Less than $25,000	8%	19%	18%
$25,000 to $49,999	23%	27%	21%
$50,000 to $74,999	25%	19%	17%
$75,000 to $99,999	17%	14%	13%
$100,000 to $149,999	19%	14%	16%
$150,000 and over	8%	7%	15%
Employment Status			
In labor force	35%	70%	77%
Not in labor force	65%	30%	23%
Educational Attainment			
Some high school or grade school	2%	11%	10%
Completed high school or GED	10%	29%	28%
Some college/tech. school	41%	37%	27%
Completed bachelor’s degree	27%	15%	22%
Completed grad degree(s)	20%	8%	13%
Job Type			
Professional, managerial, or technical	27%	16%	17%
Clerical or administrative support	18%	4%	5%
Sales or service	16%	26%	20%
Education or training	15%	24%	25%
Manufacturing, construction, maintenance, or farming	5%	14%	18%
Arts, design, entertainment, sports, and media	1%	9%	9%
Other	19%	6%	5%

Vehicle ownership in the Full Survey averages the same as for Peoria and the US as a whole. For the sample 1-vehicle households match more closely to the US than to Peoria, while 2-car households match Peoria rather than the US. The percentage of households with no vehicles is lower than the US Census, although similar to Peoria. The income distribution for the Full Survey also matches quite well to Peoria, while the highest income group matches well to Peoria, but is much lower than for the US. Full-time employment is lower for the full survey than for either Peoria, or the US, and the unemployment rate of those in the labor force is higher than for Peoria as a whole. Finally, the Full Survey sample is better educated than Peoria as a whole and also than the US. It can be concluded that the Full Survey sample matches well on all demographics to the Peoria zip codes.

As shown in Table 12, 63 percent of survey respondents indicated that they did not have a health condition that limited their mobility, while 37 percent indicated that they did have a mobility limitation. Only about 15 percent of the sample are limited in driving or using public transit, while rather more (23 and 29 percent, respectively) have limitations with respect to walking up to 15 minutes or riding a bicycle. Respondents were also asked if they used any type of wayfinding or mobility assistance. As expected from the mobility limitation responses, 84 percent indicated that they did not use such assistance. Of those who reported using such assistance, closed captions were used the most, and magnification was the second most used method. Other methods were used by one percent or fewer of the respondents.

Table 12 Mobility Characteristics

Mobility Condition	**Full Survey (N=274)**		
Limiting Health Related Conditions[5] (N=274)			
None	63%		
At least one	37%		
Nature of Limiting Health Related Condition	Yes	To Some Extent	No
Riding a Bike (N=256)	14%	15%	71%
Walking up to 15 minutes (N=255)	9%	14%	77%
Driving a Personal Vehicle (N=258)	9%	6%	84%
Riding Public Transit (N=256)	5%	10%	85%
Use of Wayfinding, Mobility Assistance Systems, and Tools (N=230)			
Closed Captions	8%		
Magnification/Large Font	5%		
Voice Control	1%		
Text to Speech	1%		
Color Modifications	<1%		
Keyboard Only	<1%		
None	84%		

5.3.3 Results

The survey was divided into three parts, namely present travel, perceptions of autonomous vehicles (AVs), and demographic information. As noted earlier, there were 274 good responses to this survey. Of these 274 respondents, 34 (12%) had ridden RoboRide at least once, while the remaining 240 respondents had not used RoboRide by the time they responded to the survey. Figure 23 shows that about one-third of respondents who had used RoboRide used it for only one ride. About 40 percent used it for two rides, and the remainder used it for between 3 and as many as 20 rides.

[5]Limiting conditions were specified as disabilities or health conditions that limit the individual from 1) driving a personal vehicle, 2) using public transit, 3) riding a bike, 4) walking up to 15 minutes

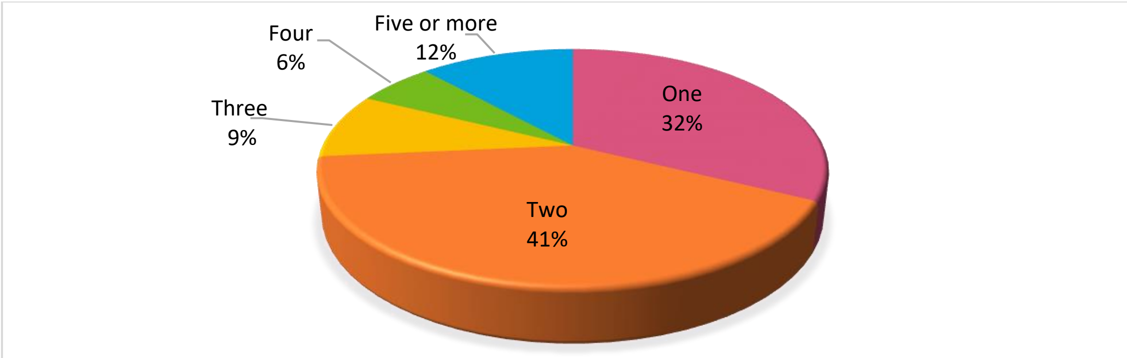

Figure 23 Number of Trips Taken by Users of RoboRide (travel one way is one ride) (N=34)

5.3.3.1 Roboride Experience

RoboRide users were presented with a number of attitudinal statements about RoboRide services. Not all RoboRide users responded to all of the attitude questions. Figure 24 shows the results of the attitudinal questions having to do with comfort and convenience. The majority (70 percent) found the ride to be comfortable and pleasant, and only 9 percent disagreed with this statement. Very few (12 percent) thought the vehicle was difficult to get into and out of, while 65 percent disagreed with this statement, most of them indicating strong disagreement. Only a small minority (15 percent) felt that RoboRide did not serve all of the medical facilities they needed to visit, while 68 percent agreed that it served all of the medical facilities they needed to visit. Overall, in terms of comfort and convenience, RoboRide users indicated a high degree of satisfaction with the service.

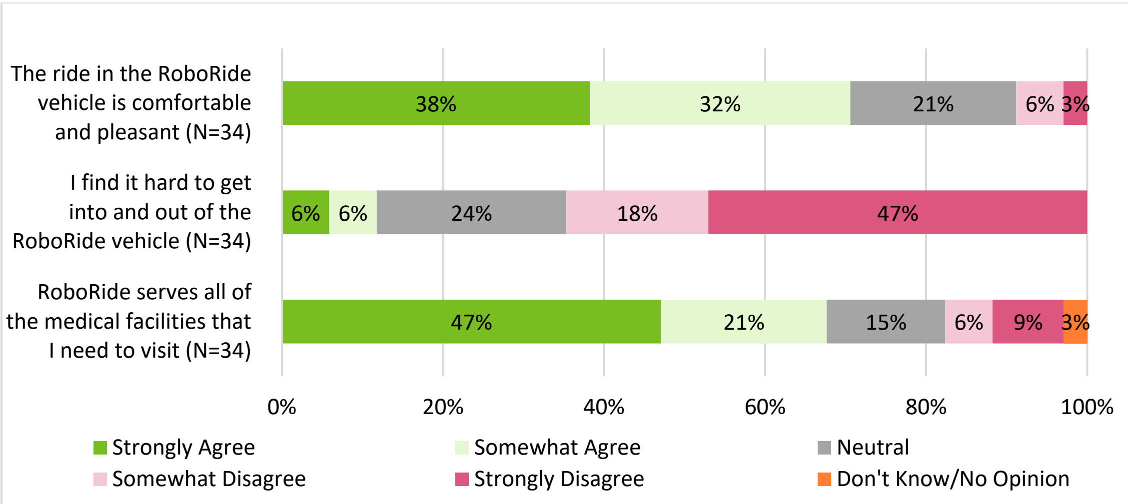

Figure 24 Full Survey RoboRide Users' Agreement with Attitudinal Statements Regarding RoboRide's Comfort and Convenience

Figure 25 shows the ratings of safety issues for the RoboRide service by RoboRide users. Concerns over technical or mechanical problems were indicated by about 27 percent of riders, while a slightly larger percentage (36 percent) disagreed with this statement. About one third were neutral. This suggests that there remain significant concerns about technical or mechanical issues with AVs. Opinions were more evenly split about the need for an attendant or operator on board, with more respondents feeling there was no such need (42 percent agreeing that an operator or attendant was not needed, compared to 33 percent who felt one was needed). Again, this suggests that there are still concerns about having no operator on board. In contrast, the large majority of riders felt safe riding in the vehicle, with 82 percent agreeing that they felt safe, 15 percent having no opinion and only 3 percent that disagreed with this statement. Overall, in terms of safety, there remain concerns with the technology and the need for an operator or attendant, although feelings of safety in the vehicle were high.

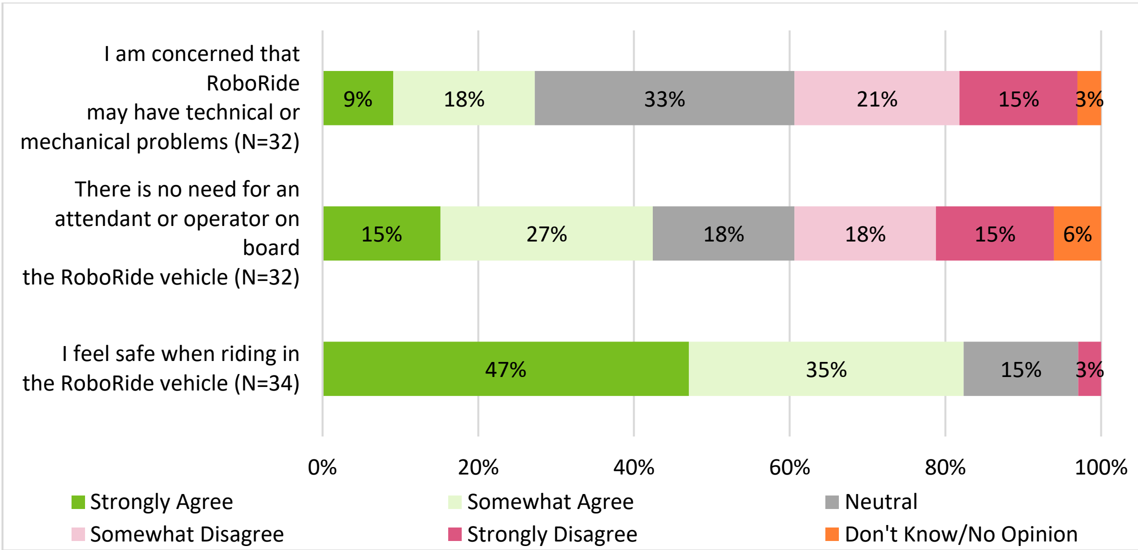

Figure 25 Full Survey RoboRide Users' Agreement with Attitudinal Statements Regarding RoboRide's Safety

Figure 26 shows the ratings of RoboRide users on statements about adoption and usage of RoboRide. Nearly 50 percent preferred riding RoboRide to a human driven vehicle, while only 21 percent preferred a human driven shuttle. Very few (12 percent) found it difficult to use the app, although only 36 percent disagreed with finding the app difficult to use. This statement had the largest "don't know/no opinion" response at 21 percent. About one third of respondents reported traveling more after the introduction of RoboRide, while 36 percent did not feel that they were traveling more. A fairly large 27 percent were neutral to this statement. Three quarters of respondent riders found it exciting to ride in the vehicle, and only 3 percent disagreed with this statement – all of them disagreeing strongly. Overall, on usage and adoption of RoboRide, there appears to be more ambivalence than on the other groups of attributes.

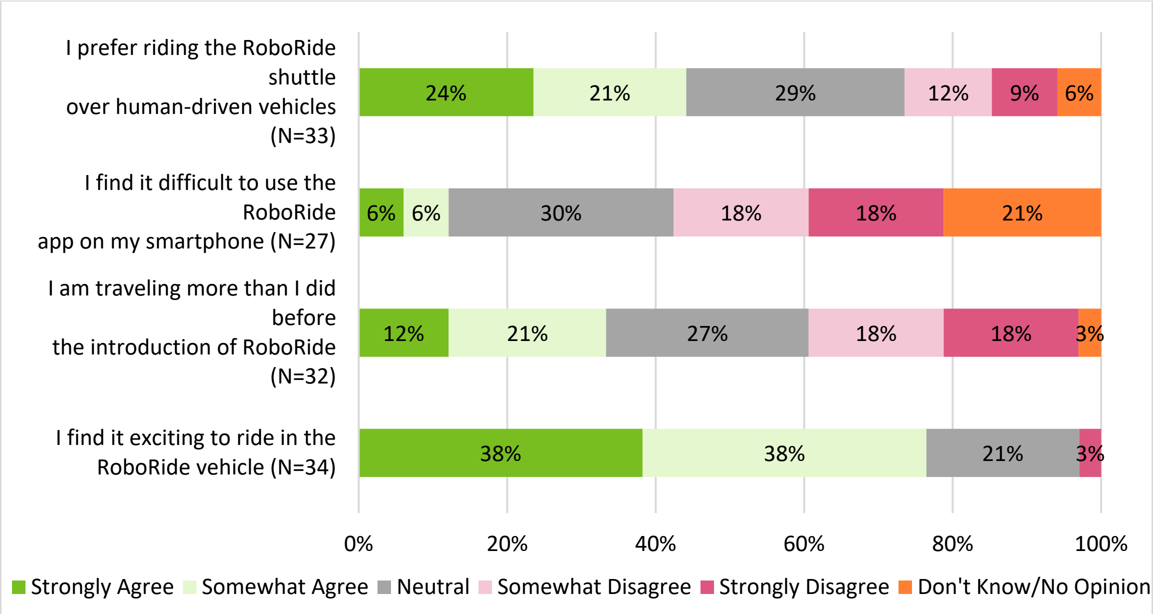

Figure 26 Full Survey RoboRide Users' Agreement with Attitudinal Statements Regarding Usage and Adoption of RoboRide

In summary, these three figures show a generally favorable attitude to RoboRide by those who used it. These were the only questions specifically about the RoboRide service that were addressed to RoboRide users.

Non-RoboRide users were asked why they had not tried RoboRide and if they still intended to try it. Figure 27 shows the reasons that respondents had not tried RoboRide. The figure shows the percentages of respondents that indicated the reason. The 239 respondents who answered this question provided a total of 492 responses or slightly more than an average of two responses per respondent. Hence, the percentages do not add to 100, because the graph shows the percentage of respondents to give that answer.

A majority (68 percent) of non-RoboRide users felt they had no need for the service. Almost half of the respondents (46 percent) did not know the schedule or felt the stops were located inconveniently. A further 32 percent felt that RoboRide was less convenient than other modes. Just 16 percent cited safety concerns, which seems to be consistent with other expressions of concern about safety.

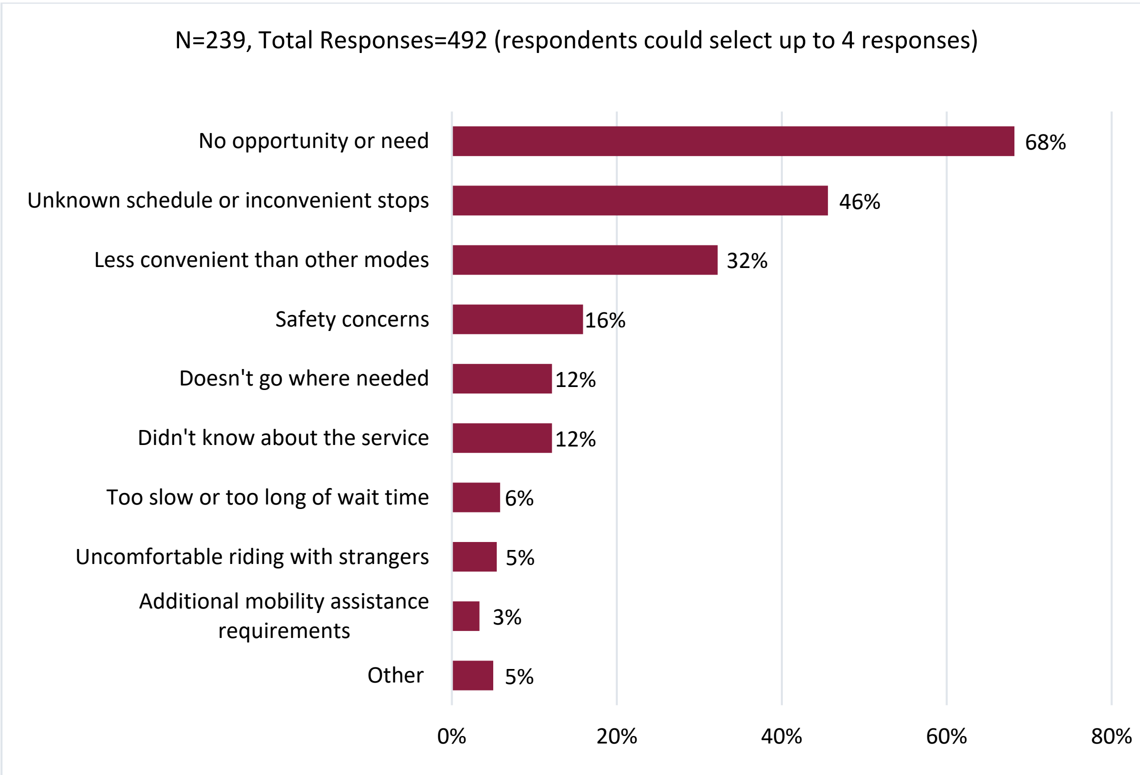

Figure 27 Non-RoboRide Users' Reasons for not Trying the Service

RoboRide non-users were also asked if they planned to try RoboRide before the end of the trial period. Of the 240 respondents to this question, 26 percent (62) of respondents said yes, while the remainder said no. This is similar to the result from the Intercept Survey, where 16 percent indicated that they would try before the end of the trial period. It is worthy of note that this means that the vast majority of respondents (74 percent in the Full Survey and 84 percent in the Intercept Survey) were not interested in trying the service.

i. Logit Regression Model for Willingness to Try RoboRide Service

This is a logit regression model on respondents' willingness to try RoboRide (using the subsample of non-RoboRide users only), with a binary response of yes (1) or no (0). The results are shown in 3.

Table 13 Logit Regression on Willingness to Try RoboRide

Explanatory Variables	**Plan to Try RoboRide**	
	Coeff.	t-stat
Age		
71 or more	-1.10*	-2.19
Gender		
Female	0.68	1.74
Worker Status		
Worker	-1.06**	-2.34
Household Vehicles		
Vehicles in HH: 3 or more	0.82	1.87
Home Characteristics		
Apartment	1.70**	3.00
Travel Characteristics		
Used Ridehailing Services in the Past 12 Months	0.78	1.90
AV Perceptions		
Perceived Safety	0.97**	2.48
Constant	-2.19**	-4.18
Data Fit Measures		
R-squared (df)	0.138 (df=7)	

* Significant at 95%
** Significant at 99%

The model shows that older adults were less inclined to try RoboRide and that, while females were less likely to take AV rides in the future and showed lower levels of AV safety perception and familiarity, they were more inclined than males to try RoboRide service. However, this latter finding is not significant at 95 percent. It is possible that the nature of the pilot program in a controlled environment with a low-speed vehicle overlooked by the local public authorities in a medical district was seen as more trustworthy, thus more appealing to females than AVs in general. Living in a household with more than two vehicles available positively affected a respondent's willingness to try RoboRide service, although again this was not significant at 95 percent. Living in an apartment increased willingness to try RoboRide. As observed before, a higher perception of safety in AVs and recent ridehailing experiences positively impacted willingness to try the RoboRide service.

5.3.3.2 AV Perceptions

In the last section of the Full Survey, respondents were asked questions about autonomous vehicles in general. Figure 28 shows that most respondents had heard of AVs (9 percent had not prior to this study), although many (49 percent) had comparatively little knowledge of them. Only 2 percent had taken a ride in an AV, other than RoboRide, although 10 percent claimed to be very familiar with AVs.

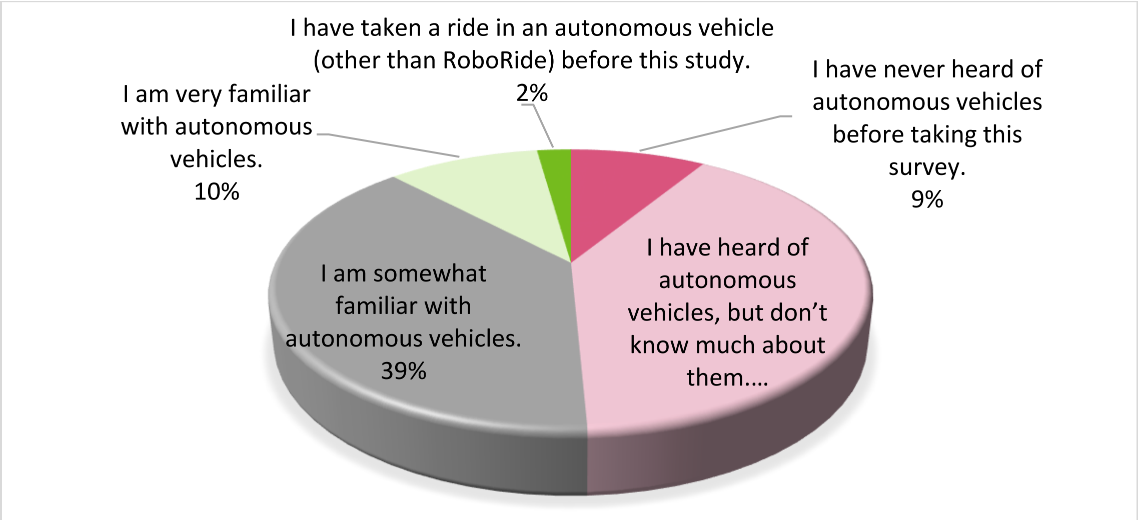

Figure 28 Full Survey Respondents' Familiarity with AVs

ii. Ordered Probit Model for AV Familiarity

This is an ordered probit model of the responses to the question on familiarity with AVs. Responses were collapsed to three options: unfamiliar, somewhat familiar, and very familiar. The results of the model are shown in Table 14.

Table 14 Ordered Probit Model for Familiarity with AVs

Explanatory Variables	AV Familiarity	
	Coeff.	t-stat
Age		
18-35	-0.60	-1.94
71 or more	-0.35	-1.78
Gender		
Female	-0.83**	-4.65
Education		
High School or Less	-0.71**	-2.34
Household Vehicles		
Vehicles in HH: 3 or more	0.44*	2.12
Travel Characteristics		
Have a Ridehailing App on Phone	0.34	1.94
No Backup Means of Travel	-0.47*	-2.12
RoboRide Experience		
Have Tried RoboRide	0.65**	2.46
Thresholds		
1|2	-0.64	-3.05
2|3	0.83	3.92
Data Fit Measures		
R-squared (df)	0.144 (df=10)	

* Significant at 95%
** Significant at 99%

The model shows that, interestingly, when compared to middle-aged adults (36-64), both younger and older respondents show lower levels of AV familiarity, although the results are not significant at 95 percent. Although this finding is expected for the older population, some may consider this unexpected for the younger population. However, given that most people with early access to AVs are likely to be middle-aged adults in the workforce, this result is not surprising. Participants who said they do not know how they would get around if their most used travel means was unavailable have lower levels of AV familiarity, which makes sense given that they are less likely to be aware of potential travel alternatives, including technology-oriented ones such as AVs. Finally, RoboRide experience significantly impacts AV familiarity, which shows once again how first-hand exposure to technologies can build public trust and raise awareness, leading to potentially greater adoption levels.

Ten attitudinal statements were presented to respondents concerning AVs. These can be grouped into safety, mobility perceptions, and willingness/intention to use.

5.3.3.3 Perceptions of Safety of AVs

Figure 29 shows the strength of agreement/disagreement with two statements concerning the safety of AVs. Only a little more than one-third of respondents agreed that autonomous vehicles are safer than human-driven vehicles and that pedestrians, cyclists, and other road users would be safer with AVs being dominant in the vehicle mix. About one third of respondents were neutral, and a little more than one quarter disagreed.

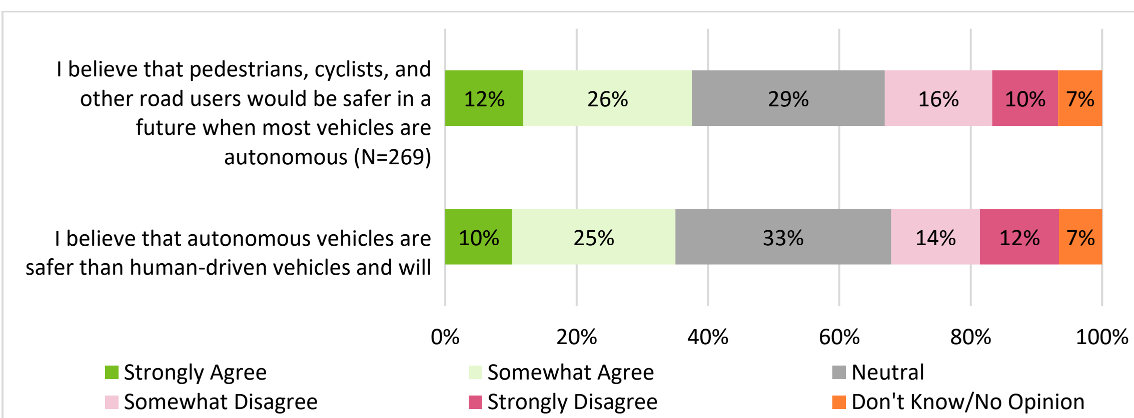

Figure 29 Full Survey Agreement with Statements on Safety of AVs

iii. Ordered Probit Model for Perceived Safety of AVs

This is an ordered probit model in which the dependent variable was agreement with the statement that pedestrians, cyclists, and other road users would be safer in a future when most vehicles are autonomous. The level of agreement was again collapsed to three levels of agree, neutral, disagree. The modeling results are shown in Table 15.

Table 15 Ordered Probit Model for Perceived Safety of AVs

Explanatory Variables	**AV Perceived Safety**	
	Coeff.	t-stat
Age		
18-35	0.50	1.87
Gender		
Female	-0.34*	-2.02
Household Size		
1	-0.48*	-2.14
Household Vehicles		
Vehicles in HH: 1	0.52**	2.58
Home Characteristics		
Senior Home	0.89*	2.16
Travel Characteristics		
Used Ridehailing Services in the Past 12 Months	0.37*	2.14
Thresholds		
1|2	-0.49	-2.87
2|3	0.39	2.28
Data Fit Measures		
R-squared (df)	0.065 (df=8)	

* Significant at 95%
** Significant at 99%

Although not significant at 95 percent, the model shows that younger respondents have higher perceptions of safety than the rest of the sample. Females are more concerned about safety in AVs, which is consistent with the literature. Individuals living in senior homes have a higher perception of safety in AVs, which can be counterintuitive for some. This finding suggests that safety concerns are not the reason they are unwilling to embrace a future with AVs. Having used ridehailing services in the past year positively impacts participants' perception of safety, probably because they have gained transportation technology trust and reliance, which can lead to similar positive perceptions of other emerging transportation technologies.

5.3.3.4 Mobility Perceptions of AVs

Responses to statements on mobility perceptions are shown in Figure 30. There was strong agreement (77 percent) that AVs would make it easier for respondents who could no longer drive to get around. Fifty-six percent of respondents thought AVs would make travel in the region easier and more convenient, while 46 percent of respondents felt that AVs would make it easier to get to rail and bus services. Levels of disagreement with these three statements were quite low.

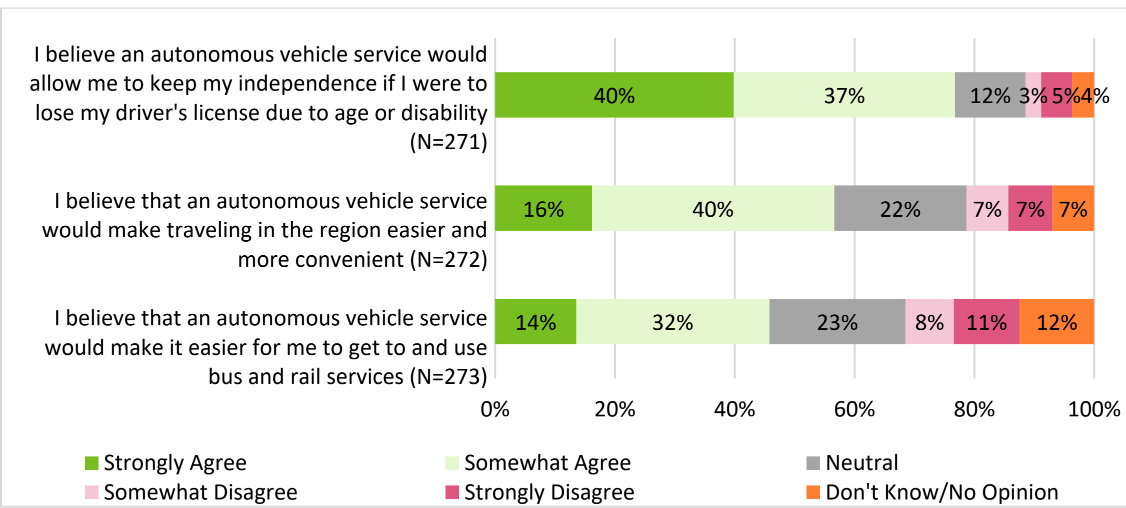

Figure 30 Full Survey Agreement with Statements on Mobility Perceptions of AVs

5.3.3.5 Intentions and Willingness to Use AVs

Figure 31 shows the strength of agreement with statements relating to the willingness and intention to use AVs of the respondents to the Full Survey. Forty percent of respondents would prefer to use a human-driven vehicle more than an AV, while only

31 percent disagreed with this statement. Slightly more than half the respondents (53 percent) would like to be early adopters of AVs and 26 percent were neutral. In terms of riding in AVs, 61 percent would ride in an AV alone, and 79 percent would ride with friends. However, only 38 percent indicated a willingness to travel in an AV with strangers, and 36 percent disagreed with the statement of being willing to ride in an AV with strangers.

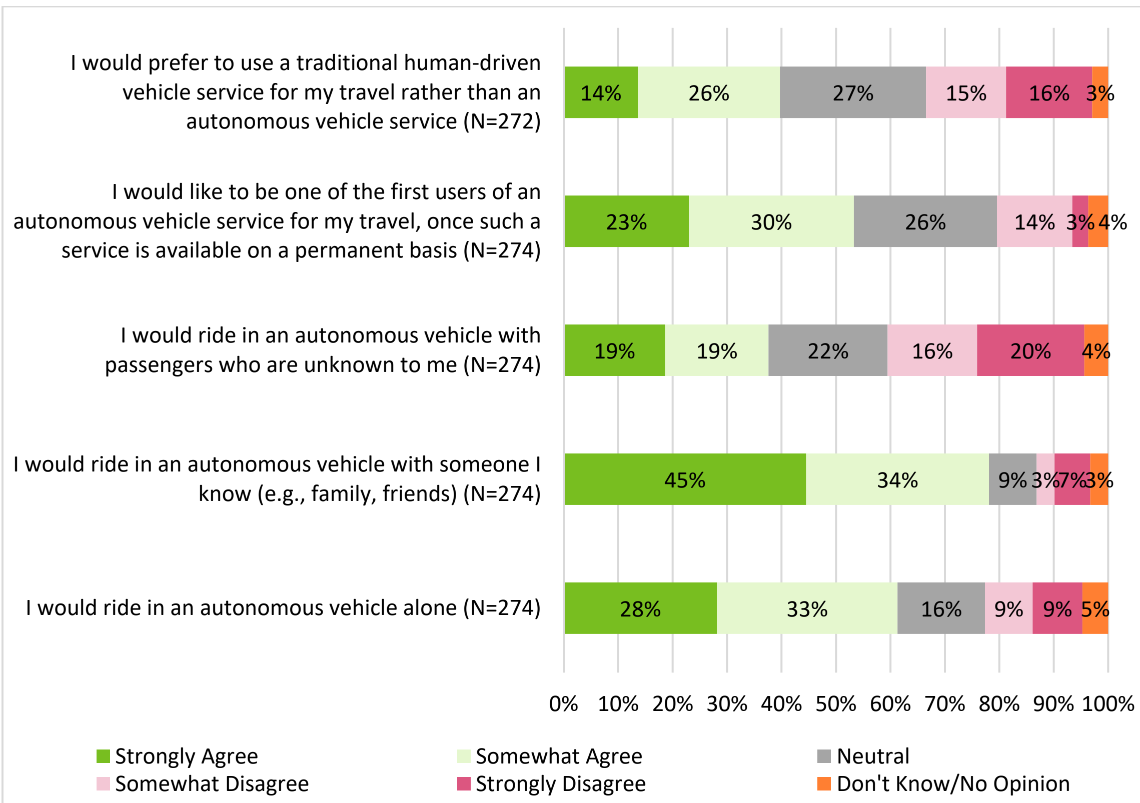

Figure 31 Full Survey Agreement with Statements on Intentions and Willingness to Use AVs

iv. Ordered Probit Model for Willingness to Use AVs

This model sought to understand what attributes might affect the willingness of respondents to use AVs under three different scenarios, namely using an AV alone, using it with passengers known to the respondent, and using an AV with strangers. The three different scenarios were the dependent variables, which were expressed as agreement with a statement that the respondent would ride in that scenario. The levels of agreement were condensed to agree, neutral, and disagree. The results of the ordered probit models are shown in Table 16.

Table 16 Ordered Probit Models for Willingness to Use AVs

	Outcome Variables					
Explanatory Variables	**AV Use Alone**		**AV Use with Known Passengers**		**AV Use with Strangers**	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Age						
36-64					0.38*	2.12
65 and older	-0.37	-1.83				
Gender						
Female	-0.76**	-3.46				
Education						
Bachelor's or Graduate degree	0.44*	2.13	0.58*	2.28	0.39*	2.22
Household Vehicles						
3 or more			-0.54*	-1.97		
Home Characteristics						
Stand-alone Home					-0.44**	-2.36
Travel Characteristics						
Most Used Means of Travel: Drive Alone	0.40	1.66				
RoboRide Experience						
Plan on Trying RoboRide	0.62*	2.26	1.26*	2.43		
Have Tried RoboRide			1.22*	2.21	0.96**	3.26
AV Perceptions						
Perceived Safety	0.58**	2.58	0.74**	2.34	0.45**	2.56
Sense of Independence	0.76**	3.20				
Early Adopter			0.65*	2.17		
Thresholds						
1|2	-0.33	-1.08	-0.68	-3.30	-0.08	-0.40
2|3	0.29	0.95	-0.22	-1.12	0.59	3.02
Data Fit Measures						
R-squared (df)	0.174 (df=9)		0.205 (df=8)		0.078 (df=7)	

* Significant at 95%
** Significant at 99%

This model set shows that RoboRide experience and willingness to use RoboRide are indicators of future AV use. More educated respondents are more inclined to use AV services, which is consistent with literature findings, especially given that more educated people tend to be more tech-savvy. Positive opinions about AVs also increase the likelihood of respondents being willing to use AVs. The older population is more skeptical and hesitant to use AVs alone, but middle-aged individuals (36-64) would be more inclined to share AV rides with unknown passengers. Women are less likely to want to ride in an AV alone, while respondents with 3 or more household vehicles are less likely to ride with known passengers, presumably because they would be more likely to use an available household vehicle for group travel.

Finally, respondents were asked how much of their travel they would undertake on an AV service if such a service became permanently available throughout Peoria. Figure 32 shows that about one quarter of respondents would not use such a service at all, while a further 40 percent would use such a service for some (less than half) of their travel needs. Just 5 percent indicated that they would use such a service for all of their travel.

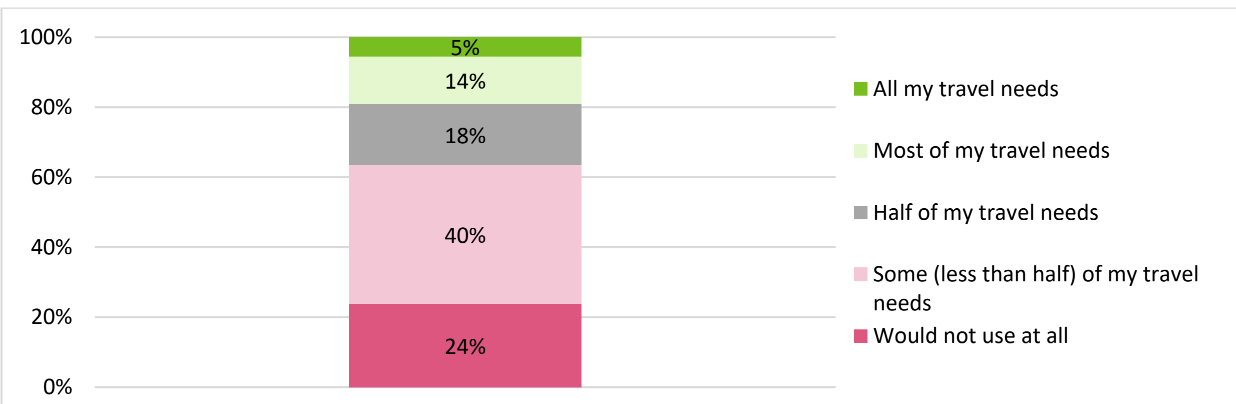

Figure 32 Full Survey Respondents' Predicted AV Use if a Service was permanently/Widely Available (N=273)

v. Ordered Probit Model for AV Early Adoption and Use in Peoria if Widely Available

This is a set of ordered probit models for two statements: desiring to be an early user of AV services once they are permanently available and being willing to switch to AV service when it becomes available across the entire city of Peoria. Each of these were collapsed to three responses of agree, neutral, and disagree for the first one, and would not use, some trips, and most trips for the second statement. The modeling results are shown in Table 17.

Table 17 Ordered Probit Model for AV Early Adoption and Use in Peoria

Explanatory Variables	Outcome Variables: AV Early Adoption Coeff.	AV Early Adoption t-stat	AV Use in Peoria Coeff.	AV Use in Peoria t-stat
Age				
18-35			0.74**	2.67
Household Size				
3 or more	0.41*	2.14		
Household Vehicles				
Vehicles in HH: Zero	1.13	1.86	1.24**	2.36
Vehicles in HH: 1			0.53**	2.82
Travel Characteristics				
Used Ridehailing Services in the Past 12 Months	0.35*	2.05	0.35*	2.01
RoboRide Experience				
Have Tried RoboRide			0.76**	2.83
AV Perceptions				
Perceived Safety	0.90**	4.82		
Sense of Independence	0.60**	2.74		
Thresholds				
1|2	-0.58	-6.08	-0.38	-2.72
2|3	0.18	1.94	1.58	8.96
Data Fit Measures				
R-squared (df)	0.135 (df=7)		0.108 (df=7)	

* Significant at 95%
** Significant at 99%

This model set shows that younger respondents are more open to hypothetical AV use in Peoria. Households with few or no vehicles are more likely to become AV users, possibly due to unmet travel demand. Adoption of alternative emerging transportation technologies (ridehailing services) is also an indicator of potential AV use in Peoria in the future. RoboRide experience positively impacts the potential AV use, possibly because of gain of trust during first-hand experiences and the perceived AV benefits in terms of safety and enhancing their travel routine by bringing a sense of independence.

Figure 33 shows the differences between those with mobility limitations and those without on willingness to use an AV service in Peoria. Not surprisingly, the biggest difference is in those who would use AVs for all their travel, which increases to 11 percent for those with mobility limitations and decreases to 1 percent for those without. Similarly, those who would use it for about half of their travel needs reduced to 11 percent for those with limitations and increased to 22 percent for those without. Results show that those with at least one limitation are more likely to use an AV service in the future more frequently, which illustrates how this AV technology can benefit those more vulnerable with mobility limitations.

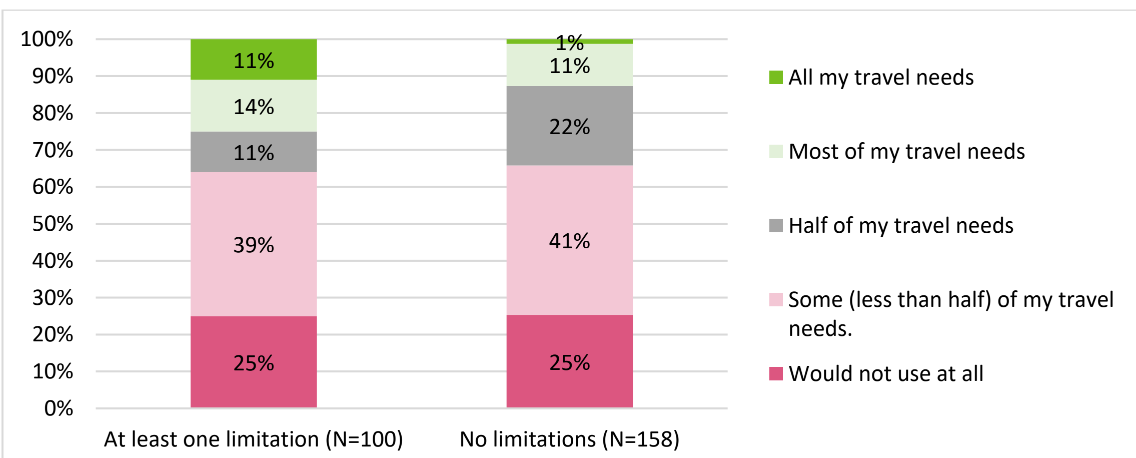

Figure 33 Full Survey Respondents' Predicted AV Use Compared to Limitation Status (N=258)

5.3.3.6 Shuttle Performance

To provide further background for the survey results, a number of performance characteristics have been compiled for the period of the pilot operation of RoboRide. The characteristics that have been compiled are the speed and distance operated by RoboRide, the overall ridership of RoboRide, operation and downtime of RoboRide, the weather, and an analysis of disengagements6.

Figure 34 shows that RoboRide began in January with 111 trips being operated, which increased in February to 133, and then to 152 in March and 154 in April. The average and top speeds of the shuttle by month and shows little variation over the four months, with an average speed of around 5.4 mph and a top speed near 12 mph.

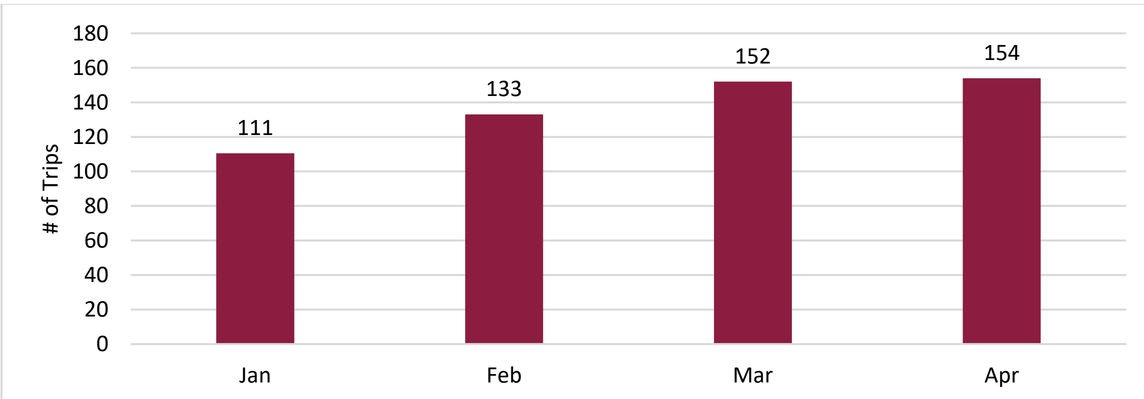

Figure 34 RoboRide Trips Operated by Month

Over the four-month pilot, 103 passengers rode RoboRide. There were a number of days on which no passengers rode the shuttle. Figure 35 shows the ridership by day and shows that the maximum number of riders in a day occurred on April 6, when nine passengers rode the shuttle. Eight passengers rode on February 13, and five or fewer passengers rode on all other days of operation of the shuttle. March had the lowest monthly total of rides with 18, while 22 people rode in each of January and February, and 41 in April.

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[6] A disengagement is a time when the on-board operator had to take control of the vehicle, due to some obstacle or other issue.

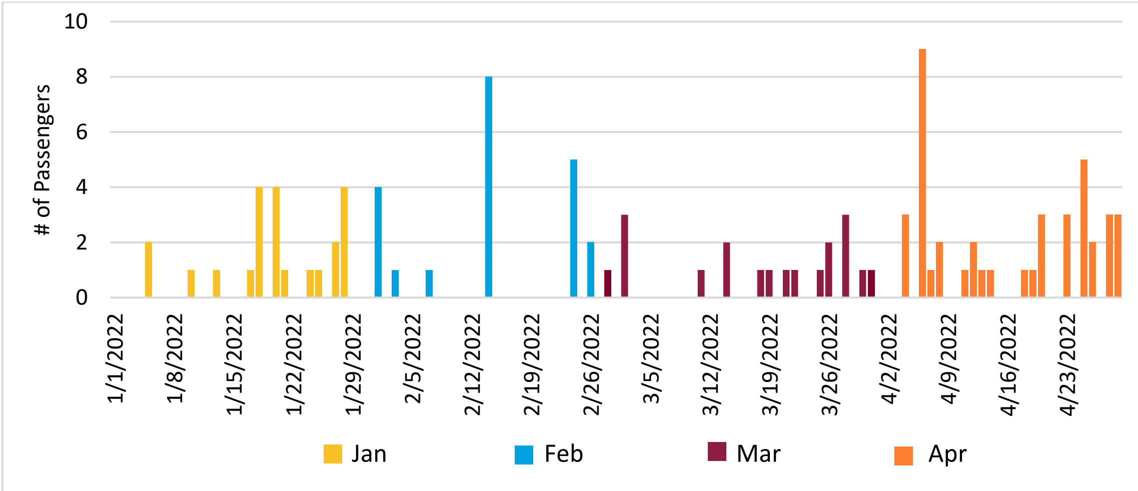

Figure 35 RoboRide Ridership by Day (N=103)

RoboRide was operated on most days of each month in which the pilot operated. In January, February, and March, the shuttle operated for 23 days each month. This increased to 26 days in the final month of April. Figure 36 shows the number of hours that RoboRide was scheduled to operate each month and the number that it actually did operate. In January, it operated 2.2 hours more than scheduled, while it operated for fewer hours than scheduled in the other three months (15.2 hours less in February, 4.2 in March, and 14.9 in April).

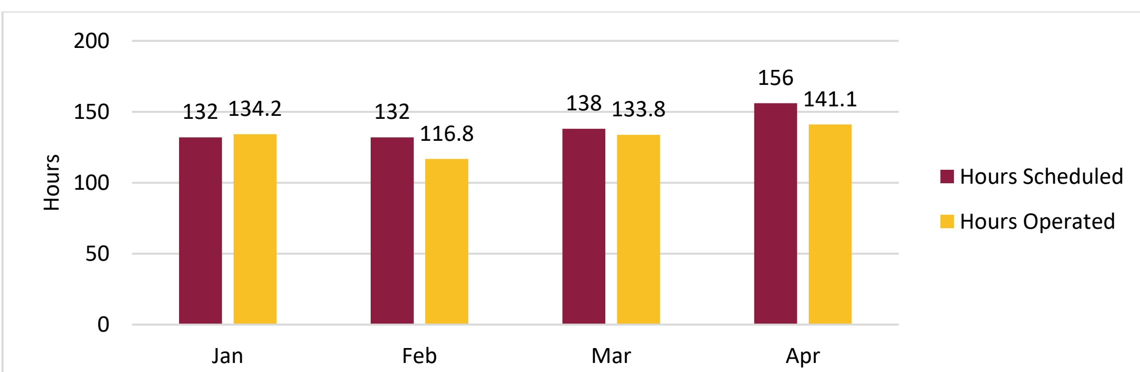

Figure 36 RoboRide Scheduled and Operated Hours by Month

To see if the weather might have had some influence on differences in operation by month and differences in ridership, the temperatures and wind speed for each month of operation were compiled. Figure 37 shows the average daily temperature over the period of the pilot service. It shows that February was the coldest month, and that the average temperature then warmed slowly into April.

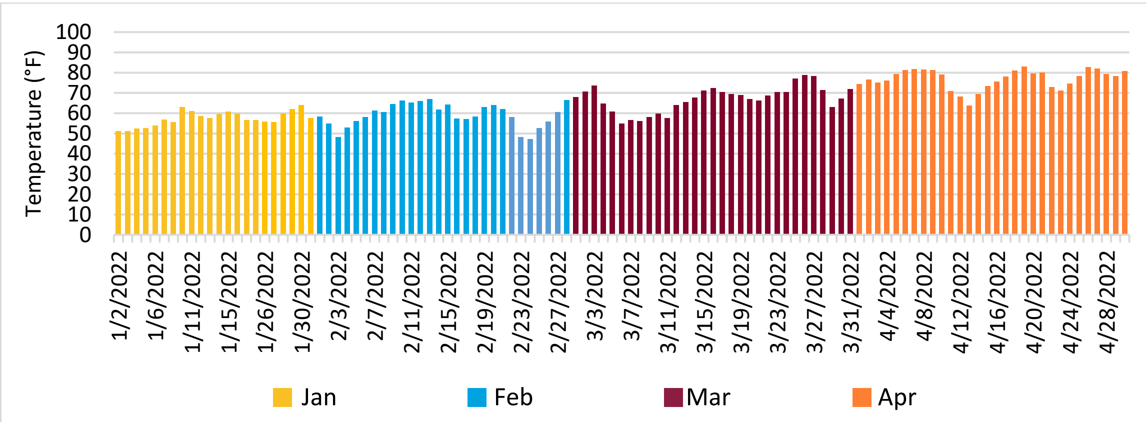

Figure 37 Average Temperatures by Day During RoboRide Operation

5.3.3.7 Disengagements

A disengagement event was defined as any time the operator aboard the RoboRide shuttle manually took control of the shuttle. These occurrences happened due to objects outside the RoboRide shuttle coming in the nearby vicinity or path of the shuttle. The shuttle was programmed to stop movement in these circumstances to avoid making contact or crashing with an external object. In cases where the object moved quickly out of the way (e.g., a car briefly drove in front of the shuttle but then moved out of the way), automated control of the shuttle would resume. However, when the object did not quickly move out of the way (e.g., vegetation was blocking the path the shuttle was programmed to take), the onboard operator would take control of the shuttle to move manually around the object.

A total of 862 disengagement events occurred during the RoboRide pilot period from January to April, with the most events (253 events) occurring in April. It makes logical sense that the most disengagement events occurred in April because the shuttle was operated 26 days in April compared to 23 days each in January, February, and March. February saw the second most disengagements (238 events), followed by March (213 events), and January (158 events). Figure 38 illustrates these statistics.

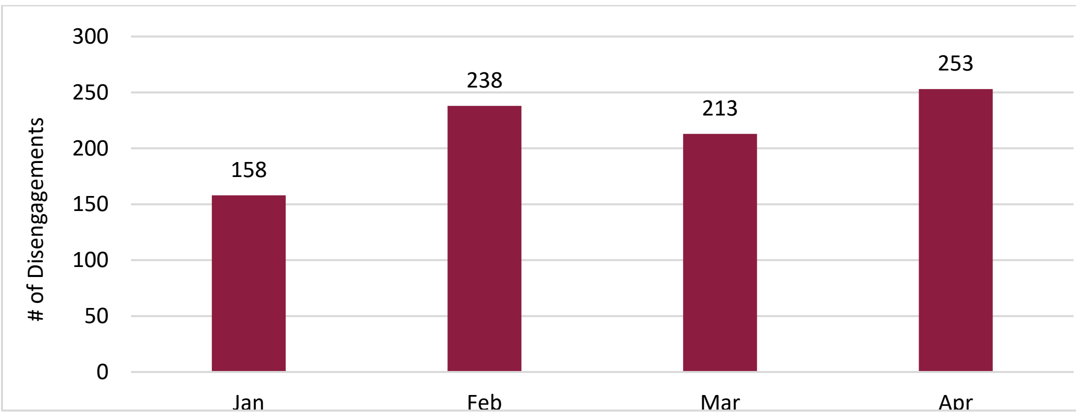

Figure 38 RoboRide Number of Disengagements by Month (N=862)

Disengagement events were also separated into categories by cause. The most frequent cause of disengagement was other road users, which accounted for 51% of occurrences. The shuttle's path and stations being blocked were the next most significant causes for disengagements, followed by vegetation, vulnerable road users, and other reasons. Figure 39 illustrates the percent of occurrences of each category.

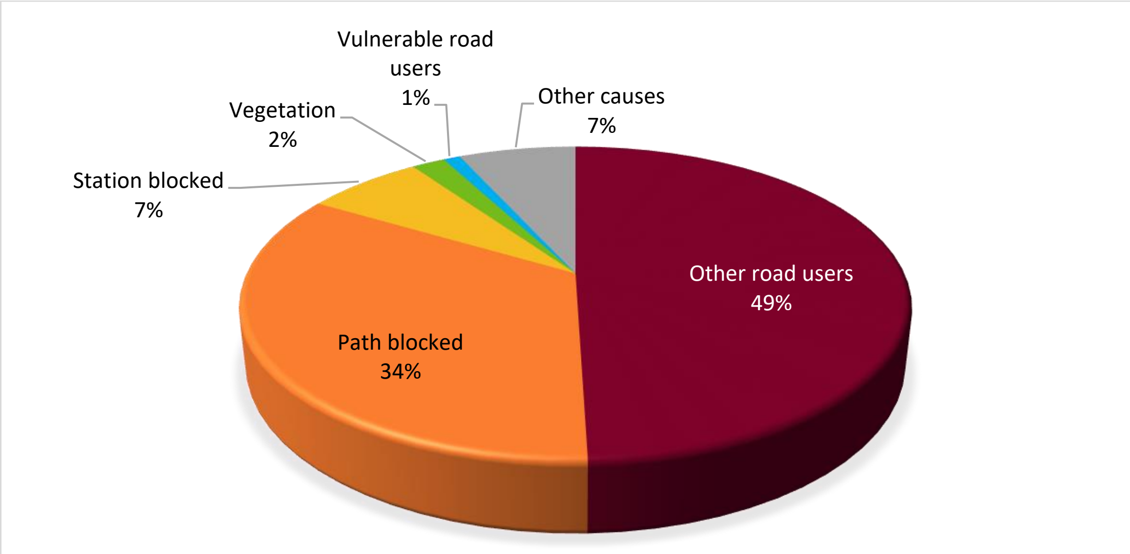

Figure 39 RoboRide Disengagements by Cause (N=862)

Locations of disengagement events were also mapped to better understand the areas where the most operator control was required and the causes of disengagement events. Figures 30 and 41 are maps of all causes of disengagement, and the red path represents the RoboRide shuttles route through the medical district. The north end of the route experienced the most disengagement events. The north end cuts through medical facility parking lots that do not have a reliably clear path like roads generally do. Parking lots experience cars that park outside the allotted parking spaces or along curbs where they are not supposed to be stopped. Parking lots also see lots of vulnerable road user traffic as people walk to and from vehicles. Vehicles also frequently pull into and out of parking spaces in parking lots. Finally, delivery and shuttle vehicles may also utilize the parking lots as pick-up and drop-off locations, adding to unexpected traffic. These scenarios provide many potential reasons for the shuttle to have objects in its path and disengage. Some events of this nature occurred on regular streets, but overall, they occurred much more frequently in parking lots. The most problematic spots for disengagement activity were located outside some of the busiest medical and senior living facilities. This makes sense because these locations likely experienced high volumes of human and vehicle traffic.

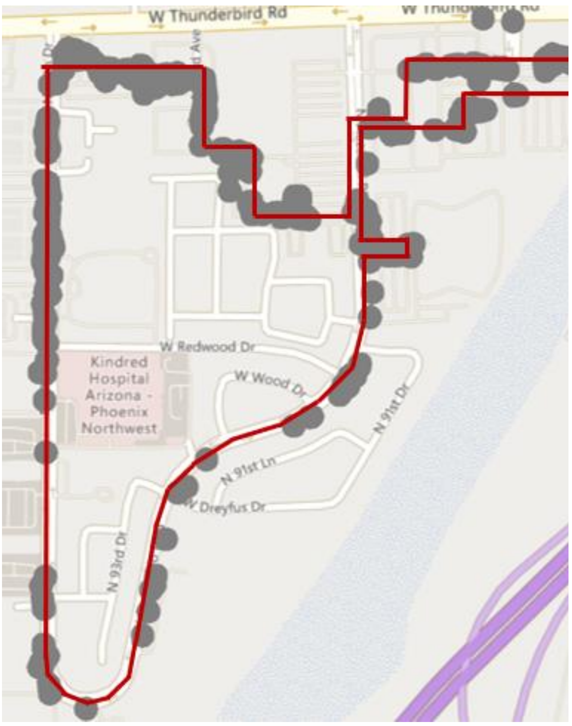

Figure 40 Map of All RoboRide Disengagement Events (N=862)

Figure 41 Heat Map of All RoboRide Disengagements Events (N=862)

5.3.4 Lessons Learned

Despite the low ridership numbers, RoboRide experiment was very insightful and helped with the promotion and dissemination of autonomous vehicle services and their acceptability to the population, resulting in various lessons regarding first-hand autonomous vehicle experiences. Once again, for readability, the major takeaways presented below are summarized by topic and presented in bullet-point format. Further details and additional discussions, including insights on research questions and supplemental materials, will be published in the project's final report later in 2023.

5.3.4.1 Travel Patterns

- In terms of ridership, RoboRide experiment was not very successful, with many trips running empty and relatively few people trying the service.
- Highly car dependent households are not easily persuaded to try an AV service.
- Lower perceptions of convenience and unknown knowledge of schedule were major impediments to use of RoboRide.
- While safety was cited as a reason for not using RoboRide by fewer respondents than convenience or the schedule, it was the only significant attribute of the shuttle that appeared in the logit model of willingness to use RoboRide.
- More than three quarters of car dependent respondents had no plans to try RoboRide
- Only those who used non-car travel means most frequently showed a 50 percent likelihood of trying RoboRide.

5.3.4.2 RoboRide Service

- Disengagements resulted from routing the shuttle through parking lots, as well as on streets where a clear right of way for the shuttle was not apparent.
- Service improvements could result from having a clearly demarcated right of way for the shuttle to operate in.
- In the short run, greater vehicle efficiency could potentially attract more users.

5.3.4.3 Public Perception

- There is an apparent need to educate the public better on autonomous vehicles in general.
- There are some significant gaps in knowledge about AVs, which, if filled, might increase the likelihood that people would be interested in using such services.
- Almost one half of respondents had either never heard of AVs or had heard of them but knew little about them.
- Negative perceptions of safety may also be subject to change through better education.
- Those who had used RoboRide showed a greater propensity to use AVs in the future.
- Promoting these first-hand experiences to the public and educating them about AV technologies will likely improve the sense of trustworthiness and comfortability, leading to greater adoption.

5.4 Study Implications and Conclusions

The emerging transportation technology of Autonomous Vehicles (AVs) has been promising to be one of the greatest changes in the future of transportation. Along with a vast list of benefits, they promise a transportation revolution in which many are skeptical or unsure if people will, in fact, embrace, and when we will face such a futuristic scenario.

As AVs are already present in our world and being offered in various markets (especially in the US), the key for the widespread adoption and, consequently, vast societal benefits, is public adoption. The degree to which people will embrace and use these services are still unknown. Many may adopt at different levels and different times for different reasons. Some will be first adopters and others will never try a driverless ride whatsoever.

In the past years, the state of Arizona welcomed various AV developers to test their driverless technologies across the state for different purposes, allowing the exploration of the relatively first publicly available interactions with AV technologies. This chapter approached two of these experiences, gathering major lessons from each project and providing key insights for safe and efficient widespread AV deployment in the future.

The first project under analysis was Waymo/Valley Metro Demonstration. Launched in 2019, it served Valley Metro's RideChoice program that aimed at understanding the potential for AVs to meet the daily needs of otherwise mobility-disadvantaged citizens. The second project explored in this chapter was the RoboRide Shuttle, a low-speed autonomous vehicle (LSAV) shuttle service operated in the first months of 2022 on a pre-designated route within a medical district in Peoria, Arizona with a goal to assess how individuals perceive and embrace autonomous vehicle (AV) technology.

Both AV pilot projects, very distinct in nature and purpose, provided valuable lessons from survey data collected, focus groups and interview analyses, and modeling efforts to explore a list of topics that helps us understand the current status of AV familiarity and adoption. Additionally, the evaluation strategies presented in both projects provide rich insights on the future of AV services and major barriers and challenges agencies and AV developers will face in order to promote public acceptance and trust in the AV technology.

A key lesson gathered from both projects is that experience matters. First-hand experiences and demonstration programs are essential to promote trustworthiness and awareness of AV technologies. Moreover, human perceptions and attitudes cannot be neglected. Exploring users' major concerns and the factors influencing them are vital to inform policymakers and AV developers to ensure a safe and widespread AV technology adoption.

As a result, projects of similar nature show a great opportunity for collaboration and partnerships. The AV industry working alongside with public agencies and policymakers should work together identifying how different AV configurations can work in specific settings for a given goal; and investigating the vulnerable users that, potentially, could not benefit from the AV technology, so strategies and actions can be developed aiming at these groups to ensure equity.

Finally, given how fast the AV technology is improving and how volatile public opinions are with new technologies, ongoing studies are warranted to track and explore the status of the AV technology and current barriers or concerns the AV industry faces.

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6. CONCLUSIONS

Emerging technologies have been increasingly an important part of our transportation system. With rapid advances in technology development and public adoption, it is crucial to understand how these services will shape the future of travel depending on whether people will, and to what extent they will, use these services; impact the transportation and infrastructure systems such as changes in use of transit and active modes of travel; and influence how technology developers create and update these transportation technologies to better serve people's mobility needs.

The goal of this dissertation is to explore how major emerging services, particularly ridehailing services and autonomous vehicles (AVs), will be used in the future when they are widely available and vastly used. The four chapters presented in this dissertation shed light on what to expect and how to plan for a safe, efficient, and sustainable transportation system using empirical data from recent travel surveys, interviews, and focus groups discussions.

By establishing a foundation in the introduction section, this dissertation presented how emerging technologies have been changing the transportation landscaping, especially in the past decade, and discussed the importance of exploring user adoption, travel behaviors, and individual-level attributes that influence the way people make their travel-related decisions. This is essential for long-term transportation planning and to ensure new mobility options will be properly adopted by society. Through a comprehensive understanding of user behavior dynamics, rigorous evaluation of travel impacts, and effective planning for overcoming potential technology deployment challenges, we can promote the development of resilient and sustainable transportation technologies. By incorporating user insights into transportation models and analyses, we can design and implement transportation solutions that are efficient, inclusive, and adaptable to the evolving needs of urban environments, driving the transformation towards a future where transportation systems seamlessly integrate with the context of our cities, ensuring equitable access, enhancing connectivity, and fostering sustainable urban development.

Although various novel transportation technologies, such as e-scooters, shared bikes, and carsharing services, have their advantages and disadvantages, including potential issues that could be raised by improper and careless deployments, deeply exploring all of them in a single dissertation would be simply unfeasible. This dissertation focused on two arguably most impacting transportation technologies: *ridehailing services* and *autonomous vehicles*. While the first has been integrated to our transportation system recently in the past decade, the latter can be considered still in its initial deployment stages. Their current and future impacts in our transportation system, however, are still under discussion and warrant further academic investigation. In the introduction section, among many, four potential issues were presented. Below is presented a summary of what was found in each issue.

Issue #1: Ridehailing services replacing transit rides

The first issue was presented in the second chapter of this dissertation, which explored how ridehailing services have been impacting bus usage, and who are the ones subject to more substantial changes in their travel patterns in the second chapter. Using a comprehensive and thorough evaluation method while controlling for a variety of socio-economic, demographic, and attitudinal factors from a detailed survey data from four US auto-oriented metropolitan areas, models that examine both the frequency of ridehailing usage and the degree to which individuals have changed their bus usage in response to ridehailing usage were estimated.

The findings of this study clearly showed that ridehailing usage negatively impacts bus use for most people. Descriptive statistics and model estimation results indicated that ridehailing use frequency is significantly associated with a decrease in bus use, which suggests that ridehailing serves as a transit substitute (more than it serves as a complement). Despite attempts to have ridehailing services provide first-mile/last-mile connectivity and serve as a complement to transit, this has not happened yet – at least in auto-oriented metropolitan regions with dispersed land use patterns and rather limited and unappealing transit service.

The findings of this study implied that transit agencies should explore ways to incorporate ridehailing services in their plans to enhance transit usage. By utilizing ridehailing services to supplement existing transit options, agencies may be able to reverse the trend of declining ridership and provide more efficient transportation choices to the public.

Issue #2: AVs leading to zero-occupancy trips

The potential negative outcomes of autonomous vehicles started to be explored in the third chapter, particularly with the context of <u>exploring intentions to use AVs to run errands</u>, which may significantly impact travel patterns, especially in terms of vehicle miles traveled and AV ownership proclivity. When analyzing a futuristic scenario in which AVs can meet mobility needs and potentially eliminate the need for private ownership, the perceived usefulness of AVs and its implications were discussed. In this chapter, the interest in using AVs to run errands and intentions to own AVs were investigated. Using the same data from the past chapter, this study employed the Generalized Heterogeneous Data Model (GHDM) to examine the relationship between interest in AVs for errands and AV ownership intention, while controlling for socio-economic and demographic factors as well as latent attitudinal constructs.

Results showed that, even after accounting for all socio-economic and demographic variables as well as latent attitudinal constructs, the level of interest in having AVs run errands has a positive and significant effect on AV ownership. In other words, those who have an interest in sending AVs to run errands are more likely to purchase and own AVs privately. While such AV feature may be of value to special market segments, their future widespread use is still uncertain. Such technological capabilities may result in large numbers of AVs being used to run errands and roam the streets in zero-occupant mode. This suggested that policies should be implemented to ensure that AVs are used in a way that avoids potential negative impacts in the transportation system, such as zero-occupant travel, increased congestion, and air pollution.

Issue #3: Insufficient utilization of shared rides within the context of AV ridehailing services

In the fourth chapter, the third identified issue, willingness to share rides in AVs, explored those who are, and those who are not, willing to do so and embrace a future of shared mobility. In this chapter, an investigation of the factors influencing the willingness to use AV-based ridehailing services in the future in a shared (with strangers) mode was conducted through a comprehensive behavioral model system using the same dataset from the two previous chapters, with information regarding attitudes, perceptions, and preferences related to the adoption of automated vehicles and shared mobility modes. Particularly, this study explored how current experience with ridehailing services can influence the willingness to use AV-based ridehailing services, both privately and shared (with unknown passengers).

Results from this study suggested that current ridehailing experiences have a considerable effect on the willingness to ride AV-based services in both private and shared modes. Moreover, mere *private* ridehailing experiences, however, are not sufficient to bring about a higher proclivity towards embracing *shared* AV-based ridehailing services in the future. Thus, campaigns that offer individuals the opportunity to experience such services in person would likely contribute to more people willing to share AV rides in the future. Furthermore, numerous attitudinal variables were found to be powerful determinants of the adoption of future mobility services, which can be used by policymakers and AV developers to identify likely early adopters of shared automated mobility services. By doing so, they may use educational awareness campaigns targeting these groups to promote such services.

Issue #4: Low adoption rates of AV services in real-world scenarios

Finally, the potential frustration of low AV adoption rates from recent real-world AV experiences was explored in the fifth chapter based on two AV pilot deployments: Waymo/Valley Metro Partnership and Peoria’s RoboRide Autonomous Shuttle. This chapter depicted what has and what has not worked from participants’ standpoint, and how different project purposes and configurations can influence the way participants engage and embrace AV services. While both projects had different goals and approaches, they provided valuable lessons and insights into public acceptance of autonomous technology and willingness to use AVs, perceptions of safety and convenience, and mobility needs. In this chapter, both projects were evaluated using quantitative methods, such as survey data descriptive analysis and modeling efforts, as well as qualitative methods, namely interviews and focus group discussions.

A major lesson learned from both projects, and that was similarly captured in previous chapters, is that experience matters. First-hand experiences are vital to promote trustworthiness and awareness of AV technologies. Additionally, human perceptions and attitudes cannot be neglected. Exploring users' major concerns and the factors influencing them are essential to inform policymakers and AV developers to ensure a safe, consistent, and sustainable AV technology adoption.

These recent first-hand AV experiences in Arizona provided key insights on the future of automated mobility and will directly benefit service providers who are looking to meet people's travel needs and stakeholders who are developing strategies to ensure that AV technology is adequately integrated into our transportation system. The fifth chapter summarized major lessons learned from these two pilot experiences and provided actionable recommendations for future AV pilot deployments based on these past experiences.

By thoroughly exploring these issues *from theory*, using robust modeling frameworks, *to practice,* assessing data from real-world AV pilot deployments, this dissertation provided a great picture on the status of technology acceptance, the major concerns and barriers for greater adoption, and the lessons learned to ensure successful AV deployments in the future. The takeaways presented in this dissertation strengthen the body of literature in a novel topic that warrants constant research, as well as inform policymakers and stakeholders to properly prepare cities and public to welcome these technologies into our transportation system in an efficient, equitable, and complementary way.

Future Research

Although the chapters presented in this dissertation shed some light and strengthen the body of literature in the emerging mobility technologies area, it is important to recognize we are still far from answering all questions around this novel topic. In fact, by expanding the discussion about a topic by hypothesis testing and attempting to shed some light on issues and contributing to the body of literature, we may raise new questions. This is in the nature of the scientific method. In this dissertation, after exploring the various issues regarding the future of transportation, provides insightful directions for future research.

Ridehailing services have been serving various markets across the country and helping individuals to meet their travel needs, especially given their accessibility and convenience to provide reliable door-to-door services. Although it was observed these services have been eschewing riders away from mass transit options, the future of these services is not all that clear. Especially after the COVID-19 pandemic, which shift travel preferences for many individuals, the extent to which they will use ridehailing services and transit remain uncertain. While some could simply avoid sharing confined spaces with strangers, impacting both ridehailing and transit options, others could simply let their environmentally friendly traits speak louder and shift them towards more active and sustainable transportation options, such as walk and/or transit.

Future research should investigate potential changes in travel behaviors, and the extent to which ridehailing services and transit, and their relationship, may change in the future if society faces major disturbances again, and given with the widespread use of AV ridehailing services. The AVs may bring additional factors to the equation that may contribute to travel pattern shifts. Additionally, in an attempt to bring transit ridership levels up again, future research efforts should investigate the potential of integration of ridehailing services and transit options, especially to cover first- and last-mile for riders.

The potential for collaboration is especially true with AV ridehailing services. This dissertation showed the importance of first-hand experience for adoption of emerging transportation technologies, a great way of exploring that in the future is by promoting partnerships between transit agencies and AV developers, which could benefit both from increased transit ridership and greater technology exposure, which tends to lead to increased trust and adoption. For the future, studying this modality and the potential effects of AVs complementing transit will be crucial to determine guidelines for future deployments.

Similarly, further exploring how much individuals will, in fact, use AVs is another key recommendation for future research. Exploring additional relevant attitudinal constructs and especially investigating potential shifts from post-COVID data is essential for understanding the stability of transportation-related attitudes. In addition, what would a widespread adoption of AVs for running errands, for example, mean in terms of time use? How would individuals use their *'new free time'* once they do not have to run errands themselves anymore? Would they work more? Rest more? Or spend more time with family and friends? Answers to these questions are important may have strong implications on wellbeing and mental health.

Finally, as travel opinions and attitudes not always match user travel behaviors, known as travel dissonance, future research should explore these potential differences and investigate how individuals will use AV services once they are available to them. Given the initial stages of AV technology, many are still unfamiliar with them and their responses to futuristic scenarios may not be fully reliable. Pilot demonstrations are key to assessing that issue and to obtaining real-world data on technology adoption. Future studies should explore the ways the technology could be deployed both from a technology evaluation standpoint, in which a controlled environment with minor disturbances could be preferred, as well as from a ridership and adoption angle, which busy and dense areas aiming at potential users with higher familiarity levels may be desired instead. This way factors such as type of vehicle and service, time of day, ride availability and frequency, cost, travel purpose, and numerous additional factors may be explored in detail to contribute to the growing body of literature involving emerging technologies in transportation that still has many uncertainties.

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APPENDIX

APPENDIX A

MATHEMATICAL FORMULATION OF THE GHDM FOR THE CURRENT STUDY INVOLVING ORDINAL OUTCOMES AND MULTINOMIAL OUTCOMES

For ease of presentation, we will suppress the index for decision-makers in our exposition below, and assume that all error terms are independent and identically distributed across decision-makers. Following Bhat's (2015) GHDM formulation, let *l* be an index for latent variables (*l*=1,2,…,*L*). Consider the latent variable z_l^* and write it as a linear function of covariates:

$$z_l^* = \boldsymbol{\alpha}_l' \boldsymbol{w} + \eta_l, \tag{1}$$

where $\boldsymbol{w}$ is a $(\tilde{D} \times 1)$ vector of observed covariates (excluding a constant), $\boldsymbol{\alpha}_l$ is a corresponding $(\tilde{D} \times 1)$ vector of coefficients, and η_l is a random error term assumed to be standard normally distributed for identification purpose. Next, define the $(L \times \tilde{D})$ matrix $\boldsymbol{\alpha} = (\boldsymbol{\alpha}_1, \boldsymbol{\alpha}_2, ..., \boldsymbol{\alpha}_L)'$, and the $(L \times 1)$ vectors $\boldsymbol{z}^* = (z_1^*, z_2^*, ..., z_L^*)'$ and $\boldsymbol{\eta} = (\eta_1, \eta_2, \eta_3, \ldots, \eta_L)'$. We allow a multivariate normal (MVN) correlation structure for $\boldsymbol{\eta}$ to accommodate interactions among the unobserved latent variables: $\boldsymbol{\eta} \sim MVN_L[\mathbf{0}_L, \boldsymbol{\Gamma}]$, where $\mathbf{0}_L$ is an $(L \times 1)$ column vector of zeros, and $\boldsymbol{\Gamma}$ is an $(L \times L)$ correlation matrix. In matrix form, we may write Equation (1) as:

$$\boldsymbol{z}^* = \boldsymbol{\alpha w} + \boldsymbol{\eta}. \tag{2}$$

Now consider *N* ordinal outcomes (indicator variables as well as main outcomes) for the individual, and let *n* be the index for the ordinal outcomes $(n = 1, 2, ..., N)$. Also, let J_n be the number of categories for the n^{th} ordinal outcome $(J_n \geq 2)$ and let the corresponding index be j_n $(j_n = 1, 2, ..., J_n)$. In our empirical case, $N = 11$ (corresponding to 9 indicators and the AV Private and AV Pooled Ridehailing dimensions, each with

$J_n = 5$). Let $\tilde{y}_n^*$ be the latent underlying variable whose horizontal partitioning leads to the observed outcome for the n^{th} ordinal variable. Assume that the individual under consideration chooses the a_n^{th} ordinal category. Then, in the usual ordered response formulation, for the individual, we may write:

$$\tilde{y}_n^* = \tilde{\boldsymbol{\gamma}}_n' \boldsymbol{x} + \tilde{\boldsymbol{d}}_n' \boldsymbol{z}^* + \tilde{\varepsilon}_n, \text{ and } \tilde{\psi}_{n,a_n-1} < \tilde{y}_n^* < \tilde{\psi}_{n,a_n}, \tag{3}$$

where $\boldsymbol{x}$ is an $(A \times 1)$ vector of exogenous variables (including a constant) as well as possibly the observed values of other endogenous ordinal variables, and other endogenous multinomial choice variables introduced as dummy variables (though only in a recursive fashion and not in a cyclic manner) , $\tilde{\boldsymbol{\gamma}}_n$ is a corresponding vector of coefficients to be estimated, $\tilde{\boldsymbol{d}}_n$ is an $(L \times 1)$ vector of latent variable loadings on the n^{th} ordinal outcome, the $\tilde{\psi}$ terms represent thresholds, and $\tilde{\varepsilon}_n$ is the standard normal random error for the n^{th} ordinal outcome (note, however, that for the indicators (but not the main outcomes), typically the $\boldsymbol{x}$ vector will not appear on the right side of Equation (3); also, there are specific identification conditions for the number of non-zero elements of $\tilde{\boldsymbol{d}}_n$ that can be present in each indicator equation and across all indicator equations; please see Bhat, 2015 for additional details). For each ordinal outcome, $\tilde{\psi}_{n,0} < \tilde{\psi}_{n,1} < \tilde{\psi}_{n,2} \ldots < \tilde{\psi}_{n,J_n-1} < \tilde{\psi}_{n,J_n}$; $\tilde{\psi}_{n,0} = -\infty$, $\tilde{\psi}_{n,1} = 0$, and $\tilde{\psi}_{n,J_n} = +\infty$. For later use, let $\tilde{\boldsymbol{\psi}}_n = (\tilde{\psi}_{n,2}, \tilde{\psi}_{n,3} \ldots, \tilde{\psi}_{n,J_n-1})'$ and $\tilde{\boldsymbol{\psi}} = (\tilde{\boldsymbol{\psi}}_1', \tilde{\boldsymbol{\psi}}_2', \ldots, \tilde{\boldsymbol{\psi}}_N)'$. Stack the N underlying continuous variables $\tilde{y}_n^*$ into an $(N \times 1)$ vector $\tilde{\boldsymbol{y}}^*$, and the N error terms $\tilde{\varepsilon}_n$ into another $(N \times 1)$ vector $\tilde{\boldsymbol{\varepsilon}}$. Define $\tilde{\boldsymbol{\gamma}} = (\tilde{\gamma}_1, \tilde{\gamma}_2, \ldots, \tilde{\gamma}_H)'$ [$(N \times A)$ matrix] and $\tilde{\boldsymbol{d}} = \left(\tilde{\boldsymbol{d}}_1, \tilde{\boldsymbol{d}}_2, \ldots, \tilde{\boldsymbol{d}}_N\right)$ [$(N \times L)$ matrix], and let

$\mathbf{IDEN}_N$ be the identity matrix of dimension N representing the correlation matrix of $\tilde{\boldsymbol{\varepsilon}}$ (the unit diagonals are needed for identification; for convergence stability and parsimony, we assume that the elements of the $\tilde{\boldsymbol{\varepsilon}}$ vector are uncorrelated with each other, though specific elements of the $\tilde{\boldsymbol{y}}^*$ vector can still be correlated through the stochatic latent constructs). Finally, stack the lower thresholds for the decision-maker $\tilde{\psi}_{n,a_n-1}(n=1,2,...,N)$ into an $(N\times 1)$ vector $\tilde{\boldsymbol{\psi}}_{\boldsymbol{low}}$ and the upper thresholds $\tilde{\psi}_{n,a_n}(n=1,2,...,N)$ into another vector $\tilde{\boldsymbol{\psi}}_{up}$. Then, in matrix form, the measurement equation for the ordinal outcomes (indicators) for the decision-maker may be written as:

$$\tilde{\boldsymbol{y}}^* = \tilde{\boldsymbol{\gamma}}\boldsymbol{x} + \tilde{\boldsymbol{d}}\boldsymbol{z}^* + \tilde{\boldsymbol{\varepsilon}}, \quad \tilde{\boldsymbol{\psi}}_{\boldsymbol{low}} < \tilde{\boldsymbol{y}}^* < \tilde{\boldsymbol{\psi}}_{\boldsymbol{up}}. \tag{4}$$

Now let there be G multionomial outcome variables for an individual, and let g be the index for the each multinomial variable $(g=1,2,3,...,G)$. Also, let I_g be the number of alternatives corresponding to the g^{th} multinomial variable ($I_g \geq 3$) and let i_g be the corresponding index $(i_g=1,2,3,...,I_g)$. In our case, G=1 and I_1 =3; however we present the framework for any number of multinomial otcomes. Consider the g^{th} multinomial variable and assume the usual random utility structure for each alternative i_g.

$$U_{gi_g} = \boldsymbol{b}'_{gi_g}\boldsymbol{x} + \boldsymbol{\vartheta}'_{gi_g}(\boldsymbol{\beta}_{gi_g}\boldsymbol{z}^*) + \varsigma_{gi_g}, \tag{5}$$

where $\boldsymbol{x}$ is an $(A\times 1)$ vector of exogenous variables (including a constant) as well as possibly the observed values of other endogenous ordinal variables (introduced in a recursive fashion), as defined earlier, $\boldsymbol{b}_{gi_g}$ is an $(A\times 1)$ column vector of corresponding coefficients, and ς_{gi_g} is normal error term. $\boldsymbol{\beta}_{gi_g}$ is an $(N_{gi_g}\times L)$-matrix of variables interacting with latent variables to influence the utility of alternative i_g, and $\boldsymbol{\vartheta}_{gi_g}$ is an $(N_{gi_g} \times 1)$-column vector of coefficients capturing the effects of latent variables and their interaction effects with other exogenous variables. If each of the latent variables impacts the utility of the alternatives for each multinomial variable purely through a constant shift in the utility function, $\boldsymbol{\beta}_{gi_g}$ will be an identity matrix of size *L*, and each element of $\boldsymbol{\vartheta}_{gi_g}$ will capture the effect of a latent variable on the constant specific to alternative i_g of nominal variable *g*. Let $\boldsymbol{\varsigma_g} = (\varsigma_{g1}, \varsigma_{g2}, ...\varsigma_{gI_g})'$ $(I_g \times 1$ vector), and $\boldsymbol{\varsigma_g} \sim MVN_{I_g}(\mathbf{0}, \mathbf{\Lambda_g})$. Taking the difference with respect to the first alternative, the only estimable elements are found in the covariance matrix $\breve{\mathbf{\Lambda}}_g$ of the error differences, $\breve{\boldsymbol{\varsigma}}_{\boldsymbol{g}} = (\breve{\varsigma}_{g2}, \breve{\varsigma}_{g3}, ..., \breve{\varsigma}_{gI_g})$ (where $\breve{\varsigma}_{gi} = \varsigma_{gi} - \varsigma_{g1}, i \neq 1)$. Further, the variance term at the top left diagonal of $\breve{\mathbf{\Lambda}}_g$ $(g = 1, 2, ..., G)$ is set to 1 to account for scale invariance. $\mathbf{\Lambda_g}$ is constructed from $\breve{\mathbf{\Lambda}}_{\mathbf{g}}$ by adding a row on top and a column to the left. All elements of this additional row and column are filled with values of zero. In addition, the usual identification restriction is imposed such that one of the alternatives serves as the base when introducing alternative-specific constants and variables that do not vary across alternatives (that is, whenever an element of $\boldsymbol{x}$ is individual-specific and not alternative-specific, the corresponding element in $\boldsymbol{b}_{gi_g}$ is set to zero for at least one alternative i_g). To proceed, define $\boldsymbol{U}_g = (U_{g1}, U_{g2}, ..., U_{gI_g})'$ $(I_g \times 1$ vector), $\boldsymbol{b}_g = (\boldsymbol{b}_{\boldsymbol{g}1}, \boldsymbol{b}_{\boldsymbol{g}2}, \boldsymbol{b}_{\boldsymbol{g}3}, ..., \boldsymbol{b}_{gI_g})'$ $(I_g \times A$ matrix), and $\boldsymbol{\beta}_g = (\boldsymbol{\beta}'_{g1}, \boldsymbol{\beta}'_{g2}, ..., \boldsymbol{\beta}'_{gI_g})'$ $\left(\sum_{i_g=1}^{I_g} N_{gi_g} \times L\right)$ matrix. Also, define the $\left(I_g \times \sum_{i_g=1}^{I_g} N_{gi_g}\right)$ matrix $\boldsymbol{\vartheta_g}$, which is initially filled with all zero values. Then, position the $(1\times N_{g1})$ row vector $\boldsymbol{\vartheta}'_{g1}$ in the first row to occupy columns 1 to N_{g1} , position the $(1\times N_{g2})$ row vector $\boldsymbol{\vartheta}'_{g2}$ in the second row to occupy columns $N_{g1}+1$ to $N_{g1}+N_{g2}$, and so on until the $(1\times N_{gI_g})$ row vector $\boldsymbol{\vartheta}'_{gI_g}$ is appropriately positioned. Further, define $\boldsymbol{\varpi}_g=(\boldsymbol{\vartheta}_g\boldsymbol{\beta}_g)$ ($I_g\times L$ matrix), $\ddot{G}=\sum_{g=1}^{G}I_g$, $\tilde{G}=\sum_{g=1}^{G}(I_g-1)$, $\boldsymbol{U}=(\boldsymbol{U}'_1,\boldsymbol{U}'_2,\dots,\boldsymbol{U}'_G)'$ ($\ddot{G}\times 1$ vector), $\boldsymbol{\varsigma}=(\boldsymbol{\varsigma}_1,\boldsymbol{\varsigma}_2,...\boldsymbol{\varsigma}_G)'$ ($\ddot{G}\times 1$ vector), $\boldsymbol{b}=(\boldsymbol{b}'_1,\boldsymbol{b}'_2,...,\boldsymbol{b}'_G)'$ ($\ddot{G}\times A$ matrix), $\boldsymbol{\varpi}=(\boldsymbol{\varpi}'_1,\boldsymbol{\varpi}'_2,...,\boldsymbol{\varpi}'_G)'$ ($\ddot{G}\times L$ matrix), and $\boldsymbol{\vartheta}=\text{Vech}(\boldsymbol{\vartheta}_1,\boldsymbol{\vartheta}_2,...,\boldsymbol{\vartheta}_G)$ (that is, $\boldsymbol{\vartheta}$ is a column vector that includes all elements of the matrices $\boldsymbol{\vartheta}_1,\boldsymbol{\vartheta}_2,...,\boldsymbol{\vartheta}_G$). Then, in matrix form, we may write Equation (5) as:

$$\boldsymbol{U}=\boldsymbol{b}\boldsymbol{x}+\boldsymbol{\varpi}\,\boldsymbol{z}^*+\boldsymbol{\varsigma}, \tag{6}$$

where $\boldsymbol{\varsigma}\sim MVN_{\ddot{G}}(\mathbf{0}_{\ddot{G}},\boldsymbol{\Lambda})$. As earlier, to ensure identification, we specify $\boldsymbol{\Lambda}$ as follows:

$$\boldsymbol{\Lambda}=\begin{bmatrix}\boldsymbol{\Lambda}_1 & \mathbf{0} & \mathbf{0} & \mathbf{0}\cdots & \mathbf{0}\\ \mathbf{0} & \boldsymbol{\Lambda}_2 & \mathbf{0} & \mathbf{0}\cdots & \mathbf{0}\\ \mathbf{0} & \mathbf{0} & \boldsymbol{\Lambda}_3 & \mathbf{0}\cdots & \mathbf{0}\\ \vdots & \vdots & \vdots & \vdots\;\dots & \vdots\\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0}\;\dots & \boldsymbol{\Lambda}_G\end{bmatrix}(\ddot{G}\times\ddot{G}\ \text{ matrix}). \tag{7}$$

In the general case, this allows the estimation of $\sum_{g=1}^{G}\left(\frac{I_g*(I_g-1)}{2}-1\right)$ terms across all the G nominal variables, as originating from $\left(\frac{I_g*(I_g-1)}{2}-1\right)$ terms embedded in each $\breve{\boldsymbol{\Lambda}}_g$ matrix; (g=1,2,…,G) .

Let $\boldsymbol{\delta}$ be the collection of parameters to be estimated: $\boldsymbol{\delta} = [\text{Vech}(\boldsymbol{\alpha}), \text{Vechup}(\boldsymbol{\Gamma}), \text{Vech}(\tilde{\boldsymbol{\gamma}}), \text{Vech}(\tilde{\boldsymbol{d}}), \tilde{\boldsymbol{\psi}}, \text{Vech}(\boldsymbol{b}), \boldsymbol{\vartheta}, \text{Vech}(\boldsymbol{\Lambda})]$, where the operator "$\text{Vech}(.)$" vectorizes all the non-zero elements of the matrix/vector on which it operates and "$\text{Vechup}(.)$" indicates strictly upper diagonal elemenets.

With the matrix definitions above, the continuous components of the model system may be written compactly as:

$$\boldsymbol{z}^* = \boldsymbol{\alpha w} + \boldsymbol{\eta}, \tag{8}$$

$$\tilde{\boldsymbol{y}}^* = \tilde{\boldsymbol{\gamma}}\boldsymbol{x} + \tilde{\boldsymbol{d}}\boldsymbol{z}^* + \tilde{\boldsymbol{\varepsilon}}, \text{ with } \text{Var}\,(\tilde{\boldsymbol{\varepsilon}}) = \mathbf{IDEN}_N \ \ (N \times N \text{ matrix}) \ , \tag{9}$$

$$\boldsymbol{U} = \boldsymbol{bx} + \boldsymbol{\varpi}\,\boldsymbol{z}^* + \boldsymbol{\varsigma}. \tag{10}$$

To develop the reduced form equations, replace the right side of Equation (8) for $\boldsymbol{z}^*$ in Equations (9) and (10) to obtain the following system:

$$\tilde{\boldsymbol{y}}^* = \tilde{\boldsymbol{\gamma}}\boldsymbol{x} + \tilde{\boldsymbol{d}}\boldsymbol{z}^* + \tilde{\boldsymbol{\varepsilon}} = \tilde{\boldsymbol{\gamma}}\boldsymbol{x} + \tilde{\boldsymbol{d}}(\boldsymbol{\alpha w} + \boldsymbol{\eta}) + \tilde{\boldsymbol{\varepsilon}} = \tilde{\boldsymbol{\gamma}}\boldsymbol{x} + \tilde{\boldsymbol{d}}\boldsymbol{\alpha w} + \tilde{\boldsymbol{d}}\boldsymbol{\eta} + \tilde{\boldsymbol{\varepsilon}}\ , \tag{11}$$

$$\boldsymbol{U} = \boldsymbol{bx} + \boldsymbol{\varpi}\,\boldsymbol{z}^* + \boldsymbol{\varsigma} = \boldsymbol{bx} + \boldsymbol{\varpi}\,(\boldsymbol{\alpha w} + \boldsymbol{\eta}) + \boldsymbol{\varsigma} = \boldsymbol{bx} + \boldsymbol{\varpi}\,\boldsymbol{\alpha w} + \boldsymbol{\varpi}\,\boldsymbol{\eta} + \boldsymbol{\varsigma}\ .$$

Now, consider the $[(N + \ddot{G}) \times 1)]$ vector $\boldsymbol{yU} = \left[[\tilde{\boldsymbol{y}}^*]', \boldsymbol{U}'\right]'$. Define

$$\boldsymbol{B} = \begin{bmatrix} \boldsymbol{B_1} \\ \boldsymbol{B_2} \end{bmatrix} = \begin{bmatrix} \tilde{\boldsymbol{\gamma}}\boldsymbol{x} + \tilde{\boldsymbol{d}}\boldsymbol{\alpha w} \\ \boldsymbol{bx} + \boldsymbol{\varpi}\,\boldsymbol{\alpha w} \end{bmatrix} \text{and}\, \boldsymbol{\Omega} = \begin{bmatrix} \boldsymbol{\Omega_1} & \boldsymbol{\Omega'_{12}} \\ \boldsymbol{\Omega_{12}} & \boldsymbol{\Omega_2} \end{bmatrix} = \begin{bmatrix} \tilde{\boldsymbol{d}}\boldsymbol{\Gamma}\tilde{\boldsymbol{d}}' + \mathbf{IDEN_N} & \tilde{\boldsymbol{d}}\boldsymbol{\Gamma}\boldsymbol{\varpi}' \\ \boldsymbol{\varpi}\,\boldsymbol{\Gamma}\tilde{\boldsymbol{d}}' & \boldsymbol{\varpi}\,\boldsymbol{\Gamma}\boldsymbol{\varpi}' + \boldsymbol{\Lambda} \end{bmatrix}. \tag{12}$$

Then $\boldsymbol{yU} \sim \boldsymbol{MVN}_{\boldsymbol{N}+\ddot{\boldsymbol{G}}}(\boldsymbol{B},\boldsymbol{\Omega})$.

We now focus on the estimation of the model. To estimate the model, note that, under the utility maximization paradigm, $U_{gi_g} - U_{gm_g}$ must be less than zero for all $i_g \neq m_g$ corresponding to the *gth* nominal variable, since the individual chose alternative m_g. Let

$u_{gi_g m_g} = U_{gi_g} - U_{gm_g} \, (i_g \neq m_g)$, and stack the latent utility differentials into a vector $\boldsymbol{u_g} = \left[\left(u_{g1m_g}, u_{g2m_g}, ..., u_{gI_g m_g} \right)'; i_g \neq m_g \right]$. Also, define $\boldsymbol{u} = \left([\boldsymbol{u}_1]', [\boldsymbol{u}_2]', ..., [\boldsymbol{u_G}]' \right)'$. We now need to develop the distribution of the vector $\boldsymbol{yu} = (\ddot{\boldsymbol{y}}', \boldsymbol{u}')'$ from that of $\boldsymbol{yU} = [\ddot{\boldsymbol{y}}', \boldsymbol{U}']'$. To do so, define a matrix **M** of size $\left[N + \tilde{G} \right] \times \left[N + \ddot{G} \right]$. Fill this matrix with values of zero. Then, insert an identity matrix of size *N* into the first *N* rows and *N* columns of the matrix **M**. Next, consider the rows from $N+1$ to $N + I_1 - 1$, and columns from $N+1$ to $N + I_1$. These rows and columns correspond to the first nominal variable. Insert an identity matrix of size $(I_1 - 1)$ after supplementing with a column of '-1' values in the column corresponding to the chosen alternative. Next, rows $N + I_1$ through $N + I_1 + I_2 - 2$ and columns $N + I_1 + 1$ through $N + I_1 + I_2$ correspond to the second nominal variable. Continue this procedure for all *G* nominal variables. With the matrix **M** as defined, we can write $\boldsymbol{yu} \sim \boldsymbol{MVN}_{N+\tilde{G}}(\tilde{\boldsymbol{B}}, \tilde{\boldsymbol{\Omega}})$, where $\tilde{\boldsymbol{B}} = \mathbf{M}\boldsymbol{B}$ and $\tilde{\boldsymbol{\Omega}} = \mathbf{M\Omega M}'$.

Next, define threshold vectors as follows:

$\ddot{\boldsymbol{\psi}}_{\boldsymbol{low}} = \left[\tilde{\boldsymbol{\psi}}'_{\boldsymbol{low}}, \left(-\boldsymbol{\infty}_{\tilde{G}} \right)' \right]'$ $([(N+\tilde{G}) \times 1]$ vector) and $\ddot{\boldsymbol{\psi}}_{\boldsymbol{up}} = \left[\tilde{\boldsymbol{\psi}}'_{up}, \left(\mathbf{0}_{\tilde{G}} \right)' \right]'$ $([(N+\tilde{G}) \times 1]$ vector), where $-\boldsymbol{\infty}_{\tilde{G}}$ is a $\tilde{G} \times 1$-column vector of negative infinities, and $\mathbf{0}_{\tilde{G}}$ is another $\tilde{G} \times 1$-column vector of zeros. Then the likelihood function may be written as:

$$L(\boldsymbol{\delta}) = \Pr \left[\ddot{\boldsymbol{\psi}}_{low} \leq \boldsymbol{yu} \leq \ddot{\boldsymbol{\psi}}_{up} \right], \tag{13}$$

$$= \int_{D_r} f_{N+\tilde{G}}(\boldsymbol{r} \mid \tilde{\boldsymbol{B}}, \tilde{\boldsymbol{\Omega}}) dr,$$

where the integration domain $D_r = \{\boldsymbol{r} : \breve{\boldsymbol{\psi}}_{low} \leq \boldsymbol{r} \leq \breve{\boldsymbol{\psi}}_{up}\}$ is simply the multivariate region of the elements of the $\boldsymbol{yu}$ vector determined by the observed ordinal outcomes, and the range $(-\boldsymbol{\infty}_{\tilde{G}}, \boldsymbol{0}_{\tilde{G}})$ for the utility differences taken with respect to the utility of the chosen alternative for the multinomial outcome. The likelihood function for a sample of Q decision-makers is obtained as the product of the individual-level likelihood functions.

Since a closed form expression does not exist for this integral and evaluation using simulation techniques can be time consuming, we used the One-variate Univariate Screening technique proposed by Bhat (2018) for approximating this integral. The estimation of parameters was carried out using the *maxlik* library in the GAUSS matrix programming language.

APPENDIX B

WAYMO VEHICLE ACCESSIBILITY FEATURES

The Waymo app and service used by RideChoice users included access to several accessibility features including:

1. An in-app button that enables the user to honk the vehicle's horn from nearby when the vehicle is ready for boarding, helping blind and low-vision users find their way to the vehicle.
2. In-vehicle audio cues describing vehicle maneuvers (e.g., “turning left onto Shoreline Boulevard”) to keep blind and low-vision users informed on their journey. These audio cues supplement default audio cues provided in the vehicle and give blind and low-vision users access to information that is also displayed on the second-row video screens. Users may turn on this in-vehicle audio cues feature in the app.
3. A setting that, when activated, minimizes walking at pickups and drop offs, including preventing the vehicle from considering a pickup or drop off point on the opposite side of the street from the rider’s selected location.
4. The option to communicate with Waymo Rider Support team through text in the app, instead of, or in addition to, communicating through the in-vehicle audio system.
5. In-vehicle displays that show text to accompany standard in-vehicle audio announcements (e.g., the vehicle will announce when the vehicle is approaching the rider’s destination, and that message will also appear on the in-vehicle video displays).
6. The ride buttons in Waymo self-driving vehicles have Braille labels. These buttons allow users to start the ride, pull over the vehicle, or call to speak to a member of the Waymo rider support team who can provide further assistance and information. These commands can also be made through the app.

APPENDIX C

EXPRESSION OF INTEREST FORM

Source: Stopher et al., 2021

1. Your name

First name: ____
Last name: ____

2. Your home address

Complete street address ______________________________
City ____
State ____
ZIP code ____

3. Your phone number (area code + number)

____

4. Your e-mail address
   - ○ E-mail: ____ OR
   - ○ I do not have an e-mail address

5. Do you have a smartphone purchased within the last 4 years?
- ○ Yes
- ○ No
- ○ Not sure

6. On average, how many one-way trips do you make using RideChoice services?
- ○ More than 3 trips per week
- ○ About 1-3 trips per week
- ○ Less than 1 trip per week
- ○ Other: ____

7. Do you currently use Waymo service for any of your trips?
   - ○ Yes
   - ○ No

8. Are you willing to participate in the Valley Metro - Waymo self-driving research study? Please note that Waymo vehicles do not currently accommodate people who use certain mobility devices or people who cannot safely enter and exit a standard minivan that is not equipped with a lift or ramp.
- ○ Yes
- ○ No
- ○ Not sure

9. Please check all of the activities in the list below that you can do on your own or with the assistance of a Personal Care Attendant (PCA).

- ☐ Download and install a mobile app on to a smartphone.
- ☐ Use a mobile app to book, check on, cancel, and pay for trips.
- ☐ Navigate to or from a self-driving vehicle, recognizing that the vehicle may be located up to 300 yards from my location, depending on traffic conditions and the availability of parking in the area where I will begin or end my trip.
- ☐ Board, secure myself, and ride in a self-driving vehicle (standard minivan).
- ☐ Carry and secure my own possessions within the vehicle.
- ☐ Speak and understand English sufficiently to communicate with support staff if necessary, either by phone or in person.
- ☐ Speak, write, and understand English sufficiently to complete surveys documenting my experience as a participant in this pilot project.
- ☐ ⊗ I cannot perform any of the above activities. Exclusive alternative, if this option is selected, all other options cannot be selected.

Display if Q7=No or Q7=Not sure

10. Please tell us why you are not interested in participating in the Valley Metro-Waymo self-driving ride service (so that we can plan for the future).

Display if Q8=No

____

____

11. Would you like a member of the study team to call you to discuss the Valley Metro-Waymo self-driving ride service further?

Display if Q8=Yes or Q8=Not sure

- ○ Yes
- ○ No

APPENDIX D

PRIOR SURVEY FORM

Source: Stopher et al., 2021

Section A: Your Use of RideChoice Service

This section asks questions about your current use of and opinions about Valley Metro's RideChoice service.

1. About how often do you use RideChoice service?
   - ○ Every day
   - ○ Weekly (not every day, but at least one day per week)
   - ○ Monthly (not every week, but one or more days per month)
   - ○ Less than once a month
   - ○ I have never used RideChoice service

2. Considering the **last trip** you recall using RideChoice, please answer the following questions. If you don't remember all of the information precisely, your best guess is fine.
   Display if Q1=Every day, Weekly, Monthly, or Less than once a month

Where did you travel using this service? *Provide address or major cross-streets and city name*.	From: ______________________________ To: ______________________________
When did you use it?	○ Weekday daytime ○ Weeknight (**excluding** Friday night) ○ Weekend daytime ○ Weekend night time (**including** Friday night)
About how long was the **wait time** for this trip?	__________ minutes
About how long was the **travel time** in the vehicle?	__________ minutes
About how much did you **pay for the trip**?	$________ *OR* ☐ I don't know.
What was the primary **purpose** of the trip? *Please check the **best answer.***	○ Work/school ○ Shopping/errands ○ Eating/drinking ○ Social/recreational ○ To access airport ○ To access public transit ○ Medical/dental ○ Going/returning home from another location ○ Other (please, specify): _______________
How many other passengers traveled with you?	○ I was the only passenger *OR* _____ Family members/friends, personal care attendants, etc.
What would you have done if the RideChoice	○ **Drive** a personal vehicle, alone ○ **Drive** a personal vehicle, with passengers

were **not** available? *Choose the most likely option.*	○ **Ride** in a vehicle, with others ○ Ride the bus ○ Ride the light rail ○ Use taxi ○ Group shuttle service (e.g., senior center group ride to grocery store) ○ Volunteer driver program (e.g., Give A Lift in Fountain Hills) ○ Use a bikesharing or e-scooter sharing service ○ Walk ○ Ride a bicycle or scooter ○ I would not have made this trip ○ Other (please, specify): ____________________________

3. In the **last month**, about how much did you spend out-of-pocket on RideChoice service?
Display if Q1=Every day, Weekly, Monthly, or Less than once a month

○ $0
○ $1 - $9
○ $10 – $29
○ $30 - $ 49
○ $50 - $74
○ $75 - $100
○ I do not know

4. In the **last month**, how much time did you spend, on average, **waiting** for the RideChoice vehicle to arrive after you placed a request for a ride? *If you book rides in advance for a specific pick-up time, indicate how long you waited (on average) for the vehicle to arrive after the requested pick-up time.*
Display if Q1=Every day, Weekly, Monthly, or Less than once a month

○ Less than 3 minutes
○ 3-5 minutes
○ 6-10 minutes
○ 11-20 minutes
○ 21-30 minutes
○ 31-60 minutes
○ More than 60 minutes
○ I do not know

5. Please rate your level of agreement with each of the following statements about current RideChoice service.
Display if Q1=Every day, Weekly, Monthly, or Less than once a month

	Strongly disagree	*Somewhat disagree*	*Neutral*	*Somewhat agree*	*Strongly agree*	*Don't know/ No Opinion*
RideChoice service allows me to get to places where I need to go.	○	○	○	○	○	○
If RideChoice service were not available, I would not	○	○	○	○	○	○

be able to make trips to different places.						
The RideChoice service is a reliable and dependable means of transportation for me.	○	○	○	○	○	○
RideChoice service is an affordable means of transportation.	○	○	○	○	○	○
The time spent waiting for the RideChoice vehicle is acceptable.	○	○	○	○	○	○
Having a human driver present during a RideChoice trip is important to me.	○	○	○	○	○	○
I would be willing to share my RideChoice trip with a stranger, if it would lower costs and add only a small amount of additional travel time.	○	○	○	○	○	○
I would be able to find reasonable substitute transportation if RideChoice service were not available.	○	○	○	○	○	○
I have generally found RideChoice drivers to drive safely and provide a good quality, comfortable, and smooth ride.	○	○	○	○	○	○
I have generally found RideChoice drivers to know their way around and get me where I need to go without any difficulty.	○	○	○	○	○	○
I have generally found RideChoice customer service to be of high quality.	○	○	○	○	○	○

6. Is the ability of a RideChoice service provider to accommodate special needs (e.g., wheelchair) important to you?

   ○ Yes, please specify: ________________________
   ○ No
   ○ Not Sure

7. How do you spend your time when riding in a RideChoice vehicle? *Select **up to four** activities.*
   Display if Q1=Every day, Weekly, Monthly, or Less than once a month

   ☐ Work, or study
   ☐ Talk on the phone/ send or read text messages/ teleconference
   ☐ Read for pleasure
   ☐ Sleep
   ☐ Entertainment (e.g., Watch movies; play games; listen to podcasts)
   ☐ Eat and drink
   ☐ Interact with the driver or other passengers
   ☐ Enjoy the scenery
   ☐ Watch the road
   ☐ Other (please, specify): ___________

8. What are the main purposes for which you use RideChoice service? *Select **up to four** purposes*.
   Display if Q1=Every day, Weekly, Monthly, or Less than once a month

   ☐ Work/school
   ☐ Shopping/errands
   ☐ Eating/drinking
   ☐ Social/recreational
   ☐ To access airport
   ☐ To access public transit
   ☐ Medical/dental
   ☐ Just to enjoy a ride/outing
   ☐ Other (please, specify): _______________

9. What other means of transportation do you use to get around? *Select **up to four** options*.

   ☐ Drive myself
   ☐ Ride as passenger with friend or family
   ☐ Carsharing services (*e.g.*, Zipcar)
   ☐ Volunteer driver program
   ☐ Bus
   ☐ ADA Paratransit service
   ☐ Group/Community Shuttle service
   ☐ Light rail
   ☐ Taxi
   ☐ Uber/Lyft
   ☐ Bike or scooter (including shared services)
   ☐ Walk
   ☐ Other (please, specify): _______________

Section B: Your Thoughts About Self-driving and On-demand Mobility Services

A **self-driving car** is a vehicle that can transport people, including those who do not drive, on its own without a human driver. When self-driving cars become available, people may purchase them for personal use or transportation providers could provide on-demand transportation in self-driving cars. A self-driving car ride may have a backup safety driver present in the vehicle; if one is not present, then the ride will be monitored remotely to handle any emergencies. Self-driving cars can provide on-demand transportation service, similar to current services (e.g., RideChoice, Uber, Lyft).

1. Which of the following statements best describes your **familiarity with self-driving cars**?

   ○ I had never heard of self-driving cars before taking this survey.
   ○ I have heard of self-driving cars, but don't know much about them.
   ○ I am somewhat familiar with self-driving cars.
   ○ I am very familiar with self-driving cars.

2. Have you ever taken a ride in a self-driving vehicle (e.g., Waymo)? Do **not** include riding in vehicles with advanced driver-assist features (such as the Tesla).

   ○ Yes, please specify:________________________
   ○ No
   ○ Not Sure

3. To what extent are you willing to ride in a self-driving car in each of the following ways when **a backup driver/operator is not present** in the vehicle? Assume that the vehicle is being monitored remotely to handle emergencies.

	Not at all Willing	*Somewhat Unwilling*	*Neutral*	*Somewhat Willing*	*Very Willing*	*Don't Know/No Opinion*
Riding a self-driving car alone	○	○	○	○	○	○
Riding a self-driving car with someone I know (*e.g.,* family, friends)	○	○	○	○	○	○
Riding a self-driving car with passengers who are unknown to me	○	○	○	○	○	○

4. Please rate your level of agreement with each of the following statements about self-driving cars?

	Strongly disagree	Somewhat disagree	Neutral	Somewhat agree	Strongly agree	Don't Know/No Opinion
Self-driving cars operate more safely on the roadways than human-driven vehicles.	○	○	○	○	○	○
Pedestrians, cyclists, and other road users will be safer in a future when most vehicles are self-driving.	○	○	○	○	○	○
Any self-driving car ride should have a human backup driver present in the vehicle to handle vehicle operation emergencies.	○	○	○	○	○	○
Human-driven vehicles should still be available even after self-driving vehicles are shown to be safer than human-driven vehicles.	○	○	○	○	○	○

5. Please rate your level of agreement with each of the following statements about your potential use of on-demand, self-driving car service?

	Strongly disagree	Somewhat disagree	Neutral	Somewhat agree	Strongly agree	Don't Know/No Opinion
If an on-demand, self-driving car service is available, I will routinely request it rather than the human-driven vehicle option for my RideChoice trips.	○	○	○	○	○	○
I would travel farther (longer distances) when on-demand, self-driving car service is available through RideChoice. *Assume you have to pay and wait for self-driving car service exactly as you do now for your RideChoice service.*	○	○	○	○	○	○
I would make additional trips (that I don't make at this time) when on-demand self-driving car service is available through RideChoice. *Assume you have to pay and wait for self-driving car service exactly as you do now for your RideChoice service.*	○	○	○	○	○	○
I would like to be one of the first to use a self-driving car service (as soon as it is available).	○	○	○	○	○	○

6. Think about your current RideChoice trips. How do you think you would spend your time on those trips if you were riding in a self-driving car **with no human operator/driver**? *Select **up to four** activities.*

☐ Work, or study
☐ Talk on the phone/ send or read text messages/ teleconference
☐ Read
☐ Sleep
☐ Entertainment (e.g., Watch movies; play games; listen to podcasts)
☐ Eat and drink
☐ Interact with other passengers
☐ Enjoy the scenery
☐ Watch the road
☐ I would not ride in a self-driving car
☐ Other (please, specify): ___________

7. To what extent will you switch to using self-driving car service for your RideChoice trips once they are available?

○ I would use self-driving cars for **all** my trips
○ I would use self-driving cars for **most** of my trips
○ I would use self-driving cars for **about half** of my trips
○ I would use self-driving cars for **a few** of my trips
○ I would **not** use self-driving cars for any of my trips

8. How much would you expect to pay for a RideChoice ride in a self-driving car?

○ $1 to $3 **less** than what I pay now *per trip*
○ Up to $1 **less** than what I pay now *per trip*
○ I would not expect to pay any more or any less than what I pay now for RideChoice trips

○ Up to $1 **more** than what I pay now *per trip*
○ $1 to $3 **more** than what I pay now *per trip*
○ I am not sure

9. How long are you willing to wait for a RideChoice vehicle pick-up after you have placed the request? *If you book rides in advance for a specific pick-up time, then indicate how long you are willing to wait for the vehicle to arrive after the requested pick-up time.*

○ Up to 5 minutes
○ Up to 10 minutes
○ Up to 20 minutes
○ Up to 30 minutes
○ Up to 60 minutes
○ Not sure

10. How important are the following features of a RideChoice trip service provider?

	Very Unimportant	*Somewhat unimportant*	*Neutral*	*Somewhat Important*	*Very Important*	*Don't Know/No Opinion*
Having to wait only a short time (less than 5 minutes) for my ride to arrive.	○	○	○	○	○	○

Having a high quality, comfortable, and smooth ride, where the vehicle operates on the roadways safely without incident.	○	○	○	○	○	○
Having a driver willing and able to provide some assistance with entering/exiting the vehicle, loading/unloading bags, or walking to/from the door.	○	○	○	○	○	○
Being picked-up and dropped off as close to the door as possible.	○	○	○	○	○	○
Having a mobile app to book, track, and pay for rides.	○	○	○	○	○	○

Section C: Background Information

To help us better understand the transportation needs of the community, we would like to ask you a few background questions. Your privacy is guaranteed.

1. How old are you? ________ years old

2. What is your gender?

   ○ Male
   ○ Female
   ○ Other
   ○ Prefer not to answer

3. At this time, are you:

   ○ Employed full-time
   ○ Employed part-time
   ○ Self-employed
   ○ Retired
   ○ Homemaker
   ○ Unable to work
   ○ Not employed and currently looking for work
   ○ Not employed and **not** currently looking for work
   ○ Other (please, specify): ________________________

4. At this time, are you:

   ○ A full-time student
   ○ A part-time student
   ○ Not a student

5. What is your occupation?
   Display if Q3=Employed full-time, Employed part-time, or Self-employed

○ Sales or service
○ Clerical or administrative support
○ Manufacturing, construction, maintenance, or farming
○ Professional, managerial, or technical
○ Education, training, and library occupations
○ Arts, design, entertainment, sports, and media occupations
○ Military specific occupations
○ Other (please, specify): _______________

6. Knowing more about your **work** location will help us understand the transportation options available to you. Please give the address or, if you prefer, major cross streets closest to your main workplace location. *If you travel to more than one work location on a regular basis, enter the location to which you travel most often.*
Display if Q3=Employed full-time, Employed part-time, or Self-employed

____

City: ___________________________________ State: ______ Zip code:

7. Knowing more about your **school** location will help us understand the transportation options available to you. Please give the address or, if you prefer, major cross streets closest to your main school location. *If you travel to more than one school location on a regular basis, enter the location to which you travel most often.*
Display if Q4=A full-time Student or a part-time student

____

City: ___________________________________ State: ______ Zip code:

8. Please provide the address of up to **five** (other) **locations** that you visit most frequently. These may be locations such as a grocery store, a movie theater, a favorite restaurant, a friend's house, a place of worship, a doctor's office, or a place where you volunteer your time. *This information will be used to determine if the self-driving car service can meet most of your transportation needs*. *Your privacy is guaranteed.*

a.____

City: ___________________________________ State: ______ Zip code:

b.____

City: ___________________________________ State: ______ Zip code:

c.____

City: ___________________________________ State: ______ Zip code:

d.____

City: ___________________________________ State: ______ Zip code:

e.____

City: ________________________________ State: ______ Zip code:

9. What is your educational background? *Check the highest level of education you have attained.*

   ◯ Some grade/high school
   ◯ Completed high school or GED
   ◯ Some college or technical school
   ◯ Bachelor's degree(s) or some graduate school
   ◯ Completed graduate degree(s)

10. Do you have any disabilities or health-related conditions that prevent or limit you from … (If needed, feel free to add more details into the last column.)

	No	*To some extent*	*Yes*	*Please explain (optional)*
Driving a personal vehicle	◯	◯	◯	
Using public transit (bus or light rail)	◯	◯	◯	
Riding a bike	◯	◯	◯	
Walking up to three city blocks	◯	◯	◯	

11. Do you use any of the following way-finding, mobility assistance systems, or tools? Please check all that apply.
   ◯ None
   ◯ Screen reader / text to speech
   ◯ Magnification / zoom / large font
   ◯ Keyboard only
   ◯ Color modifications
   ◯ Closed captions
   ◯ Voice control
   ◯ Switch device
   ◯ Other (please, specify): ___________________________

12. What best describes the home you **currently** live in?

   ◯ Stand-alone home ◯ Attached home/townhome
   ◯ Condo/apartment
   ◯ Mobile home ◯ Other (please, specify): _______________

13. Do you live in a **gated** community or apartment complex?
   ◯ Yes ◯ No

14. **Including yourself**, how many people live in your household? ___________
By "household" we mean "people who live together and share at least some financial resources." Unrelated housemates/roommates are usually **not** *considered members of the same household even if they live in the same housing unit.*

15. How many personal vehicles (automobiles) and/or motorcycles does your household own, lease, or have available for personal use at any time? _________

16. Do you have a ride-hailing service app (*e.g*., Uber, Lyft) on your phone?
   ○ Yes ○ No ○ Not Sure

17. Have you taken a ride through a ride-hailing service (*e.g*., Uber, Lyft) at any time in the past six months (outside of the RideChoice program)?
   ○ Yes ○ No ○ Not Sure

18. About how frequently do you take a ride through a ride-hailing service (*e.g*., Uber, Lyft) outside of the RideChoice program?
   Display if Q17=Yes

   ○ Rarely (less than once a month)
   ○ At least once a month, but less than weekly
   ○ At least once a week, but less than daily
   ○ About every day
   ○ Not sure

19. What type of smartphone do you have?

   ○ iPhone/ iOS (Apple)
   ○ Android
   ○ Other (please, specify): ___________

20. We will be sending you a $100 gift card as a token of appreciation for your response to this survey. Have you received or are you receiving any other payments or incentives from Arizona State University (ASU) during the 2019 calendar year?
   ○ Yes ○ No

21. Please check the appropriate category for your annual *household* income before taxes.

   ○ Less than $25,000
   ○ $25,000 to $49,999
   ○ $50,000 to $74,999
   ○ $75,000 to $99,000
   ○ $100,000 to $149,999
   ○ $150,000 to $249,999
   ○ $250,000 or more

If you have any additional comments about your current travel, and new transportation options such as self-driving vehicles, you are welcome to share them in the space below.

Thank you for your valuable participation in this survey!
All of your responses have been successfully recorded.

APPENDIX E

DURING SURVEY FORM

Source: Stopher et al., 2021

Section A: Your Transportation Choices

This section asks questions about your recent transportation choices. Please think about the RideChoice rides that you have taken when answering questions in this section.

1. About how many **Waymo rides** have you taken in total since the beginning of this study (include **all Waymo rides**, even if the Waymo ride was not officially part of this study or taken under the RideChoice program)? Note: A one-way trip is counted as a ride.
   ____________ rides

2. Please rate your level of agreement with each of the following statements about how you use **RideChoice** and the needs that you have when going places.

	Strongly agree	*Somewhat agree*	*Neutral*	*Somewhat disagree*	*Strongly disagree*	*Don't now/No Opinion*
I use RideChoice to travel within the city of Chandler.	○	○	○	○	○	○
I generally need assistance from the driver when using RideChoice services (*e.g.*, help getting in and out of vehicle; loading and unloading groceries)	○	○	○	○	○	○
I enjoy the social aspect of RideChoice and often talk with the driver.	○	○	○	○	○	○

3. Please rate your level of agreement with each of the following statements about your experience riding in **Waymo vehicles**.
   Display if Q1>0

	Strongly agree	*Somewhat agree*	*Neutral*	*Somewhat disagree*	*Strongly disagree*	*Don't now/No Opinion*
Waymo vehicles serviced all of the locations that I needed to go.	○	○	○	○	○	○
I had no trouble getting into and out of the Waymo vehicle.	○	○	○	○	○	○
Waymo vehicles provided a social aspect that fulfilled my desire to talk to other people.	○	○	○	○	○	○

4. Now consider your rides in traditional RideChoice vehicles (**not Waymo vehicles)**. Please rate your level of agreement with each of the following statements about your experience riding in **traditional RideChoice vehicles**.

	Strongly agree	*Somewhat agree*	*Neutral*	*Somewhat disagree*	*Strongly disagree*	*Don't now/No Opinion*
RideChoice vehicles serviced all of the locations that I needed to go.	○	○	○	○	○	○
I had no trouble getting into and out of the traditional (non-Waymo) RideChoice vehicles.	○	○	○	○	○	○
Riding in traditional (non-Waymo) RideChoice vehicles provided a social	○	○	○	○	○	○

aspect that fulfilled my desire to talk to other people.	

5. Consider the most recent ride that you took **using Waymo service**. *For this specific ride, please answer the following questions. If you don't remember all of the information precisely, your best guess is fine.* **Display if Q1>0**

What is the month and year when the ride for which you are reporting information was taken?	Month: (September-March)___________________________________ Year: (2019-2020)____
Where did you travel using this service? *Provide address or major cross-streets and city.*	From: ____ To: ____
What was the day of week when the ride was taken?	○ Monday, Tuesday, Wednesday, or Thursday ○ Friday ○ Saturday ○ Sunday
What time of day was this ride?	○ Daytime (6 AM to 7 PM) ○ Nighttime (7 PM to 12 Midnight) ○ Late night (12 midnight to 6 AM)
About how long was the **wait time** for this ride?	___________ minutes
About how long was the **travel time** in the vehicle?	___________ minutes
What was the primary **purpose** of the ride? *Please check the **best answer.***	○ Work/school ○ Shopping/errands ○ Eating/drinking ○ Social/recreational ○ To access airport ○ To access public transit ○ Medical/dental ○ Going/returning home from another location ○ Other (please, specify): _______________
How many other passengers traveled with you?	○ I was the only passenger *OR* ☐ Family members/friends (enter a number): ______ ☐ Personal care attendants (enter a number): ______
What would you have done if the RideChoice were **not** available for this trip? *Choose the most likely option.*	○ I would not have made this trip ○ **Drive** a personal vehicle, alone ○ **Drive** a personal vehicle, with passengers ○ **Ride** in a vehicle, with others ○ Ride the bus ○ Ride the light rail

○ Use taxi
○ Use an Uber/Lyft
○ Group shuttle service (*e.g.*, senior center group ride to grocery store)
○ Volunteer driver program (*e.g.*, Give A Lift in Fountain Hills)
○ Use a bikesharing or e-scooter sharing service
○ Walk
○ Ride a bicycle or scooter
○ Other (please, specify): ____________________________

Please rate how satisfied you were with the following aspects of this ride.

	Strongly agree	*Somewhat agree*	*Neutral*	*Somewhat disagree*	*Strongly disagree*	*Don't Know/No Opinion*
I was satisfied with the wait time for this ride.	○	○	○	○	○	○
I was satisfied with the travel time (*i.e.*, time spent riding in the vehicle) for this ride.	○	○	○	○	○	○
I was satisfied with the cost of this ride.	○	○	○	○	○	○
I was satisfied with the comfort of the vehicle during this ride.	○	○	○	○	○	○

How did you spend your time in the vehicle during this ride? *Select **up to four** activities.*

☐ Work or study
☐ Talk on the phone/ send or read text messages/ teleconference
☐ Read for pleasure
☐ Sleep
☐ Entertainment (*e.g.*, Watch movies; play games; listen to podcasts)
☐ Eat and drink
☐ Interact with the driver
☐ Interact with other passengers
☐ Enjoy the scenery
☐ Watch the road
☐ Other (please, specify): ___________

6. Please rate your level of agreement with each of the following statements about Waymo service.
   Display if Q1>0

	Strongly agree	*Somewhat agree*	*Neutral*	*Somewhat disagree*	*Strongly disagree*	*Don't Know/No Opinion*
I feel safe when riding in the Waymo vehicle.	○	○	○	○	○	○
The ride in the Waymo vehicle is smooth and comfortable.	○	○	○	○	○	○
I feel confident that my Waymo ride will not have any problems.	○	○	○	○	○	○

I find it exciting to ride in a Waymo vehicle.	○	○	○	○	○	○
I am making new trips (that I did not make previously) in the RideChoice program after the inclusion of the Waymo option.	○	○	○	○	○	○
I find it easy to use the Waymo ride-hailing app on my smartphone to order service.	○	○	○	○	○	○
I like riding in the Waymo self-driving vehicle more than riding in traditional RideChoice vehicles with a human driver (taxi, Uber/Lyft).	○	○	○	○	○	○

7. In the past 30 days, about how many RideChoice rides have you taken (**include Waymo rides** taken as part of the RideChoice service)?

    _____________ rides

8. Consider the most recent ride that you took in a **traditional RideChoice vehicle (that is not a Waymo vehicle)**. *For this specific **non-Waymo** ride, please answer the following questions. If you don't remember all of the information precisely, your best guess is fine. If you have never taken a RideChoice ride in a traditional non-Waymo vehicle, then please skip this question.*

What is the month and year when the ride for which you are reporting information was taken?	Month: (January-December)____________________________________ Year: (2019-2020)____
Where did you travel using this service? *Provide address or major cross-streets and city*.	From: ____ To: ____
What was the day of week when the ride was taken?	○ Monday, Tuesday, Wednesday, or Thursday ○ Friday ○ Saturday ○ Sunday
What time of day was this ride?	○ Daytime (6 AM to 7 PM) ○ Nighttime (7 PM to 12 Midnight) ○ Late night (12 midnight to 6 AM)
About how long was the **wait time** for this ride?	___________ minutes
About how long was the **travel time** in the vehicle?	___________ minutes
What was the primary **purpose** of the ride? *Please check the **best answer.***	○ Work/school ○ Shopping/errands ○ Eating/drinking ○ Social/recreational

	○ To access airport ○ To access public transit ○ Medical/dental ○ Going/returning home from another location ○ Other (please, specify): _______________
How many other passengers traveled with you?	○ I was the only passenger *OR* ☐ Family members/friends (enter a number): ______ ☐ Personal care attendants (enter a number): ______
What would you have done if the RideChoice were **not** available for this trip? *Choose the most likely option.*	○ I would not have made this trip ○ **Drive** a personal vehicle, alone ○ **Drive** a personal vehicle, with passengers ○ **Ride** in a vehicle, with others ○ Ride the bus ○ Ride the light rail ○ Use taxi ○ Use an Uber/Lyft ○ Group shuttle service (*e.g.*, senior center group ride to grocery store) ○ Volunteer driver program (*e.g.*, Give A Lift in Fountain Hills) ○ Use a bikesharing or e-scooter sharing service ○ Walk ○ Ride a bicycle or scooter ○ Other (please, specify): ___________________________

Please rate how satisfied you were with the following aspects of this ride.

	Strongly agree	*Somewhat agree*	*Neutral*	*Somewhat disagree*	*Strongly disagree*	*Don't Know/No Opinion*
I was satisfied with the wait time for this ride.	○	○	○	○	○	○
I was satisfied with the travel time (*i.e.*, time spent riding in the vehicle) for this ride.	○	○	○	○	○	○
I was satisfied with the cost of this ride.	○	○	○	○	○	○
I was satisfied with the comfort of the vehicle during this ride.	○	○	○	○	○	○

How did you spend your time in the vehicle during this ride? *Select **up to four** activities.*

☐ Work or study
☐ Talk on the phone/ send or read text messages/ teleconference
☐ Read for pleasure
☐ Sleep
☐ Entertainment (*e.g.*, Watch movies; play games; listen to podcasts)
☐ Eat and drink

☐ Interact with the driver
☐ Interact with other passengers
☐ Enjoy the scenery
☐ Watch the road
☐ Other (please, specify): ___________

9. Please rate your level of agreement with each of the following statements about **traditional RideChoice service** (*i.e.*, **non-Waymo service**).

	Strongly agree	*Somewhat agree*	*Neutral*	*Somewhat disagree*	*Strongly disagree*	*Don't Know/No Opinion*
I feel safe when riding in the traditional RideChoice vehicle.	○	○	○	○	○	○
The ride in the traditional Ride Choice vehicle is smooth and comfortable.	○	○	○	○	○	○
I feel confident that my traditional RideChoice vehicle ride will not have any problems.	○	○	○	○	○	○
I find it exciting to ride in a traditional RideChoice vehicle.	○	○	○	○	○	○
I find it easy to order and use the traditional RideChoice service.	○	○	○	○	○	○
I like riding in traditional RideChoice vehicles more than in Waymo vehicles.	○	○	○	○	○	○

10. In the past 30 days, what other means of transportation have you used to get around? *Select **up to four** options used most often*.

☐ Drive alone
☐ Drive with other passengers in the vehicle
☐ Ride as passenger with friend or family
☐ Carsharing services (*e.g.*, Zipcar)
☐ Volunteer driver program
☐ Bus
☐ ADA Paratransit service
☐ Group/Community Shuttle service
☐ Light rail
☐ Traditional Taxi
☐ Uber/Lyft
☐ Bike or scooter (including shared services)
☐ Walk
☐ Other (please, specify): _______________

Section B: Your Thoughts About Self-driving and On-demand Mobility Services

This section asks questions about your perceptions of and expectations for new mobility services and technologies. Please think about your transportation needs and experiences in general, and not just about traditional RideChoice or Waymo vehicles.

11. Which of the following statements best describes your **current familiarity with fully self-driving vehicles**?

    ○ I have heard of fully self-driving vehicles, but don't know much about them.
    ○ I am somewhat familiar with fully self-driving vehicles.
    ○ I am very familiar with fully self-driving vehicles.

12. Please rate your level of agreement with each of the following statements about riding in a **fully self-driving vehicle with no driver**.

	Strongly agree	*Somewhat agree*	*Neutral*	*Somewhat disagree*	*Strongly disagree*	*Don't Know/No Opinion*
I would ride in a fully self-driving vehicle alone.	○	○	○	○	○	○
I would ride in a fully self-driving vehicle with someone I know (*e.g.*, family, friends).	○	○	○	○	○	○
I would ride in a fully self-driving vehicle with passengers who are unknown to me.	○	○	○	○	○	○

13. How much do you agree or disagree with each of the following statements about fully self-driving vehicles?

	Strongly agree	*Somewhat agree*	*Neutral*	*Somewhat disagree*	*Strongly disagree*	*Don't Know/No Opinion*
I believe that self-driving vehicles are safer than human-driven vehicles and will reduce accidents and fatalities.	○	○	○	○	○	○
I believe that pedestrians, cyclists, and other road users would be safer in a future when most vehicles are fully self-driving.	○	○	○	○	○	○

14. How much do you agree or disagree with each of the following statements about your potential use of an on-demand, fully self-driving vehicle service?

	Strongly agree	*Somewhat agree*	*Neutral*	*Somewhat disagree*	*Strongly disagree*	*Don't Know/No Opinion*
I would prefer to use a fully self-driving vehicle service over a traditional human-driven vehicle service for my RideChoice trips.	○	○	○	○	○	○
I would like to be one of the first users of a fully self-driving vehicle	○	○	○	○	○	○

service for my RideChoice trips, once such a service is available on a permanent basis.						
I believe that a fully self-driving vehicle service would make it easier for me to access and use bus and rail service.	○	○	○	○	○	○
I believe that a fully self-driving vehicle service will make traveling in the region easier and more convenient.	○	○	○	○	○	○

15. To what extent will you switch to using a fully self-driving vehicle service for your RideChoice trips if the service is available on a permanent basis across the entire Phoenix metropolitan area?
    - ○ I would use fully self-driving vehicles for **all** my trips
    - ○ I would use fully self-driving vehicles for **most** of my trips
    - ○ I would use fully self-driving vehicles for **about half** of my trips
    - ○ I would use fully self-driving vehicles for **a few** of my trips
    - ○ I would **not** use fully self-driving vehicles for any of my trips

16. Rate each of the following modes on a scale of 1 to 5 for the characteristics listed in the first column. **The scale is as follows: 1=poor; 2=fair; 3=good; 4=very good; 5=excellent.** *If you have not used a particular service, or have no opinion on a particular characteristic, enter a ZERO.* ***Do not leave any blanks.***

Characteristic	***Regular Taxi***	***Uber/Lyft***	***Waymo***
Waiting time			
Ride comfort			
Travel time			
Drop-off and pick-up locations			
Cleanliness of vehicle			
Ease of getting into and out of vehicle			
Ease of requesting the ride			

17. How has your use of other modes of transportation changed after the inclusion of Waymo as an option in the RideChoice program?

	Decreased	*Increased*	*Stayed the Same*
Drive a personal vehicle, alone	○	○	○
Drive a personal vehicle, with passengers	○	○	○
Ride in a vehicle, with others	○	○	○
Bus	○	○	○
Group shuttle service (*e.g.*, senior center group ride)	○	○	○
Light rail	○	○	○

Traditional taxi	○	○	○
Uber/Lyft	○	○	○
Bikesharing or e-scooter sharing service	○	○	○
Walk	○	○	○
Ride a bicycle or scooter	○	○	○

Section C: Background Information

To help us better understand the transportation needs of the community, we would like to ask you a few background questions. Please answer these questions even if there is no change from the last survey. Your privacy is guaranteed.

18. At this time, you are:

    - ○ Employed full-time
    - ○ Employed part-time
    - ○ Self-employed
    - ○ Retired
    - ○ Homemaker
    - ○ Unable to work
    - ○ Not employed and currently looking for work
    - ○ Not employed and **not** currently looking for work
    - ○ Other (please, specify): ________________________

19. At this time, you are:

    - ○ A full-time student
    - ○ A part-time student
    - ○ Not a student

20. What is your occupation?
    Display if Q18=Employed full-time, Employed part-time, or Self-employed

    - ○ Sales or service
    - ○ Clerical or administrative support
    - ○ Manufacturing, construction, maintenance, or farming
    - ○ Professional, managerial, or technical
    - ○ Education, training, and library occupations
    - ○ Arts, design, entertainment, sports, and media occupations
    - ○ Military specific occupations
    - ○ Other (please, specify): _______________

21. Knowing more about your **work** location will help us understand the transportation options available to you. Please give the address or, if you prefer, major cross streets closest to your main workplace location. *If you travel to more than one work location on a regular basis, enter the location to which you travel most often.*
    Display if Q18=Employed full-time, Employed part-time, or Self-employed

    ____

City: ________________________________ State: ______ Zip code: _______

22. Knowing more about your **school** location will help us understand the transportation options available to you. Please give the address or, if you prefer, major cross streets closest to your main school location. *If you travel to more than one school location on a regular basis, enter the location to which you travel most often.*
Display if Q19=A full-time Student or a part-time student

____

City: ________________________________ State: ______ Zip code: _______

23. **Including yourself**, how many people live in your household? (1-10 or more)__________
*By "household" we mean "people who live together and share at least some financial resources." Unrelated housemates/roommates are usually **not** considered members of the same household even if they live in the same housing unit.*

24. How many personal vehicles (automobiles) and/or motorcycles does your household own, lease, or have available for personal use at any time? (0-6 or more)________

25. Do you have a ride-hailing service app (*e.g.*, Uber, Lyft) on your phone?
○ Yes ○ No ○ Not Sure

26. Have you taken a ride through a ride-hailing service (*e.g.*, Uber, Lyft) at any time in the past 30 days (outside of the RideChoice program)? Include trips ordered by somebody else (and you rode along).
○ Yes ○ No ○ Not Sure

27. About how frequently do you take a ride through a ride-hailing service (*e.g.*, Uber, Lyft) outside of the RideChoice program? Include rides ordered by somebody else (where you ride along).

○ Rarely (less than once a month)
○ At least once a month, but less than weekly
○ At least once a week, but less than daily
○ About every day
○ Not sure

28. We will be sending you a $100 gift card as a token of appreciation for your response to this survey. Have you received or are you receiving any other payments or incentives from Arizona State University (ASU) during the 2019 or 2020 calendar years (do not include payments or incentives you are receiving as part of this Valley Metro/Waymo study)?

○ Yes○ No

29. Please check the appropriate category for your annual *household* income before taxes.

○ Less than $25,000
○ $25,000 to $49,999
○ $50,000 to $74,999
○ $75,000 to $99,000

○ $100,000 to $149,999
○ $150,000 to $249,999
○ $250,000 or more

30. If you have any additional comments about your current travel, and new transportation options such as self-driving vehicles, you are welcome to share them in the space below.

Thank you for your valuable participation in this survey!
All of your responses have been successfully recorded.

APPENDIX F

POST SURVEY FORM

Source: Stopher et al., 2021

Section A: Your Travel Choices and Experiences

This section asks questions about your recent transportation choices and Waymo experience.

1. Have you taken at least one **Waymo ride** over the past 12 months (include **all Waymo rides**, even if the Waymo ride was not officially part of this study or taken under the RideChoice program)? Note: A one-way trip is counted as a ride.

   ◯ Yes
   ◯ No
   ◯ Not sure

2. Do you currently have the **Waymo app** on your smartphone?

   ◯ Yes
   ◯ No
   ◯ Not sure

3. Have you taken at least one ride using any **non-Waymo RideChoice service provider** (*e.g.*, taxi, Uber, Lyft, etc.) in the past 12 months?

   ◯ Yes
   ◯ No
   ◯ Not sure

4. Have you taken at least one ride using any **non-Waymo RideChoice service provider** (*e.g.*, taxi, Uber, Lyft, etc.) after March 15, 2020 (after the Waymo service suspension due to COVID-19)?
   Display if Q3=YES

   ◯ Yes
   ◯ No
   ◯ Not sure

5. Please rate your level of agreement with each of the following statements based on your experience riding in **Waymo vehicles**.
   Display if Q1=YES

	Strongly agree	*Somewhat agree*	*Neutral*	*Somewhat disagree*	*Strongly disagree*	*Don't Know/No Opinion*
Waymo served as a reliable means of transportation for me.	◯	◯	◯	◯	◯	◯
Waymo's customer service provided high quality assistance when I needed help. If you didn't need Waymo support, then check *Don't Know/No Opinion.*	◯	◯	◯	◯	◯	◯
Waymo provided a comfortable and smooth ride to my destinations.	◯	◯	◯	◯	◯	◯
The amount of time that I waited for my Waymo rides was acceptable.	◯	◯	◯	◯	◯	◯

I would like to have Waymo service available as a regular and permanent RideChoice option.	◯	◯	◯	◯	◯	◯

6. Please rate your level of agreement with each of the following statements based on your experience using **non-Waymo RideChoice services** (*e.g.*, taxi, Uber, Lyft, etc.) over the past 12 months.
Display if Q3=YES

	Strongly agree	*Somewhat agree*	*Neutral*	*Somewhat disagree*	*Strongly disagree*	*Don't Know/No Opinion*
non-Waymo RideChoice services served as a reliable means of transportation for me.	◯	◯	◯	◯	◯	◯
Valley Metro's RideChoice customer service provided high quality assistance when I needed help. If you didn't need Valley Metro's RideChoice support, then check *Don't Know/No Opinion.*	◯	◯	◯	◯	◯	◯
non-Waymo RideChoice services provided a comfortable and smooth ride to my destinations.	◯	◯	◯	◯	◯	◯
The amount of time that I waited for my non-Waymo RideChoice rides was acceptable.	◯	◯	◯	◯	◯	◯

7. About how often have you used RideChoice services **in the past 30 days (during the COVID-19 pandemic)**?
   - ◯ Never
   - ◯ Rarely (less than one day a week)
   - ◯ About 1-2 days per week
   - ◯ Several days per week (3-7 days per week)

8. After the COVID-19 pandemic is over, how often do you think you will use RideChoice services?
   - ◯ Every day
   - ◯ Weekly (not every day, but at least one day per week)
   - ◯ Monthly (not every week, but one to three days per month)
   - ◯ Less than once a month
   - ◯ I will not use RideChoice services after the COVID-19 pandemic
   - ◯ Not sure

9. In the past 30 days (during the COVID-19 pandemic), what other means of transportation (i.e., other than RideChoice services) have you used to get around? *Select **up to four** options used most often*.

   ◯ I did not make any trips at all (stayed home all the time)

   OR CHOOSE UPTO 4 OPTIONS BELOW

   ☐ Drive alone

   ☐ Drive with other passengers in the vehicle

- ☐ Ride as passenger with friend or family
- ☐ Carsharing services (*e.g.*, Zipcar)
- ☐ Volunteer driver program
- ☐ Bus
- ☐ ADA Paratransit service
- ☐ Group/Community Shuttle service
- ☐ Light rail
- ☐ Traditional Taxi
- ☐ Uber/Lyft)
- ☐ Bike or scooter (including shared services)
- ☐ Walk
- ☐ Other (please, specify): _______________

10. **In the past 30 days (during the COVID-19 pandemic)**, about how frequently have you taken a ride through a ride-hailing service (*e.g.*, Uber, Lyft) **outside of the RideChoice program**? Include rides ordered by somebody else (where you ride along).

    - ◯ Never
    - ◯ Rarely (less than one day a week)
    - ◯ About 1-2 days per week
    - ◯ Several days per week (3-7 days per week)

11. After the COVID-19 pandemic is over, about how frequently might you take a ride through a ride-hailing service (*e.g.*, Uber, Lyft) **outside of the RideChoice program**? Include rides ordered by somebody else (where you would ride along).

    - ◯ Never
    - ◯ Rarely (less than once a month)
    - ◯ At least once a month, but less than weekly
    - ◯ At least once a week, but less than daily
    - ◯ About every day
    - ◯ Not sure

Section B: Your Thoughts About Self-driving and On-demand Mobility Services

This section asks questions about your perceptions of and expectations for new mobility services and technologies. Please think about your transportation needs and experiences in general, and not just about RideChoice or Waymo vehicles and services. In answering these questions, assume that the COVID-19 pandemic is over.

12. Please rate your level of agreement with each of the following statements about riding in a **fully self-driving vehicle with no driver.**

	Strongly agree	*Somewhat agree*	*Neutral*	*Somewhat disagree*	*Strongly disagree*	*Don't Know/No Opinion*
I would ride in a fully self-driving vehicle alone.	◯	◯	◯	◯	◯	◯
I would ride in a fully self-driving vehicle with someone I know (*e.g.*, family, friends).	◯	◯	◯	◯	◯	◯

I would ride in a fully self-driving vehicle with passengers who are unknown to me.	◯	◯	◯	◯	◯	◯

13. To what extent will you switch to using a fully self-driving vehicle service for your RideChoice rides once the service is available on a permanent basis across the entire Phoenix metropolitan area?

◯ I would use fully self-driving vehicles for **all** my RideChoice rides.
◯ I would use fully self-driving vehicles for **most** of my RideChoice rides.
◯ I would use fully self-driving vehicles for **about half** of my RideChoice rides.
◯ I would use fully self-driving vehicles for **a few** of my RideChoice rides.
◯ I would **not** use fully self-driving vehicles for any of my RideChoice rides.

14. Please rate your level of agreement with each of the following statements about self-driving vehicles.

	Strongly agree	*Somewhat agree*	*Neutral*	*Somewhat disagree*	*Strongly disagree*	*Don't Know/No Opinion*
Self-driving vehicles can significantly enhance mobility for all people.	◯	◯	◯	◯	◯	◯
Self-driving vehicles will make traveling by car less stressful for me.	◯	◯	◯	◯	◯	◯
I am excited to see technology innovations in transportation.	◯	◯	◯	◯	◯	◯
Self-driving vehicles can especially improve mobility for individuals with special needs or mobility limitations (*e.g.*, senior, disabled).	◯	◯	◯	◯	◯	◯
I would like to see self-driving vehicles become common on our roadways.	◯	◯	◯	◯	◯	◯

Section C: Employment Status and Incentive

15. At this time, you are:

◯ Employed full-time
◯ Employed part-time
◯ Self-employed
◯ Retired
◯ Homemaker
◯ Unable to work
◯ Not employed and currently looking for work
◯ Not employed and **not** currently looking for work
◯ Other (please, specify): ________________________

16. We will be sending you a $100 gift card as a token of appreciation for your response to this survey. Have you received or are you receiving any other payments or incentives from Arizona State University (ASU) during the 2019 or 2020 calendar years (do not include payments or incentives you are receiving as part of this Valley Metro/Waymo study)?

    ○ Yes ○ No

17. If you have any additional comments about your current travel, and new transportation options such as self-driving vehicles, you are welcome to share them in the space below.

Thank you for your valuable participation in this survey!

APPENDIX G

RIDER FOCUS GROUP QUESTIONS

Source: Stopher et al., 2021

Group 1: RideChoice Users Focus Group
May 27 and 28, 2020

Part I: Introduction

1. Tells us your first name and about one of your most memorable Waymo trips.

Part II: AV Technology Attitudes and Perceptions

2. How does it feel to ride in a self-driving car? What parts do you like and not like?
3. What are your current thoughts, feelings, or perceptions of self-driving cars? Have they changed while using Waymo as a *RideChoice* option?
4. How would you feel about receiving a driverless ride (i.e., a ride without a Waymo trained driver)?

Part III: User Experience

5. How does Waymo as a *RideChoice* option with Valley Metro compare to other *RideChoice* options?
6. What do you like the most about Waymo? What do you like the least?
7. What would make you take Waymo more frequently?

Part IV: Ride Choice and Behavior

8. How well did Waymo meet your transportation and mobility needs for the trips you took with it?
9. On trips where you used Waymo, what other modes did you have available and why did you use Waymo over other transportation options?
10. How do you see yourself using self-driving cars in the future?

Part V: Closing Comments

11. Would you keep using Waymo if it remained a *RideChoice* option? Would you use Waymo if it was not part of *RideChoice*?
12. Any final comments, questions, or thoughts about your experiences with Waymo or about self-driving cars?

Group 2: Valley Metro Employee Users Focus Group
May 20, 2020

Part I: Introduction

1. Tells us your first name and about one of your most memorable Waymo trips.

Part II: AV Technology Attitudes and Perceptions

2. How does it feel to ride in a self-driving car? What parts do you like and not like?
3. What are your current thoughts, feelings, or perceptions of self-driving cars? Have they changed while using Waymo?
4. How would you feel about receiving a driverless ride (i.e., a ride without a Waymo trained driver)?

Part III: User Experience

5. How does the Waymo service compare to other mobility options you have available to you?
6. What do you like the most about Waymo? What do you like the least?
7. What would make you take Waymo more frequently?

Part IV: Ride Choice and Behavior

8. How well did Waymo meet your transportation and mobility needs for the trips you took with it?
9. On trips where you used Waymo, what other modes did you have available and why did you use Waymo over other transportation options?
10. How do you see yourself using self-driving cars in the future?

Part V: Closing Comments

11. Would you keep using Waymo if it was not part of Valley Metro service?
12. Any final comments, questions, or thoughts about your experiences with Waymo or about self-driving cars?

APPENDIX H

SUBJECT MATTER EXPERT FOCUS GROUP QUESTIONS

Source: Stopher et al., 2021

Group 3: Subject Matter Expert (SME) Focus Group
July 6 and 7, 2020

Part I: Introduction

1. By jurisdiction, tell us your name and what you hope to get out of or learn from today's event.

Part II: Transportation, Mobility and Autonomous Vehicles

2. Where do AVs fit within your city's goals and plans for (1) public transportation and (2) mobility?
3. What opportunities and challenges do you see in planning for AVs in your community?
4. How has or might your community engage the public about AVs?

Part III: Pilot Projects

5. How familiar are you with the Valley Metro Waymo Pilot Project? What elements of this pilot do you think are most useful to your community and/or to the region?
6. What other types of pilot projects are you interested in seeing and/or developing?
7. What, if any, barriers do you see in developing successful pilot project?

Part IV: Mobility Partnerships

8. What are your thoughts on public private partnerships in the mobility sector? What might partnerships with AV companies look like?
9. Are there barriers in your community to developing public private partnerships with AV companies?

Part V: Closing Comments

10. What additional information about AVs would be most useful to your community?
11. Any final comments, questions, or thoughts?

APPENDIX I

POLICY MAKER ROUNDTABLE AGENDA AND QUESTIONS

Source: Stopher et al., 2021

Group 4: Policy Maker Roundtable
July 8, 2020

Agenda
Part I: Introduction

a. Overview and goals for the roundtable
b. Introduction to Valley Metro Waymo Mobility-on-Demand Demonstration Program
c. Broader ecosystem of AV testing and pilot projects in U.S.

Part II: Presentation of Results for Valley Metro Waymo Mobility-on-Demand Demonstration Program

a. Survey results
b. Rider focus group results

Part III: Discussion

a. Implications of Valley Metro Waymo pilot project
b. AVs in public transit
c. AVs in Phoenix area jurisdictions
d. Next Steps

Part IV: Closing Comments
Discussion questions, Part III:
Implications of pilot project:

a. What are the implications of the Valley Metro Waymo Pilot Project for Valley Metro and transportation policy more generally?
b. What are the main issues that the Valley Metro pilot raises for you?

AVs in public transit

a. How do you envision AVs interacting with transit in the future?
b. What other types of pilot projects would you like to see in the Phoenix region?

AVs in Phoenix area jurisdictions

a. How is your jurisdiction thinking about AVs?
b. How does this align with potential regional opportunities and challenges?
c. What types of transportation issues would you like to see AVs address?

Closing Comments questions, Part IV:

a. What are some next steps that Valley Metro and/or the region can take?
b. What types of information would be useful to have moving forward that would help with decision making?

APPENDIX J

ROBORIDE FULL SURVEY

Source: Stopher et al., 2023

Section A: Your Travel Choices

This section asks questions about your recent travel choices. Please think about rides that you have taken within Peoria and surrounding areas when answering questions in this section.

1a. About how many **RoboRide rides** have you taken in total since the beginning of January 2022? *Note: Travel one-way is counted as **one** ride. So, if you have taken a ride to a place and then back home again, that is **two** rides.*

____________ rides

1b. Please rate your level of agreement with each of the following statements about how you feel riding in a **RoboRide vehicle**.

Display if Q1>0

	Strongly agree	*Somewhat agree*	*Neutral*	*Somewhat disagree*	*Strongly disagree*	*Don't Know/No Opinion*
The RoboRide shuttle serves all of the medical facilities that I need to visit.	○	○	○	○	○	○
I find it hard to get into and out of the RoboRide vehicle.	○	○	○	○	○	○
The ride in the RoboRide vehicle is comfortable and pleasant.	○	○	○	○	○	○

1c. Please rate your level of agreement with each of the following statements about RoboRide service.

Display if Q1>0

	Strongly agree	*Somewhat agree*	*Neutral*	*Somewhat disagree*	*Strongly disagree*	*Don't Know/No Opinion*
I feel safe when riding in the RoboRide vehicle.	○	○	○	○	○	○
I feel that there is no need for an attendant or operator on board the RoboRide vehicle.	○	○	○	○	○	○
I am concerned that RoboRide may have technical or mechanical problems.	○	○	○	○	○	○

1d. Please rate your level of agreement with each of the following statements about RoboRide service.

Display if Q1>0

	Strongly agree	*Somewhat agree*	*Neutral*	*Somewhat disagree*	*Strongly disagree*	*Don't Know/No Opinion*
I find it exciting to ride in a RoboRide vehicle.	○	○	○	○	○	○

I am traveling more than I did before the introduction of the RoboRide service.	○	○	○	○	○	○
I find it difficult to use the RoboRide app on my smartphone.	○	○	○	○	○	○
I prefer the RoboRide shuttle over traditional human-driven vehicles (e.g., taxi, Uber/Lyft).	○	○	○	○	○	○

1b. Why have you not taken any rides on RoboRide so far? Please check up to FOUR reasons.
Display if Q1=0

☐ I haven't had the opportunity or need to ride RoboRide yet
☐ RoboRide doesn't go to places I need to go
☐ I don't know the RoboRide service schedule
☐ The RoboRide stop location is too far or not conveniently located
☐ The wait time for the shuttle is too long
☐ The RoboRide shuttle is too slow
☐ I am concerned about safety of the RoboRide
☐ I am concerned the RoboRide will experience a breakdown
☐ I am not comfortable riding with strangers
☐ The other means of travel that I use are more convenient
☐ I need assistance when I go places
☐ Other (please, specify): ___________

1c. Do you plan to ride RoboRide at least once before the trial period is over in June 2022?
Display if Q1=0

○ Yes
○ No

2a. In the past 30 days, what means of travel have you used to get around? Select ***up to four*** *options*.
Display if Q1=0

❑ Drive alone
❑ Drive with other passengers in the vehicle
❑ Ride as passenger with friend or family
❑ Volunteer driver program
❑ Bus
❑ Light Rail
❑ ADA Paratransit service
❑ Group/Community shuttle service
❑ Traditional taxi
❑ Uber/Lyft
❑ Bike or scooter (including shared services)
❑ Walk
❑ Other (please, specify): _______________

2a. In the past 30 days, what other means of travel have you used to get around? Select ***up to four*** *options*.
Display if Q1>0

❑ Drive alone
❑ Drive with other passengers in the vehicle
❑ Ride as passenger with friend or family
❑ Volunteer driver program
❑ Bus
❑ Light Rail
❑ ADA Paratransit service
❑ Group/Community shuttle service
❑ Traditional taxi
❑ Uber/Lyft
❑ Bike or scooter (including shared services)
❑ Walk
❑ Other (please, specify): _______________

2b. Drag and rank your selected choices, with the travel means used most often ranked number 1 (at the top).

Display if Q1=0 AND if the selected choices in 2a>1

The (up to) four options selected in question 2a are the option choices that will appear in question 2b. If only one option was selected in 2b, then the respondent will skip to question 2c.

Selection 1 $\boxed{1}$
Selection 2 $\boxed{2}$
Selection 3 $\boxed{3}$
Selection 4 $\boxed{4}$

2b. Drag and rank your selected choices, with the travel means used most often ranked number 1 (at the top).

Display if Q1>0 AND if the selected choices in 2a>1

The (up to) four options selected in question 2a are the option choices that will appear in question 2b. If only one option was selected in 2b, then the respondent will skip to question 2c.

Selection 1 $\boxed{1}$
Selection 2 $\boxed{2}$
Selection 3 $\boxed{3}$
Selection 4 $\boxed{4}$

2c. How would you get around if none of the travel means you identified in the previous question was available? *Choose the most likely alternative.* Display logic applied to each option, so options were only displayed if it was NOT	○ I don't know how I would get around ○ **Drive** a personal vehicle, alone ○ **Drive** a personal vehicle, with passengers ○ **Ride** in a vehicle, with others ○ Ride the bus ○ Ride the light rail ○ Use taxi ○ Use an Uber/Lyft ○ Use group shuttle service (*e.g.*, senior center group ride to grocery store) ○ Use a volunteer driver program ○ Use a bikesharing or e-scooter sharing service ○ Walk

selected as a most used travel means in question 2a.	◯ Ride a bicycle or scooter ◯ Other (please, specify): ____________________________

3. For **your most frequently-used travel means**, please rate how satisfied you are with the following aspects.

	Very Satisfied	*Somewhat Satisfied*	*Neutral*	*Somewhat Dissatisfied*	*Very Dissatisfied*	*Don't Know/No Opinion*
Wait time	◯	◯	◯	◯	◯	◯
Travel time	◯	◯	◯	◯	◯	◯
Cost	◯	◯	◯	◯	◯	◯
Comfort	◯	◯	◯	◯	◯	◯

4a. How do you typically **spend your time** when traveling by your most frequently-used means of travel? *Select **up to four** activities.*

☐ Work or study
☐ Talk on the phone/send or read text messages/teleconference
☐ Read for pleasure
☐ Sleep
☐ Entertainment (*e.g.*, watch movies; play games; listen to podcasts)
☐ Eat and drink
☐ Interact with the driver
☐ Interact with other passengers
☐ Enjoy the scenery
☐ Watch the road
☐ Other (please, specify): ___________

Section B: Your Thoughts About Autonomous Vehicles

This section asks questions about your thoughts and hopes for new mobility services and technologies. Please think about your travel needs and experiences in general, and not just about traditional or RoboRide vehicles.

***Autonomous vehicles** are those vehicles that do not require a driver or operator and are capable of driving themselves.*

5. Which of the following statements best describes your **current familiarity with autonomous vehicles**?

◯ I have never heard of autonomous vehicles before taking this survey.
◯ I have heard of autonomous vehicles, but don't know much about them.
◯ I am somewhat familiar with autonomous vehicles.
◯ I am very familiar with autonomous vehicles.
◯ I have taken a ride in an autonomous vehicle (other than RoboRide) before this study.

6. Please rate your level of agreement with each of the following statements about riding in an **autonomous vehicle with no operator or attendant onboard**.

	Strongly agree	*Somewhat agree*	*Neutral*	*Somewhat disagree*	*Strongly disagree*	*Don't Know/No Opinion*
I would ride in an autonomous vehicle alone.	○	○	○	○	○	○
I would ride in an autonomous vehicle with someone I know (*e.g.*, family, friends).	○	○	○	○	○	○
I would ride in an autonomous vehicle with passengers who are unknown to me.	○	○	○	○	○	○

7. How much do you agree or disagree with each of the following statements about autonomous vehicles?

	Strongly agree	*Somewhat agree*	*Neutral*	*Somewhat disagree*	*Strongly disagree*	*Don't Know/No Opinion*
I believe that autonomous vehicles are safer than human-driven vehicles and will reduce accidents and fatalities.	○	○	○	○	○	○
I believe that pedestrians, cyclists, and other road users would be safer in a future when most vehicles are autonomous.	○	○	○	○	○	○

8a. How much do you agree or disagree with each of the following statements about your potential use of an on-demand, autonomous vehicle service?

	Strongly agree	*Somewhat agree*	*Neutral*	*Somewhat disagree*	*Strongly disagree*	*Don't Know/No Opinion*
I would prefer to use a traditional human-driven vehicle service for my travel rather than an autonomous vehicle service.	○	○	○	○	○	○
I would like to be one of the first users of an autonomous vehicle service for my travel, once such a service is available on a permanent basis.	○	○	○	○	○	○

8b. How much do you agree or disagree with each of the following statements about the potential effects of an on-demand, autonomous vehicle service?

	Strongly agree	*Somewhat agree*	*Neutral*	*Somewhat disagree*	*Strongly disagree*	*Don't Know/No Opinion*
I believe that an autonomous vehicle service would make it easier for me to get to and use bus and rail services.	○	○	○	○	○	○
I believe that an autonomous vehicle service would make traveling in the region easier and more convenient.	○	○	○	○	○	○
I believe an autonomous vehicle service would allow me to keep my independence if I were to lose my driver's license due to age or disability.	○	○	○	○	○	○

9. To what extent will you switch to using an autonomous vehicle service for your travel if the service is available on a permanent basis across the entire City of Peoria?

○ I would use autonomous vehicles for **all** my travel in Peoria
○ I would use autonomous vehicles for **most** of my travel in Peoria
○ I would use autonomous vehicles for **about half** of my travel in Peoria
○ I would use autonomous vehicles for **some (less than half)** of my travel in Peoria
○ I would **not** use autonomous vehicles for any of my travel in Peoria

10a. Which of the following services have you used in the past 12 months? (Check all that apply)

○ Dial a Ride
○ Uber/Lyft

10b. Please rate each of the following services on a scale of 1 to 5 for the aspects listed in the first column. You may provide a rating even if you have not used a particular travel means. **The scale is as follows: 1=poor; 2=fair; 3=good; 4=very good; 5=excellent.** *If you have no opinion on a characteristic, select a ZERO.* ***Do not leave any blanks.***

Characteristic	***Dial a Ride***	***Uber/Lyft***	***RoboRide***
Waiting time			
Ride comfort			
Travel time			

10c. Please rate each of the following services on a scale of 1 to 5 for the aspects listed in the first column. You may provide a rating even if you have not used a particular travel means. **The scale is as follows:**

1=poor; 2=fair; 3=good; 4=very good; 5=excellent. *If you have no opinion on a characteristic, select a ZERO.* ***Do not leave any blanks.***

Characteristic	***Dial a Ride***	***Uber/Lyft***	***RoboRide***
Drop-off and pick-up locations			
Cleanliness of vehicle			
Ease of getting into and out of vehicle			
Ease of using the service			

11a. How has your use of the following travel means changed since the RoboRide service started? *If you have never used a travel means (in the past or present), please choose "Stayed the Same".*

	Decreased	*Increased*	*Stayed the Same*
Drive a personal vehicle, alone	○	○	○
Drive a personal vehicle, with passengers	○	○	○
Ride in a vehicle, with others	○	○	○

11b. How has your use of the following travel means changed since the RoboRide service started? *If you have never used a travel means (in the past or present), please choose "Stayed the Same".*

	Decreased	*Increased*	*Stayed the Same*
Bus	○	○	○
Group shuttle service (*e.g.*, senior center group ride)	○	○	○
Traditional taxi	○	○	○
Uber/Lyft	○	○	○

11c. How has your use of the following travel means changed since the RoboRide service started? *If you have never used a travel means (in the past or present), please choose "Stayed the Same".*

	Decreased	*Increased*	*Stayed the Same*
Bikesharing or e-scooter sharing service	○	○	○
Walk	○	○	○
Ride a bicycle or scooter	○	○	○

Section C: Background Information

To help us better understand the travel needs of the community, we would like to ask you a few background questions. Your privacy is guaranteed.

12. In what year were you born? ____________

13. What is your gender?

○ Male
○ Female
○ Other
○ Prefer not to answer

14. At this time, you are:

○ Employed full-time
○ Employed part-time
○ Self-employed
○ Retired
○ Homemaker
○ Unable to work
○ Not employed and currently looking for work
○ Not employed and **not** currently looking for work
○ Other (please, specify): ________________________

15. At this time, you are:

○ A full-time student
○ A part-time student
○ Not a student

16a. What is your occupation?
Display if Q14=Employed full-time, Employed part-time, or Self-employed

○ Sales or service
○ Clerical or administrative support
○ Manufacturing, construction, maintenance, or farming
○ Professional, managerial, or technical
○ Education, training, and library occupations
○ Arts, design, entertainment, sports, and media occupations
○ Military specific occupations
○ Other (please, specify): _______________

16b. Knowing more about your **work** location will help us understand the travel options available to you. Please give the address or, if you prefer, major cross streets closest to your main workplace location. *If you travel to more than one workplace on a regular basis, enter the workplace to which you traveled most often last week.* ***If you work primarily at home, please enter information about your home location.***
Display if Q14=Employed full-time, Employed part-time, or Self-employed

____

City: ___________________________________ State: ______ Zip code: _______

16c. Knowing more about your **school** location will help us understand the travel options available to you. Please give the address or, if you prefer, major cross streets closest to your main school location. *If you travel to more than one school location on a regular basis, enter the school location to which you travel* *most often*. ***If you attend classes primarily from home (e.g., taking online classes), please enter information about your home location.***

Display if Q15=A full-time Student or a part-time student

____

City: ______________________________ State: ______ Zip code: _______

17. **Including yourself**, how many people live in your household? *By "household" we mean "people who live together and share at least some financial resources." Unrelated housemates/roommates are usually* ***not*** *considered members of the same household even if they live in the same housing unit.*

- ○ 1
- ○ 2
- ○ 3
- ○ 4
- ○ 5
- ○ 6
- ○ 7
- ○ 8
- ○ 9
- ○ 10 or more

18. What is your educational background? *Check the highest level of education you have reached.*

- ○ Some grade/high school
- ○ Completed high school or GED
- ○ Some college or technical school
- ○ Bachelor's degree(s) or some graduate school
- ○ Completed graduate degree(s)

19. Do you have any disabilities or health-related conditions that prevent or limit you from any of the following? *Please feel free to provide details in the last column.*

	No	*To some extent*	*Yes*	*Please explain (optional)*
Driving a personal vehicle	○	○	○	
Using public transit (bus or light rail)	○	○	○	
Riding a bike	○	○	○	
Walking up to three city blocks	○	○	○	

20. Do you use any of the following wayfinding, mobility assistance systems, or tools? Please check all that apply.

- ○ None (exclusive choice, no other options can also be selected)
- ○ Screen reader / text to speech
- ○ Magnification / zoom / large font
- ○ Keyboard only
- ○ Color modifications
- ○ Closed captions
- ○ Voice control
- ○ Switch device

○ Other (please, specify): ___________________________

21. What best describes the home you **currently** live in?

○ Stand-alone home
○ Mobile home
○ Attached home/townhome
○ Assisted/senior/group living
○ Condo/apartment
○ Other (please, specify): ________________

22. How many personal vehicles (cars and/or motorcycles) does your household own, lease, or have available for personal use at any time?

○ 1
○ 2
○ 3
○ 4
○ 5
○ 6 or more

23. Do you have a ridehailing service app (*e.g.*, Uber, Lyft) on your phone?

○ Yes
○ No
○ Not Sure

24. About how frequently do you take a ride through a ridehailing service (*e.g.*, Uber, Lyft)? Include rides ordered by somebody else (where you ride along).
Display if Uber/Lyft was selected in Q10a

○ Never
○ Rarely (less than once a month)
○ At least once a month, but less than weekly
○ At least once a week, but less than daily
○ About every day
○ Not sure

25. Please check the appropriate category for your annual *household* income (including retirement income) before taxes.

○ Less than $25,000
○ $25,000 to $49,999
○ $50,000 to $74,999
○ $75,000 to $99,000
○ $100,000 to $149,999
○ $150,000 to $249,999
○ $250,000 or more

26. We will be sending you a $5 gift card through email as a token of appreciation for your response to this survey. Please provide a valid email address where we can send the electronic gift card. If you do not wish to receive the gift card, please feel free to skip this question.

Email Address: ___________________________________

27. If you have any additional comments about your current travel, and new travel options such as autonomous vehicles, you are welcome to share them in the space below.

We thank you for your response, which has been recorded successfully. If you provided a valid email address, we will send a $10 gift card through email as a token of appreciation. Please allow us a few weeks to process the surveys and send out the electronic gift cards. Thank you for your time and help.