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Consumer Preferences and Determinants of Transportation Mode Choice Behaviors in the Era of Autonomous Vehicles

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ABSTRACT: The supply-side advancement in the transportation modes may bring a new mobility paradigm in the proximate future because consumers in the era of autonomous vehicles (AVs) would be able to choose from a variety of modes of transportation that would be likely to co-exist, including private AVs, conventional automobiles, and shared mobility services. Accordingly, research on the demand response is needed since it can provide insights on who would use and how the market would react to these emerging modes, which helps develop a more solid long-term transportation planning. Thus, this study conducted nationwide stated choice experiments in the U.S. and employed the Mixed Logit (MXL) model. Combined with market share summary, parameter estimation, and marginal effect estimates, this study offered several notable findings and implications. For instance, descriptive statistics underscored a significant propensity for private and shared AVs, with approximately 24% of respondents indicating their intention to use these modes, while shared mobility services garnered less than 10% of the market share. However, conventional personal cars retained their dominance, with around 50% of respondents favoring this mode in the AV era. Moreover, parameter estimation of the MXL model indicates that trip purposes, alternative-specific characteristics, individual features, transportation-related factors, and attitudinal factors significantly and differently influence the outcome probability of choosing a certain mode. Furthermore, marginal effects estimated from the model suggest that the potential users of AVs and SAVs seem to be more cost-conscious than drivers of a personal car, while SAV users are slightly less cost-sensitive than AV users. These findings underscore the need for adaptive policies that cater to the diverse preferences and behaviors of future mobility consumers, ensuring the development of sustainable and equitable transportation systems.

KEYWORDS: Consumer Preferences; Transportation Mode Choice; Autonomous Vehicles; Stated Choice Experiment; Discrete Choice Modeling

1. INTRODUCTION

In the dynamic landscape of transportation planning, the emergence of autonomous vehicles (AVs) and the proliferation of shared mobility services represent paradigm-shifting phenomena (Fagnant & Kockelman, 2015; Bennett, Vijaygopal, & Kottasz, 2020; Lee, 2022). This study delves into the intricate realm of consumer preferences and mode choice behaviors within this transformative milieu, a crucial endeavor for contemporary transportation planners. Since consumers could choose from various modes of transportation in the era of AVs for commute and non-commute trips, the advent of AVs and the burgeoning popularity of shared mobility services have introduced unprecedented complexity into the transportation decision-making process of the consumers. These disruptive innovations are poised to redefine travel behaviors, necessitating a thorough understanding of consumer reactions and mode selection dynamics. That is, the supply-side innovations are expected to disrupt and transform travel behavior, creating a new paradigm of transportation mode choice behaviors that have not been observed before. Consequently, it is vital to explore and understand the reactions of customers to the choice patterns when all potential emerging transportation modes would be available. However, understanding customer reactions has remained relatively limited; for instance, none of the studies has put AVs, shared mobility services, and currently available modes side-by-side in an experiment, even if they would likely co-exist.

Therefore, this study investigated the choice patterns of emerging modes in addition to existing ones for commute and non-commute trips using a mixed (random parameter) logit model with the U.S. nationwide stated choice experiments. By elucidating the intricate nuances of mode choice behaviors in the era of AVs and shared mobility, this research provides invaluable insights for transportation planners grappling with the complexities of future mobility systems. Armed with this knowledge, policymakers can formulate more nuanced and adaptive strategies to steer transportation infrastructure towards a sustainable and equitable future.

This paper is organized as follows. Section 2 reviews and synthesizes previous literature and finds research gaps. Section 3 and 4 describe the stated choice experiment survey data and methodological approaches. Section 5 presents and interprets the results of this study. Finally, sections 6 and 7 discuss notable findings and conclude this paper.

2. LITERATURE REVIEW

This section provides a comprehensive review of existing literature, focusing particularly on studies employing the stated choice experiment design utilized in this research. The literature review is structured into three subsections, preceded by a theoretical background, (1) the market share forecast, (2) factors influencing transportation mode choices, and (3) marginal effects.

2.1 Theoretical Background

Theoretical frameworks such as the technology acceptance model (Davis et al., 1989) have been instrumental in elucidating the motivating factors driving user intentions and behaviors, operating within an expectancy-value framework (Madden, Ellen, & Ajzen, 1992; Hankins, French, & Horne, 2000). These theories offer valuable insights into the broader concepts surrounding the adoption of AVs. Specifically, behavioral theories underscore the imperative of delving into demand-side discussions to comprehensively grasp travel behavior in the era of AVs (J. P. Zmud & Sener, 2017). This necessity arises from both the endeavors of automobile manufacturers and transportation planners to stimulate modal shifts and, more significantly, from the perspectives and choices of potential users. Secondly, the transition to AVs is not dictated by a single factor but rather influenced by a confluence of factors such as consumer characteristics, spatial arrangements, and cultural significance. Consequently, this research highlights the relevance of demand-side discourse, a perspective bolstered by behavioral theories. Moreover, this study adopts conceptual frameworks for understanding transportation mode choice behaviors, elucidating how diverse contextual factors shape such behaviors (Bamberg, Ajzen, & Schmidt, 2003; Haustein & Hunecke, 2007). By integrating these theoretical underpinnings, this research aims to provide a comprehensive understanding of the complex dynamics driving transportation mode choices in the context of AV adoption.

2.2 Market Share Forecast

Given that full automation will be available by 2050 or sooner (Singleton, 2019), previous literature has forecasted the market share of AVs, and generally expected that AVs would account for half of the trips (J. Zmud, Sener, & Wagner, 2016; Litman, 2021). For instance, J'son & Partners Management Consulting (2017) forecasted that by 2030, the market share of AVs would be around 21 percent and 50 percent by 2035, respectively. Also, Liu et al. (2017) forecasted that total trips using shared AVs (SAVs) would be 16.7 percent.

2.3 Factors Associated with Transportation Mode Choice

Previous research has emphasized factors influencing the adoption of PAVs and SAVs. A literature review by Becker and Axhausen (2017) categorized the factors into primarily four groups: (1) alternative-specific features (e.g., travel time), (2) socio-demographic characteristics (e.g., gender), (3) attitudinal factors (e.g., technology awareness), and (4) transportation-related features (e.g., driver's license).

First, previous studies have explored alternative-specific features, such as travel time, and found that these are significant factors influencing the adoption of PAVs and SAVs (Webb, Wilson, & Kularatne, 2019; Lavieri & Bhat, 2019; Clayton, et al., 2020). For instance, Stoiber et al. (2019) found that travel cost, time, and waiting time substantially affected the new mode of transportation chosen. Likewise, Krueger et al. (2016) revealed that travel time, waiting time, and fares were important predictors of whether or not people would use SAVs. Furthermore, according to Philipsen et al. (2019), the exact pickup and arrival times were critical for SAV acceptance.

Second, a body of previous literature has examined the association between socio-demographic variables and the adoption of PAVs and SAVs and concluded that the choice patterns would most likely differ across different population sub-groups (Krueger et al., 2016; Zmud et al., 2016; Hulse, Xie, & Galea, 2018; Guo et al., 2021; Rahimi, Azimi, & Jin, 2020). For instance, Tan et al. (2020) found that young people, students, and employees of businesses and organizations were among those who were more likely to use AVs than others. Similarly, Webb et al. (2019) suggested that personal attributes such as income, age, employment status, marital status, and the number of children impacted whether or not respondents would use SAVs.

Third, another body of literature has examined attitudinal factors (Haboucha, Ishaq, & Shiftan, 2017; Shabanpour et al., 2017; Asgari & Jin, 2019; Lavieri & Bhat, 2019; Guo et al., 2021; Wang et al. 2020) , in the context of technology acceptance theory (Davis, Bagozzi, & Warshaw, 1989). For instance, Acheampong and Cugurullo (2019) found that personal attitudes, such as public worries and anxieties, perceived AV usefulness, and attitude toward the environment were associated with adopting PAVs and SAVs. In addition, a qualitative analysis of Zmud et al. (2016) suggested that persons who expressed a greater degree of intention to adopt AVs were those who (1) had a favorable opinion of them, (2) were less concerned about data privacy, and (3) had trustworthy people who valued utilizing AVs.

Fourth, regarding transportation-related features, Webb et al. (2019) discovered that car ownership had a significant and negative impact on whether or not SAVs were accepted. Some other research highlighted the importance of individual modality styles: for example, Krueger et al. (2016) discovered that respondents with multimodal patterns had a higher probability of using SAVs than those with monomodal patterns. Also, Zmud et al. (2016) also discovered that people who had any physical impediments to driving had a higher intention to use AVs. Interestingly, Hossain and Fatmi (2022) found that the experiences with advanced vehicle technologies, such as parking assist and lane control, were significant factors to impact AV adoption.

2.4 Marginal Effect

A few studies have estimated marginal effects or elasticities to assess the influence of policy scenarios, particularly on the adoption of PAVs and SAVs. For example, Webb et al. (2019) conducted a sensitivity analysis on pricing and discovered that as the cost of travel per kilometer quadrupled, the likelihood of using SAVs increased by 3 percent, and the likelihood of choosing a conventional car decreased by 6 percent. Haboucha et al. (2017) recommended policies to encourage SAVs, including increased parking prices, reduced SAV costs, increased cost of a conventional car, and education programs. Moreover, Shabanpour et al. (2018) found the favorable influence of (1) raising driver culpability for AV accidents, (2) establishing special lanes for AVs, and (3) granting subsidies to cut the purchase price.

2.5 Research Gaps and Contribution of this Study

The literature review has identified several critical research gaps that this study seeks to address. First, existing research has failed to comprehensively explore the diverse array of transportation modes available in the era of autonomous vehicles (AVs), despite the anticipated coexistence and competition among these modes. Previous studies typically examined only a limited selection of transportation modes, ranging from two to four, thus deviating from the principle of mutually exclusive and collectively exhaustive mode choice modeling as proposed by Ben-Akiva and Lerman (1985). Second, there is a dearth of studies that have obtained representative samples across the United States, with only a few attempts made to collect nationwide data. This gap undermines the generalizability and applicability of findings to the broader population. Third, while much of the existing literature has focused on statistical inference regarding coefficients of interest, studies simulating the effects of policy scenarios using marginal effect or elasticity estimation have been notably limited. Fourth, the previous studies have had a relatively small sample size of stated choice experiments (approximately 400 to 1,200). Fifth, a few studies have explored both commute and detailed non-commute trips in the era of AVs. Therefore, this paper examined the data that (1) provides a comprehensive set of potentially available transportation modes to respondents in the stated choice experiment, (2) gathers geographical representative and relatively large samples across the U.S., (3) collects detailed information on respondents and trip attributes, and (4) includes both commute and detailed non-commute trips.

3. STATED CHOICE EXPERIMENT DESIGN

3.1 Structure

This study used stated choice (SC) experiment survey data collected in a project by L. Wang, Broach, & Yang, (2018) funded by the National Institute for Transportation and Communities at Portland State University. This study employed the data set since the SC research is appropriate for this research that investigates hypothetical circumstances (Rose & Bliemer, 2009; Gkartzonikas & Gkritza, 2019). However, the experiments can suffer from hypothetical bias in this study since respondents may have difficulties envisioning fully automated vehicles (Fifer, Rose, & Greaves, 2014). Nonetheless, the SC experiment is an appropriate research approach since it has the potential to explore transportation mode choice patterns when this technology is still in its infancy (Milakis, Arem, & Wee, 2017).

3.2 Sampling Process

The sampling process for the stated choice (SC) experiment involved defining the sampling frame as individuals with internet access residing in the 50 most urbanized areas across the United States, including metropolitan regions such as San Francisco-Oakland, California, determined by population size. To recruit participants, incentives were offered through platforms such as Amazon Mechanical Turk and the InfoUSA email distribution lists.

3.3 Multiple Choice

Each respondent is tasked with completing ten choice experiments, as depicted in Figure 1. Specifically, participants engage in five experiments for both commute and non-commute trips. This approach aligns with the findings of Caussade et al. (2005), who determined that ten choice situations yielded the least negative impact on experiment validity. Thus, the allocation of ten experiments per respondent is deemed appropriate and conducive to reliable data collection.

3.4 Alternatives: Transportation Modes

SC experiment in this study adopted a single-alternative selection approach, where each respondent was tasked with selecting the most preferred alternative from a choice set. For each experiment, participants were presented with three different transportation modes, as illustrated in Figure 1. This decision was informed by research suggesting that providing three alternatives per choice set is optimal for minimizing error variance in SC experiments, as outlined by Caussade et al. (2005).

Furthermore, the selection of alternatives was tailored to specific participant criteria. For instance, car-sharing options were exclusively presented to licensed drivers, while bike-sharing alternatives were offered solely to individuals physically capable of cycling. Additionally, the experiment operated under the assumption of AVs with a level of automation rated at 5.

3.5 Attributes of Alternatives

Each experiment presents alternative-specific attributes corresponding to the assigned transportation mode, as detailed in Figure 1. These attributes encompass various factors such as in-vehicle time, out-of-pocket cost, wait time, and walk time. Rather than arbitrarily setting attribute levels, the experiment employed a data-driven approach. It leveraged a combination of revealed trip characteristics and estimated attribute levels derived from prior studies or publicly available data sources, such as the National Household Travel Survey (NHTS), to establish a realistic range of attribute values. This methodology ensured that the attributes presented in the experiments were grounded in empirical evidence and reflective of actual travel scenarios.

3.6 Additional Data Collection

The survey collected a comprehensive array of information pertaining to the respondents' profiles. This included sociodemographic attributes such as age, household income, gender, race/ethnicity, and employment status. Additionally, respondents were queried about their attitudes towards technology, AVs, and alternative transportation modes. In terms of transportation-related characteristics, participants provided details on factors such as driver's license possession, car and bike ownership, as well as any barriers encountered in utilizing current transportation modes.

Table 1 displays key characteristics of the respondents. Overall, the survey data exhibited a high level of representativeness across gender, household income, educational attainment, student and job statuses, and race/ethnicity. However, there were marginal variations observed in age distribution among respondents.

4. DISCRETE CHOICE MODELING DESIGN

4.1 Mixed (Random Parameter) Logit Model

Discrete choice modeling (DCM) with stated choice experiments has mainly been used to understand public's acceptance of autonomous vehicles in a hypothetical setting. For instance, a body of literature with DCM has engaged by using the multinomial logit model (Shabanpour et al., 2018; Webb et al., 2019; Tan et al., 2020; S. Wang et al., 2020), mixed logit model (Krueger et al., 2016; Shabanpour et al., 2017), and other DCM models (Maeng & Cho, 2022).

This study employed the Mixed Logit (MXL) Model (also called Random Parameters Logit Model) with Halton of 500 draws using NLOGIT software for the following reasons. First, the discrete choice model based on the random utility maximization framework (McFadden, 1974) is appropriate to analyze the choice behaviors of respondents in the SC ex-

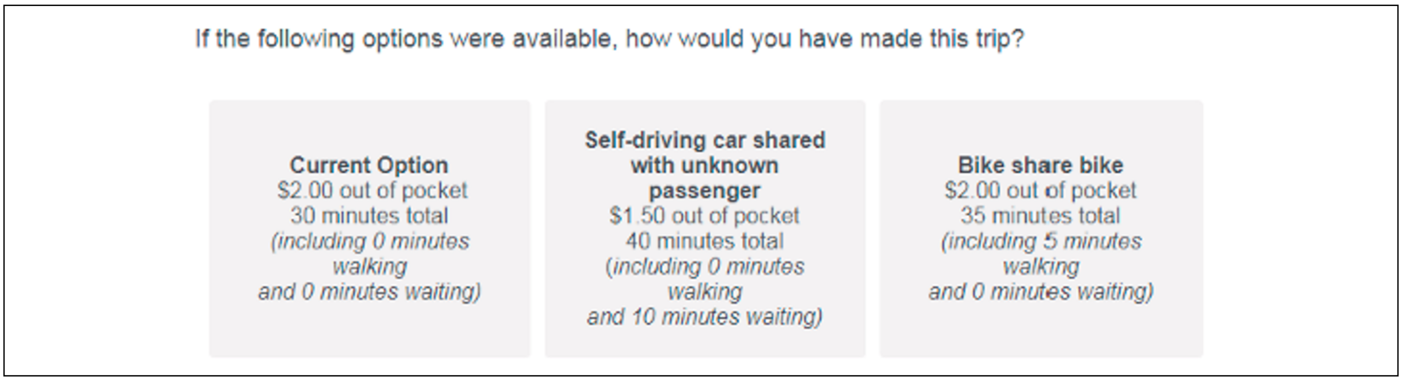

Figure 1. An example of a stated choice experiment (Source: Wang et al., 2018, p.26)

Categories		Data	ACS	
		Study area	Study area	The U.S.
Gender	Female	43.0%	49.0%	50.8%
	Male	57.0%	51.0%	49.2%
Age	15-24	12.3%	13.8%	13.5%
	25-34	52.3%	15.4%	13.8%
	35-44	19.6%	13.1%	12.6%
	45-54	9.5%	13.0%	13.2%
	55-64	4.2%	12.0%	12.8%
	Over 64	2.1%	14.0%	15.3%
Household Income	Less than 44,999	36.4%	30.3%	33.1%
	$45,000 - $99,999	46.0%	40.5%	39.2%
	More than $100,000	17.6%	29.2%	27.7%
Education Attainment	Less than College	7.8%	36.4%	39.6%
	Some College, no or associate degree	28.6%	28.3%	28.9%
	Bachelor's degree	46.4%	21.8%	19.4%
	Graduate or professional degree	17.1%	13.6%	12.0%
Student Status	Student	35.2%	26.9%	26.1%
	Non-student	64.8%	73.1%	73.9%
Employment Status	Employed	73.6%	65.3%	63.1%
	Unemployed	6.7%	3.8%	3.7%
Race/Ethnicity	Non-Hispanic White	64.4%	68.4%	72.7%
	Non-Hispanic Black	13.3%	14.1%	12.7%
	Asian	9.7%	7.3%	5.4%
	Others	12.6%	10.2%	9.3%

Note: ACS data means American Community Survey 2014-2018 (5-year estimates) at the Zip code level. The study area of ACS examined 1,871 Zip codes from the 50 U.S. urbanized areas. The U.S. of ACS examined 33,122 Zip codes across the U.S.

Table 1. Selected descriptive statistics on the respondents

periments and their association with variables. Second, since each respondent in our survey completed multiple-choice experiments, theoretically, the experiments completed by the same respondent are likely to share some characteristics that may be unobserved by the researcher. Thus, it suggests the need to account for unobserved heterogeneity (also called random heterogeneity) in the population of respondents (McFadden & Train, 2000). MXL was suitable because it overcomes limitations of the closed-form Multinomial Logit Model and assumes that the random parameters follow a distribution whose parameters are to be estimated (Revelt & Train, 1998; Hensher & Greene, 2003). Lastly, since the maximum likelihood estimation of MXL is computationally expansive (Bhat, 2003; Milton, Shankar, & Mannering, 2008; Train, 2000), the final model used Halton of 500 draws typically employed in previous literature. Additionally, this study searched for the best MXL specification with a forward stepwise approach adopted from the previous literature (Murray-Tuite et al., 2021). The final model kept only significant covariates in the utility functions in the Multinomial Logit Model and used the same covariates in the final MXL.

The structure of estimating probability in MXL model is shown below (Koppelman & Bhat, 2006; Train, 2009):

$$P_{ni} = \int \left(\frac{\exp\left(\beta_i X_i + \varepsilon_i\right)}{\sum_{i=1}^{t} \exp\left(\beta_{ni} X_{ni} + \varepsilon_{ni}\right)} \right) f(\beta) d(\beta)$$

where P_{ni} is the probability that individual n chooses alternative i, X_{ik} denotes a vector of observed variables to individual n chooses alternative i, β_{ni} represents parameter estimation (coefficient) in the utility functions. $f(\beta)$ indicates a density function of a normal distribution, which is the most common assumption for a random coefficient structure. Due to the density function, the parameter estimation with the random coefficient has a normal distribution with the mean and standard deviation.

4.2 Dependent Variables: Transportation Modes

This study had nine alternatives, such as private autonomous vehicles (PAVs) and shared autonomous vehicles (SAVs) (see Table 2). In detail, the SC experiment considered PAV and SAV distinctly, which was stated in the experiment and assigned to the respondents. HERE Technologies (2017) categorizes AVs into two types of transportation modes: (1) autonomous Car-as-a-Product (PAV) and (2) autonomous Car-as-a-Service (SAV). PAV means that each traveler uses the mode independently, as to how the conventional personal car operates. Similarly, but differently, SAV allows more than one rider to share a ride (Stoiber et al., 2019; Turoń & Kubik, 2020). SAVs have two types: (1) shared ownership and (2) shared use by combining not only ride-sharing services, carpools, or taxis but also car-sharing services with AVs (Krueger et al., 2016; Metz, 2018; Hyland & Mahmassani, 2020).

4.3 Independent Variables

Table 3 presents the final set of variables utilized in this study, comprising five distinct categories: (1) alternative-specific attributes, (2) trip purposes, (3) socio-demographic characteristics, (4) attitudinal factors, and (5) transportation-related features.

For the attitudinal factors, an explanatory factor analysis was conducted on twelve attitudinal questions to streamline dimensionality and enhance interpretability, as outlined in Table 4. Both parallel analysis and the scree plot of eigenvalues suggested that the optimal number of components was four. The interpretation of factor loadings furt her supported this, indicating that four factors more accurately captured the underlying latent constructs. Consequently, this study delineated and defined the four latent factors as depicted in Table 4.

Final choices	Acronym	Description
Private autonomous vehicle	PAV	PAV means that each traveler uses AVs independently, as to how the conventional personal car operates
Shared autonomous vehicle	SAV	SAV allows more than one rider to share a ride (Stoiber et al., 2019; Turoń & Kubik, 2020), which means that SAVs can provide mobility-on-demand services by combining car-sharing services or taxis with AVs (Krueger et al., 2016).
Ride-hailing service	RH	RH (e.g., Uber and Lyft), which refers to an app-based on-demand ride-sharing service, allows a passenger to hire a personal driver or ride it with another passenger(s).
Car-sharing service	CS	CS (e.g., Zipcar and Car2Go) allows their members to reserve, use a car from a smartphone app and return it at a designated or a regular on-street parking space nearby destination.
Bike-sharing service	BS	BS (e.g., Biketown) allows members to check out a bike, ride it to their destination, and return it at the end of the trip.
Personal car	CAR	Drive a personal car
Carpool	CP	Carpool and vanpool, Get a ride from other people
Public transportation	PT	Transit, bus, and taxi
Active transportation	AT	Walking and biking

Table 2. The final set of alternatives in the best fit Mixed Logit Model

Variable Name	Description	N	Mean	Std. Dev
Alternative-specific attributes				
IV	In-vehicle time in minutes	11,118	15.90	15.51
Wait	Wait time in minutes	11,080	8.92	10.04
Walk	Walk time in minutes	11,220	4.17	9.97
Cost	Out of pocket cost in dollars	10,996	11.70	39.15
Trip purposes				
Commute	1 if the trip purpose is commute-trip, 0 otherwise	11,239	0.41	0.49
Shopping	1 if the trip purpose is for shopping or errands, 0 otherwise	11,239	0.37	0.48
Recreation	1 if the trip purpose is recreational or social, 0 otherwise	11,239	0.19	0.39
Meal-out	1 if the trip purpose is for eating a meal out, 0 otherwise	11,239	0.15	0.36
Medical	1 if the trip purpose is for medical or dental, 0 otherwise	11,239	0.10	0.30
Personal	1 if the trip purpose is for family and personal business or obligations, 0 otherwise	11,239	0.08	0.27
School	1 if the trip purpose is for going to school or daycare, 0 otherwise	11,239	0.03	0.18
Socio-demographic characteristics				
Female	1 if the respondent is female, 0 otherwise	11,192	0.43	0.49
Age	The age of the respondent in 2018	11,192	34.12	10.45
White	1 if the respondent is non-Hispanic White, 0 otherwise	11,132	0.64	0.48
Rent	1 if the respondent rents current residential place, 0 otherwise	11,102	0.45	0.50
Low income	1 if the household income of the respondent is below $44,999, 0 otherwise	11,162	0.36	0.48
High income	1 if the household income of the respondent is above $100,000, 0 otherwise	11,162	0.18	0.38
Graduate	1 if the respondent has graduate or professional degree, 0 otherwise	11,192	0.17	0.38
College	1 if the respondent attains less than high-school, high-school diploma, or GED, 0 otherwise	11,192	0.08	0.27
Adult	The number of adults in the household of the respondent	11,032	2.17	1.06
Children	The number of children in the household of the respondent	11,022	0.72	1.05
Attitudinal Factors				
Enjoy-Driving	Factor 1: Enjoy driving	8,751	-0.01	0.87
Pro-Tech	Factor 2: Pro- attitude toward technology	8,751	0.01	0.83
Pro-AVs	Factor 3: Pro- attitude toward autonomous vehicles	8,751	-0.01	0.99
Pro-Alt	Factor 4: Pro-attitude toward alternative transportation modes	8,751	-0.01	0.78
Transportation-related features				
License	1 if the respondent has a valid driver license, 0 otherwise	11,192	0.93	0.26
Car ownership	1 if the respondent owns a car, 0 otherwise	11,192	0.72	0.45
Bike ownership	1 if the respondent has a bike, 0 otherwise	11,192	0.40	0.49
Transit pass	1 if the respondent has a transit pass, 0 otherwise	11,192	0.31	0.46
Parking pass	1 if the respondent has a parking pass, 0 otherwise	11,192	0.22	0.41
Barriers	1 if the respondent faces barriers to driving a car, taking public transportation, or walking, 0 otherwise	11,126	0.21	0.41

Table 3. Descriptions and descriptive statistics on the variables used in the best fit Mixed Logit Model

Questions	Factor 1	Factor 2	Factor 3	Factor 4
Do you agree that technology will provide solutions to many of our problems?	0.05	0.73	0.11	-0.04
Do you agree that it is important to keep up with the latest trends in technology?	0.09	0.65	0.07	0.07
Do you agree that new technology makes life more complicated?	0.09	-0.30	0.00	0.28
Do you agree that I am dependent on my technology?	0.10	0.45	0.10	0.05
Do you agree that I like walking?	-0.01	0.07	-0.02	0.61
Do you agree that I like riding a bike?	0.11	0.02	0.05	0.57
Do you agree that I like taking public transportation?	-0.11	-0.03	0.10	0.51
Do you agree that being a driver is an important part of who I am?	0.80	0.00	0.03	0.07
Do you agree that I like driving?	0.68	0.06	0.00	0.10
Do you agree that I need a car to do many of the things I like to do?	0.52	0.14	-0.01	-0.14
Has what you have seen or heard about AVs been mostly positive?	0.05	0.05	0.99	0.13
Has what you have seen or heard about AVs been mostly negative?	0.01	-0.14	-0.36	-0.02

Note:
Factor 1: Enjoy driving
Factor 2: Pro attitude toward technology
Factor 3: Pro attitude toward autonomous vehicles (AVs)
Factor 4: Pro attitude toward alternative transportation modes (ALTs)

Table 4. Factor loadings for attitudinal variables

Transportation Modes	Commute Trips		Non-Commute Trips	
	Current	AV Era	Current	AV Era
Total sample	937 (100.00%)	4,633 (100.00%)	1,326 (100.00%)	6,606 (100.00%)
Autonomous Vehicles				
PAV	-	635 (13.70%)	-	439 (6.65%)
SAV	-	620 (13.40%)	-	725 (11.00%)
Shared Mobility Services				
RH	32 (3.42%)	325 (7.01%)	94 (7.09%)	479 (7.25%)
CS	10 (1.07%)	239 (5.16%)	12 (0.90%)	257 (3.89%)
BS	4 (0.43%)	45 (0.97%)	14 (1.06%)	65 (0.68%)
Conventional Transportation Modes				
CAR	631 (67.34%)	2,103 (45.4%)	783 (59.05%)	2,952 (44.70%)
CP	51 (5.44%)	121 (2.61%)	168 (12.67%)	582 (8.81%)
PT	148 (15.80%)	360 (7.77%)	127 (9.58%)	290 (4.39%)
AT	61 (6.51%)	185 (3.99%)	128 (9.65%)	439 (6.65%)

Note: The total sample sizes between recalled trip and stated choice experiments were different, since each respondent answered recalled trips once and answered stated choice experiments as many as 10 times.

Table 5. The descriptive statistics of recalled trips and stated choice experiments by trip purpose

5. RESULTS

This section is divided into three subsections, each of which corresponds to one of the three research questions addressed in this study: (1) market share summary in the era of autonomous vehicles (AVs) using descriptive statistics in Tables 5, (2) factors influencing transportation mode choice using mixed logit (MXL) model in Table 6, and (3) direct and cross marginal effect estimation based on the final MXL model in Table 7.

5.1 Market Share of Transportation Modes in the Era of Autonomous Vehicles

Table 5 illustrates the distribution of mode shares for both current transportation practices and anticipated trends in the AV era, categorized by trip purpose (commute and non-commute trips). Currently, the predominant mode choice for both commute and non-commute trips is personal vehicles, with 67.3% and 59.1% of respondents opting for them, respectively. Conversely, shared mobility services are utilized by less than 10% of respondents in the present context.

In contrast, the envisioned AV era portrays a notable shift in mode preferences. Despite personal vehicles remaining popular with approximately 50% of respondents, significant percentages of travelers express their intent to utilize autonomous vehicles (AVs) and shared autonomous vehicles (SAVs). Specifically, respondents indicated their inclination to use AVs and SAVs in approximately 26% of commute trips and 18% of non-commute trips. Notably, SAVs emerge as a particularly favored option, surpassing the utilization rates of other contemporary shared mobility services.

5.2 Determinants of Transportation Mode Choice Behaviors in the Era of Autonomous Vehicles

Table 6 displays the estimated coefficients in the best-fitting Mixed Logit (MXL) specification, along with standard errors, z-statistics, p-values, and model statistics. Out of the 68 variables examined, 11 exhibited heterogeneous effects across respondents, resulting in estimated random parameters based on the statistical significance of the standard deviation. The McFadden R-squared value of 0.714 indicates a strong fit for the best-fitting MXL model.

For the private autonomous vehicles (PAV) alternative, nine variables had statistically significant impacts on an individual's probability of choosing the mode. Of the factors, two had heterogeneous effects across individuals. They had normally distributed random parameters based on the statistical significance of the standard deviation. Specifically, based on a normal distribution, 61.3% of individuals were more likely to choose AVs when respondents had a pro-technology attitude. The second factor with heterogeneous effects was related to out-of-pocket cost. With an estimated coefficient mean of -0.328 and a standard deviation of 0.201, only 5.1% of respondents were more likely to choose PAV if the cost increased. Regarding the fixed effects, interestingly, in-vehicle time was not a statistically significant predictor of choosing

PAV, while it was found to be significant in the multinomial logit model. Female respondents were more likely to choose PAV. As expected, the log odds of choosing PAV increased by 0.258 if respondents had a positive attitude toward AVs. Also, respondents were more likely to choose PAV for recreational trips. As observed in the previous subsection, the direction of parameter estimates of age was negative.

For shared autonomous vehicles (SAV), seven factors were statistically significant in their utility function. Of the seven factors, two had random parameters. When out-of-pocket costs decreased, most respondents (95.5%) were more likely to choose SAV. Moreover, with an estimated parameter mean of -0.074 and a standard deviation of 0.085, 80.8% of them were likely to choose SAV if the wait time decreased. Additionally, respondents were more likely to choose SAV for commute trips. The parameter estimates of -0.026 for the age covariate suggest that older respondents were less likely to adopt the new technology.

For ride-hailing services (RH), seven coefficients were statistically significant. For this alternative, there are two factors with an estimated random parameter. With an estimated parameter mean of -0.122 and a standard deviation of 0.117, 85.2% of respondents were more likely to choose RH if the in-vehicle time decreased. Also, 92.8% of them were more likely to choose RH if the out-of-pocket cost decreased. The results imply that people prefer to use RH for shorter and cheaper trips. Also, full-time students and those who have barriers to conventional transportation modes showed a higher probability of choosing RH.

The utility for choosing car-sharing services (CS), such as Zipcar, included four significant factors. First, for the in-vehicle time variable, with an estimated parameter mean of -0.108 and a standard deviation of 0.073, 93.1% of respondents were more likely to choose CS if the in-vehicle time decreased. Also, respondents who hold graduate or professional degrees were more likely to choose it.

For bike-sharing services (BS), four factors were statistically significant in their utility function, with no factors showing heterogeneous effects across individuals. Specifically, if out-of-pocket costs increased, respondents were less likely to choose bike-sharing services. Also, non-Hispanic white showed a lower possibility of choosing bike-sharing services. Also, as respondents got older, the possibility of choosing them decreased.

For conventional personal cars (CAR), trip-specific attributes, including in-vehicle time, out-of-pocket cost, and wait time, were negatively associated with choosing CAR. Specifically, 71.3% of respondents were more likely to choose CAR if the cost increased. Also, people who own a bike or people in the high-income group had a higher probability of choosing CAR.

For carpool (CP), four factors were statistically significant in their utility functions, with one with random parameters. Specifically, most respondents (77.8%) were more likely to choose CP if wait time decreased. Also, in-vehicle time was negatively associated with the probability of choosing CP. Interestingly, non-Hispanic whites showed a higher probability of choosing CP than people of color.

Utility for choosing public transportation (PT), with an estimated parameter mean of -0.141 and a standard deviation of 0.159, 81.2% of respondents was likely to choose PT if walk time decreased. For those who enjoyed driving, PT was not an appealing transportation mode (parameter estimates of -0.692). Interestingly, if the trip purpose was for meal-out and recreation, the probability of choosing PT increased.

Finally, for active transportation (AT), including walking and biking, if the respondent had a barrier to using conventional transportation modes, including a personal car, public transportation, and active transportation, the possibility of choosing AT significantly decreased (parameter estimates of -2.715). Also, those who had a positive attitude toward alternative transportation modes showed a higher probability of choosing AT.

5.3 Marginal Effect Estimations

This subsection simulates the consequences of potential policy scenarios primarily by changing four alternative-specific attributes: out-of-pocket cost (COST), in-vehicle time (IV), wait time (WAIT), and walk time (WALK). The analysis of marginal effects reveals the elasticity of the covariates by calculating the change in probability of given transportation modes corresponding to a one-unit increase in alternative-specific attributes while holding all other variables equal to their means.

As shown in Table 7, a one-dollar increase in COST of PAV led to a decrease in the predicted probability of choosing PAV by 0.055. In terms of cross-marginal effects, due to the cost increase, the predicted probability of choosing CAR increased by 0.028, while that of choosing other modes increased by around 0.005. A one-dollar increase in COST of SAV resulted in a decrease in the predicted probability of choosing SAV by 0.044, while that of choosing a personal car increased by 0.022. However, a one-dollar increase in COST of using CAR led to a decrease of CAR by 0.028 and an increase in the predicted probability of PAV SAV, RH, and CS by 0.008, 0.010, 0.006, and 0.005, respectively.

A one-minute increase in IV for a PAV trip can be negligible (marginal effect of -0.001). However, a one-minute increase in IV of SAV led to the decrease in the predicted probability of choosing SAV by 0.009, while that of choosing CS, CAR, CP, and PT increased by 0.001, 0.005, 0.001, and 0.001, respectively. Whereas a one-minute increase in IV of RH caused the decrease in the predicted probability of choosing RH by 0.005, the increase of CS declined that of choosing CS by 0.018. The predicted probability of choosing CAR decreased by 0.040 for a one-minute increase in IV of CAR, and an increase in the predicted probability of choosing PAV, SAV, RH, and CS by 0.014, 0.017, 0.005, and 0.005, respectively.

In contrast to IV, the marginal effects of WAIT were much more prominent in magnitude. Specifically, a one-minute increase in WAIT of PAV decreased the predicted probability of choosing PAV by 0.023 and increased that of choosing CAR by 0.013. Also, the increase in WAIT of SAV led to the decrease in the predicted probability of choosing SAV by 0.017 and an increase in that of choosing CAR by 0.007. Reversely, the predicted probability of choosing CAR decreased by 0.025 for a one-minute increase in WAIT of the mode.

The direct marginal effects of WALK of CP, PT, and AT on each mode were -0.010, -0.012, and -0.004, respectively. The predicted average probability of choosing PAV and SAV increased by roughly 0.003 if the walk time of CP, PT, and AT increased by one minute.

6. DISCUSSION

6.1 Implications

The market share forecast offers several notable implications. First, the predicted market shares of private and shared AVs in the stated choice experiments were within the range of previous literature. However, the estimation was relatively conservative to others in previous studies (Litman, 2021). Second, the persistence of conventional personal cars as a dominant transportation mode in the AV era suggests that the transformative potential of AVs may be less dramatic than anticipated. The expected benefits such as reduced car ownership, traffic volume, and parking demands may require a reevaluation, prompting a closer examination of the broader impacts of AV adoption. Third, given a certain proportion

Variable	Parameter estimates	Standard Error	Z-statis-tics	P-value
Private Autonomous Vehicles (PAV)				
Constant	-0.490	0.307	-1.59	0.111
IV	-0.001	0.008	-0.14	0.890
WAIT	-0.101***	0.020	-4.89	0.000
COST	-0.328***	0.037	-8.65	0.000
(Std. dev. of parameter)	0.201***	0.025	7.95	0.000
Recreation	0.377*	0.194	1.94	0.052
Low income	-0.411***	0.145	-2.83	0.004
Children	0.136**	0.066	2.05	0.040
Female	0.426***	0.141	3.01	0.002
Age	-0.018***	0.006	-2.72	0.006
Pro-AVs	0.258***	0.069	3.69	0.000
Pro-Tech	0.452***	0.104	4.31	0.000
(Std. dev. of parameter)	1.569***	0.306	5.12	0.000
Shared Autonomous Vehicles (SAV)				
Constant	0.534	0.398	1.34	0.179
IV	-0.012	0.008	-1.47	0.141
COST	-0.338***	0.040	-8.28	0.000
(Std. dev. of parameter)	0.200***	0.029	6.73	0.000
WAIT	-0.074***	0.016	-4.37	0.000
(Std. dev. of parameter)	0.085***	0.026	3.23	0.001
Commute	0.347**	0.141	2.45	0.014
College	-0.726***	0.245	-2.95	0.003
Age	-0.026***	0.006	-3.94	0.000
Pro-AVs	0.362***	0.064	5.59	0.000
License	-1.053***	0.266	-3.95	0.000
Ride-hailing Services (RH)				
Constant	-2.960***	0.276	-10.70	0.000
IV	-0.122***	0.028	-4.32	0.000
(Std. dev. of parameter)	0.117***	0.020	5.68	0.000
COST	-0.143***	0.023	-6.09	0.000
(Std. dev. of parameter)	0.098***	0.016	6.02	0.000
Recreation	0.472*	0.263	1.79	0.073
Full-time student	0.634***	0.216	2.93	0.003
Enjoy-Driving	0.361***	0.122	2.94	0.003
Car ownership	-0.681***	0.230	-2.95	0.003
Barriers	0.836***	0.247	3.38	0.000
Car-sharing Services (CS)				
Constant	-2.045***	0.448	-4.57	0.000
IV	-0.108***	0.020	-5.29	0.000
(Std. dev. of parameter)	0.073***	0.015	4.74	0.000
Graduate degree	0.697***	0.264	2.64	0.008
Rent	-0.402*	0.216	-1.86	0.062
Age	-0.029***	0.011	-2.66	0.007
Bike-sharing Services (BS)				
Constant	-1.783**	0.722	-2.47	0.013
COST	-.550***	0.160	-3.43	0.000
White	-0.633**	0.286	-2.22	0.026
Adults	0.450***	0.118	3.80	0.000
Age	-0.044**	0.017	-2.54	0.011
Personal Car (CAR)				
IV	-0.055***	0.006	-8.25	0.000
COST	-0.255***	0.028	-9.01	0.000
(Std. dev. of parameter)	0.454***	0.054	8.41	0.000
WAIT	-0.047***	0.007	-6.08	0.000
School	1.454***	0.455	3.19	0.001
Personal business	-0.455	0.279	-1.63	0.103
High income	0.499***	0.142	3.50	0.000
Pro-Alt	-0.223***	0.072	-3.09	0.002
Barrier	-0.637***	0.185	-3.44	0.000
Bike ownership	-0.299***	0.112	-2.66	0.007
Carpool (CP)				
Constant	0.402	0.362	1.11	0.266
IV	-0.080***	0.018	-4.27	0.000
WALK	-0.286***	0.048	-5.86	0.000
(Std. dev. of parameter)	0.373***	0.092	4.04	0.000
Recreation	1.245***	0.471	2.64	0.008
White	0.934***	0.352	-2.65	0.008
Public Transportation (PT)				
Constant	-3.285***	0.419	-7.83	0.000
WALK	-0.141***	0.030	-4.63	0.000
(Std. dev. of parameter)	0.159***	0.046	3.45	0.000
Meal-out	2.521***	0.526	4.79	0.000
Shopping	0.904***	0.350	2.58	0.009
Enjoy-Driving	-0.692***	0.172	-4.02	0.000
Barriers	-2.541***	0.492	-5.16	0.000
Active Transportation (AT)				
Constant	0.099	0.378	0.26	0.792
IV	-0.047***	0.009	-4.79	0.000
WALK	-0.056***	0.019	-2.93	0.003
(Std. dev. of parameter)	0.132**	0.061	2.16	0.030
Meal-out	-0.672**	0.313	-2.14	0.032
Recreation	1.018**	0.456	2.23	0.025
White	-0.626**	0.303	-2.07	0.038
Pro-Alt	0.947***	0.212	4.46	0.000
Enjoy-Driving	-0.466***	0.141	-3.29	0.001
Barriers	-2.715***	0.469	-5.79	0.000
Bike ownership	0.507*	0.278	1.82	0.068
Model Statistics				
Number of Observation			7,872	
Log-likelihood function			-4,872.829	
Restricted log likelihood			-17,015.307	
McFadden Pseudo R-squared			0.714	

Table 6. Best Fit Mixed Logit Model (Random Parameter Logit Model) Specifications

	PAV	SAV	RH	BS	CS	CAR	CP	PT	AT
Out-of-pocket cost (unit: dollar)									
PAV	-0.055	0.000	0.008	0.002	0.005	0.028	0.004	0.007	0.002
SAV	0.000	-0.044	0.007	0.002	0.005	0.022	0.003	0.006	0.002
RH	0.005	0.005	-0.021	0.000	0.002	0.007	0.001	0.002	0.001
BS	0.002	0.002	0.000	-0.007	0.000	0.002	0.000	0.001	0.000
CAR	0.008	0.010	0.006	0.001	0.005	-0.028	0.000	0.000	0.000
In-vehicle time (unit: minute)									
PAV	-0.001	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.000
SAV	0.000	-0.009	0.001	0.000	0.001	0.005	0.001	0.001	0.000
RH	0.002	0.002	-0.005	0.000	0.001	0.000	0.000	0.001	0.000
CS	0.003	0.004	0.002	0.000	-0.018	0.006	0.001	0.002	0.000
CAR	0.014	0.017	0.005	0.001	0.005	-0.040	0.000	0.000	0.000
CP	0.002	0.002	0.001	0.000	0.001	0.000	-0.005	0.000	0.000
AT	0.003	0.003	0.001	0.000	0.001	0.000	0.000	0.000	-0.007
Wait time (unit: minute)									
PAV	-0.023	0.000	0.002	0.001	0.002	0.013	0.002	0.002	0.002
SAV	0.000	-0.017	0.003	0.001	0.002	0.007	0.001	0.003	0.002
CAR	0.010	0.010	0.003	0.001	0.003	-0.025	0.000	0.000	0.000
Walk time (unit: minute)									
CP	0.003	0.004	0.002	0.000	0.001	0.000	-0.010	0.000	0.000
PT	0.004	0.004	0.002	0.000	0.002	0.000	0.000	-0.012	0.000
AT	0.002	0.002	0.000	0.000	0.000	0.000	0.000	0.000	-0.004

Note:
The effect of a one-unit change in each attribute (Out of pocket cost, in vehicle time, wait time, walk time) of the alternative in the row on the average probability change that individual would choose alternative at the aggregate level in the column choice.
Abbreviation: active transportation (AT), autonomous vehicle (AV), bike-sharing (BS), carpool (CP), car-sharing (CS), public transportation (PT), ride-hailing (RH), shared autonomous vehicle (SAV), and personal car (CAR).

Table 7. Selected marginal effect estimations

of people would still choose currently available alternative transportation modes, including shared mobility services, public transportation, and active transportation, planning efforts to effectively manage infrastructures for multimodal transportation and implement strategies to support them. Fourth, given that those who have barriers to currently available transportation modes showed a higher probability of adopting PAV and SAV than other groups, AVs may assist those excluded from the current automotive-dominant market in gaining access to destinations and expanding opportunities (Becker & Axhausen, 2017).

Furthermore, our analysis, coupled with parameter estimation and marginal effect estimates from the mixed logit model, offers additional insights. First, the negative association between alternative-specific attributes and the probability of choosing PAV and SAV underscores the principles of transportation economics at play. Second, the heightened responsiveness to financial incentives suggests that individuals in the AV era prioritize cost considerations over other factors such as in-vehicle time, wait time, and walk time. Third, the observed decrease in probability due to increased attributes of PAV and SAV primarily contributes to an increased probability of choosing conventional personal cars, indicating a preference for familiar modes in response to rising costs and wait times. However, the impact of increased attributes on other available transportation modes is more evenly distributed. Fourth, PAV and SAV users exhibit higher cost-consciousness compared to conventional car drivers, highlighting the importance of pricing strategies in shaping mode choice behaviors. Notably, SAV users appear slightly less sensitive to costs than PAV users, suggesting differing preferences within the AV market. Fifth, there may be strategic implications for SAV operators, emphasizing the importance of minimizing wait times to enhance user satisfaction. While longer in-vehicle times may be tolerated if offset by shorter wait times, operators should prioritize efficient passenger pickups to optimize service quality and user experience. These findings underscore the need for dynamic and adaptable policies to navigate the evolving landscape of AV adoption and urban mobility.

6.2 Limitations of this Study

There are limitations to this study. First, it is important to acknowledge the limitations of the stated choice experiment research design. One of the most significant constraints is that stated preferences may not be compatible with actual behavior (Holmes, Adamawicz, & Carlsson, 2017). Also, since the public may not be knowledgeable about AVs at the time of the experiment, the results of this paper may alter when they will be well-aware (Zmud et al., 2016). Thus, the inherent limitations of stated choice experiments may affect the accuracy of predictions, particularly for emerging technologies like AVs, where the public lacks direct experience. Second, the SC experiments conducted in this study did not encompass all transportation modes available in the era of AVs. For instance, micro-mobility options such as e-scooters, which have gained prominence in recent years, were not included in the study due to their nascent status at the time of data collection. Similarly, electric bikes were not accounted for within the study framework. Third, it is essential to acknowledge that the sample collected for the SC experiments may not fully represent the study area or the broader U.S. population. Fourth, the analysis in this study primarily captures snapshot views of mode choice preferences at a specific point in time. However, transportation preferences and behaviors are dynamic and subject to change over time due to various external factors. Fifth, this study relies on self-reported data obtained through stated choice experiments and surveys, which may be subject to biases such as social desirability bias or recall bias. This could influence the accuracy and reliability of the findings.

7. CONCLUDING REMARKS

The ongoing advancements in transportation modes on the supply side have the potential to profoundly reshape travel behavior in the era of autonomous vehicles (AVs), necessitating a thorough examination of the demand-side response (Singleton, 2019). Understanding the potential demand-side dynamics is crucial for providing essential implications to planners and policymakers, offering insights into who would utilize these emerging modes and how the market would respond. In this context, employing the Mixed (Random Parameter) Logit Model with U.S. nationwide stated choice experiments, this research aimed to address three fundamental research questions. By investigating future travel demand, identifying influential factors in transportation mode choice behavior, and estimating marginal effects, this study contributes valuable insights to the development of robust mid- to long-term transportation strategies. These insights are particularly significant given the challenges posed by uncertainties surrounding consumer reactions to emerging transportation technologies. By shedding light on the complex interplay between consumer preferences, mode characteristics, and policy interventions, this research offers a foundation for informed decision-making in transportation planning and policy formulation. Ultimately, by leveraging these insights, stakeholders can better anticipate and adapt to the transformative impacts of AVs, fostering sustainable and efficient mobility solutions for the future.

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