Undercutting Transit? Exploring Potential Competition between Automated Vehicles and Public Transportation in the U.S.

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ABSTRACT
Automated vehicles (AVs) have the potential to dramatically disrupt current transportation patterns and practices. One particular area of concern is AVs' impacts on public transit systems. If vehicle automation enables significant price decreases or performance improvements for ride-hailing services, some fear that it could undercut public transit, which could have important implications for the environment and transportation equity. The extent to which individuals adopt automated transportation modes will drive many system-level outcomes, and research on public preferences for AVs is immature and inconclusive. In this study, we use responses from an online choice-based conjoint survey fielded in the Washington, D.C. Metropolitan Region (N = 1,736) in October 2021 to estimate discrete choice models of public preferences for different automated (ride-hailing, shared ride-hailing, bus) and non-automated (ride-hailing, shared ride-hailing, bus, rail) modes. We use the estimated models to simulate future marketplace competition across a range of trip scenarios. Respondents on average were only willing to pay a premium for automated modes when a vehicle attendant was also present, limiting the potential cost savings that AV operators might achieve by removing the driver. Additionally, scenario analysis revealed that for trips where good transit options were available, transit remained competitive with automated ride-hailing modes. These results suggest that fears of a mass transition away from transit to AVs may be limited by people's willingness to use AVs, at least in the short term. Future AV operators should also recognize presence of an AV attendant as a critical feature for early AV adoption.

Keywords: Automated vehicles; public preferences; transit competition; stated preference; mixed logit

INTRODUCTION

Automated vehicles (AVs) have the potential to dramatically disrupt current transportation patterns and practices, and how they will interact with or displace current transportation modes remains uncertain. Over the past decade, ride-hailing companies like Uber and Lyft have raised billions of dollars by promoting the promise of a future of driverless taxi fleets that could potentially replace car ownership entirely [1]. At the same time, transportation planners are grappling with how AVs might shape future transportation systems, especially public transportation systems.

Transit systems have already had to reckon with competition from ride-hailing services that offer greater flexibility and convenience than many transit options [2]. If vehicle automation enables significant price decreases and increased availability for ride-hailing services, some fear that it could undercut public transit, which could have important implications for the environment and transportation equity [3]. Public transit plays a critical role in reducing emissions from transportation, mitigating road congestion, and providing basic mobility for individuals with limited to no other transportation options.

Ultimately, the extent to which individuals adopt automated transportation modes will drive many system-level outcomes. Research on preferences for AVs is both immature and inconclusive, especially with regard to competition with transit. Some studies have found that individuals prefer automated modes over public transit [4], [5], while others find that current transit users lack significant interest in automated modes [6], [7]. Furthermore, public attitudes towards and preferences for public transit are often context dependent. Despite the AV testing and pilots occurring in multiple cities across the United States, limited research exists regarding the potential impacts of automation on the billions of annual public transportation trips taken in the U.S. each year (9.9 billion in 2019) [8]. Prior U.S.-based studies have either focused on one mode or omitted transit, limiting the ability to compare preferences between different automated modes. This study aims to fill this gap by investigating the public preferences for transit and ride-hailing modes with and without automation. We center our analyses on the following two research questions:

1. What are individuals' preferences for automated modes (ride-hailing, shared ride-hailing, bus) and non-automated modes (ride-hailing, shared ride-hailing, bus, rail)?
2. Under what conditions might automated ride-hailing services be competitive with public transit modes?

We address these questions using data from an online choice-based conjoint survey fielded in the Washington, D.C. Metropolitan Region (N = 1,736) in October 2021. We estimate discrete choice models of public preferences for different automated and non-automated transportation modes, and then we use the estimated models to simulate future marketplace competition across a range of trip scenarios.

Literature on AV Preferences

Many studies on preferences for AVs have focused on factors associated with private AV ownership, often employing Likert scales or other similar rating systems to assess attitudes towards different automated modes. While these studies provide insights into general consumer perceptions of AVs, they lack the ability to gauge potential substitution patterns between automated and non-automated transportation modes.

To address this, some researchers have used choice-based conjoint (CBC) surveys. In CBC surveys, respondents choose from a set of options with varying attributes, and researchers estimate discrete choice models to infer the relative importance of each attribute and the relative desirability of each option. Rather than gauge preferences for different modes in isolation, conjoint surveys allow researchers to simulate the menu of transportation options available to an individual, typified by the experience of looking up directions via GoogleMaps or via a transportation planning app. **Table 1** presents a selection of recent CBC studies investigating public preferences for different automated and non-automated transportation modes. The majority of these prior studies compare automated modes to conventional, non-automated private cars.

TABLE 1 Summary of modes investigated in prior AV conjoint studies

		Non-Automated					Automated			
Study	**Location**	**Private Car**	**Ride-hailing**	**Shared Ride-hailing**	**Transit**	**Other (walking, biking)**	**Private Car**	**Ride-hailing**	**Shared Ride-hailing**	**Transit**
Krueger et al. 2016*	Australia	X	X	X	X	X		X	X	
Yap et al. 2016	Netherlands	X			X	X		X	X	
Steck et al. 2018	Germany				X	X	X	X	X	
Ashkrof et al. 2019	Netherlands	X			X			X		
Winter et al. 2020	Netherlands	X	X		X			X		
Etzioni et al. 2020	Cyprus, UK, Slovenia, Montenegro, Hungary, Iceland	X					X	X	X	
Daziano et al. 2017	U.S.	X					X			
Haboucha et al. 2017	U.S., Canada & Israel	X					X	X		
Lavieri & Bhat 2019	U.S.							X	X	
Gurumurthy & Kockelman 2020	U.S.						X	X		
Zhong et al. 2020	U.S.	X					X	X	X	
This study	Washington, D.C.		X	X	X			X	X	X

*Non-automated modes were collected as a self-reported reference trip

The general consensus across most of these studies is that conventional, non-automated vehicles continue to dominate preferences. For example, in Krueger et al.'s [4] study, respondents chose an automated mode in only 28% of the choice situations. Etzioni et al. [9] surveyed individuals across six EU countries and similarly found strong preferences for conventional vehicles, with respondents selecting conventional vehicles in 70% of the choices. Respondents in Zhong et al.'s [10] survey of U.S. residents preferred their current private vehicles over private AVs and AV ride-hailing options. These studies signal that individuals are not likely to relinquish their personal vehicles in favor of AVs in the near future.

The strong preferences for conventional vehicles, however, may mask other potential substitution effects that could occur with the introduction of AVs. Many of the aforementioned studies restricted their survey sample to individuals who have a driver's license, with some also requiring that respondents drive a personal vehicle frequently. In doing so, these studies fail to capture the preferences of individuals who do not currently rely on personal vehicles as their primary mode of transportation, including individuals with disabilities or those who do not own a car. Such individuals are typically the primary users of public transit.

The existing literature on AV substitution with transit is limited and inconclusive. Some studies find a preference for AVs over transit modes. In Steck et al.'s [5] survey, respondents found the private AV option most attractive, followed by AV ride-hailing, and finally transit. Ashkrof et al. [11] explored preferences for conventional cars, AV ride-hailing, and transit. Individuals similarly preferred AVs over transit, especially when the choice question was framed in terms of a long-distance trip. Yet other studies suggest more limited competition of AVs with transit. In Yap et al.'s [12] study of AVs as a potential egress mode for train trips, first-class train passengers valued AVs more than transit modes, but second-class train passengers actually preferred transit over AVs. Winter et al. [7] that survey respondents who currently commute by public transport actually show the lowest preference for automated modes, affirming Krueger et al. [4]'s finding that current transit users were not more likely to switch to an automated mode.

There are some mode features that are particularly relevant when considering an AV future. Ride-sharing is already available in some cities via services like UberPool. Sharing rides decreases the cost for both riders, and these cost savings could become even more substantial if the services are automated. Further, sustainability advocates emphasize that fleets of shared AVs are critical for ensuring a sustainable AV future [3]. The desire for shared rides may remain limited in an AV future. In Lavieri and Bhat's [13] conjoint study on automated ride-hailing with sharing and non-sharing options, respondents chose to ride alone in 48.3% of choice occasions with work trips and 54% of choice occasions for leisure trips.

A second mode feature—the presence of an AV attendant—is associated with additional roles that a driver might fulfill beyond operating the vehicle. Though AVs would be operated by computer systems, an attendant could help individuals enter and exit the vehicle—a potential barrier to AV use for elderly individuals and individuals with disabilities—and provide a social monitoring function. This monitoring function might affect who feels comfortable using shared AV services. The consensus from many stated preference surveys and choice studies on AVs is that women appear less likely to use AVs than men [14], and some hypothesize that this hesitation towards AVs may stem in part from personal security concerns [15]. Attendant presence might be an important feature that impacts whether individuals would prefer AVs over traditional modes. While some AV companies are already operating their vehicles with attendants onboard in small pilots, companies will eventually need to decide whether the attendant feature is worth the additional operating cost in large-scale deployments.

Conjoint studies have enabled an avenue of research to explore potential substitution patterns between various transportation modes in an AV future. This area of research, however, is still quite immature, with many studies conducted only within the past six years. Few studies have considered the impacts of AVs on current transit use, and no conjoint studies have examined impacts of AVs on transit in a U.S. context. Furthermore, there is a lack of understanding about key features associated with AV use, such as ride-sharing and the presence of an AV attendant. We address these gaps by fielding a U.S.-based conjoint study on preferences for automated and non-automated modes.

METHODS

AV services are primarily in the pilot and development phases, limiting the availability of revealed-preference (RP) data. In this study, we use a stated-preference (SP) conjoint approach to measure public preferences for various automated modes. In CBC surveys, individuals evaluate a series of randomized alternatives and choose which option they prefer. From these selections, we can estimate discrete choice models to quantify the relative importance of each attribute and to simulate market competition between hypothetical choice sets. An advantage of CBC surveys is that one can create hypothetical choices in order to tease out preferences for different attributes that might otherwise be highly correlated in the marketplace (e.g., determining the importance of price versus travel time which are often directly correlated). Ideally, we would calibrate the estimated models using real market data or combined RP and SP data since real-world behavior may deviate from reported behavior on a survey. Unfortunately, RP and market data for the various types of automated modes explored in this study are not currently available. The inability to effectively calibrate model results remains a limitation of studies on AVs, though we attempted to minimize this limitation by briefing respondents on the features of potential automated modes, further discussed below. The following sections describe the design of this study's CBC survey and subsequent modeling approach. Survey design and data analysis were conducted in R using the *cbcTools* package [17], and the full survey, data, code used, and paper appendices are available at:
https://github.com/lkaplan25/AV_conjoint_survey_2022

Survey design and target sample

The survey was created and administered using formr.org—a customizable, R-based survey platform [18]. The survey was fielded within the Washington, DC Metropolitan Region to situate decision tradeoffs within a local context and included three main parts: 1) background information and current transportation routines, 2) choice-based conjoint questions, and 3) demographic questions. The background information section included a video clip describing the six levels of automation as defined by SAE International [19]. We defined automated modes as SAE level 5 vehicles.

In part two, we asked respondents eight CBC questions. For each question, we asked respondents to imagine they were going out for an evening leisure activity and to choose between four modes (bus, rail, ride-hailing, and shared ride-hailing) with randomized attribute values. **Figure 1** shows an example choice question. We selected this framing to provide new insights into AV preferences for non-commuting trips. The majority of prior AV preference studies have focused on commuting journeys, yet non-commuting trips account for approximately 78% of trips within the Washington, DC Metropolitan Region [20], [21]. Additionally, we hypothesized that focusing on evening trips would increase any potential value of having an attendant on board, per the aforementioned discussion regarding personal security. Future studies might investigate the extent to which time-of-day framing impacts individuals' responses.

The five attributes investigated in this study were mode, automation (yes/no), attendant (yes/no), total trip time, and price. While other attributes, such as wait time, have been found to impact individuals' mode choices, respondents on initial pilot surveys reported feeling overwhelmed by the complexity of the choice questions that included more attributes, including wait time. We subsequently chose to decrease the number of attributes to focus on identifying potential impacts of attendant presence for automated modes, which has received less attention in the literature.

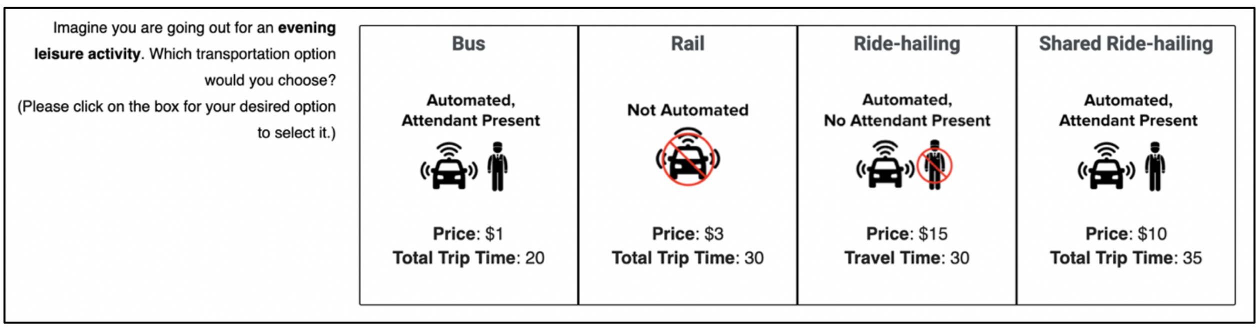

Figure 1 Sample choice-based conjoint question

We determined ranges for the attribute values for each mode based on current travel times and prices for the region as determined by GoogleMaps, the CityMapper transportation planning app, and ride-hailing price calculators (see **Table 2**) [22]–[24]. The times and prices were mode-specific (i.e., a bus trip could cost $1, $2, $3, $4, or $5 whereas a ride-hailing trip could cost $5, $7, $10, $12, or $15). We applied discounts of between 20-50% of the regular ride-hailing price to generate prices for the shared ride-hailing mode to simulate cost-savings from shared rides. Shared ride-hailing travel times were also set between 80-120% of the ride-hailing times. While shared rides often have longer trip times, shorter times can occur if an available shared vehicle is already closer to the rider than a solo vehicle. In addition to capturing status quo prices and travel times, we also included a limited number of more extreme values to reflect uncertainty about how automation might affect prices and travel times in the future. Only the bus, ride-hailing, and shared ride-hailing modes could be automated, and only automated modes could include an attendant. The survey explained the attendant feature as follows: "Vehicles with an attendant would have a company official on board to help passengers. This attendant would not be responsible for operating the vehicle."

We created a full factorial design of experiment (DOE) using all of the combinations of attributes possible for each individual mode but with the restrictions previously described (e.g., only automated modes could have an attendant) for a total of 40,000 possible choice questions. The choice questions were then arranged such that each respondent answered eight choice questions randomly drawn from this DOE and such that each choice question showed each of the four available modes. The final section of the survey collected demographic information including age, gender, race, education level, and household income (full survey available in Appendix A).

Prior to a full launch of the survey, we conducted two pilot surveys using Amazon Mechanical Turk (N = 287) to test for areas of confusion, potential dominant alternatives, and potential survey fatigue. As mentioned above, we adjusted the survey design following the initial pilot test and then performed a second pilot test to check the revised survey design. After pilot testing, we partnered with a market research firm to recruit the full survey sample. We limited the survey sample to adults (individuals over 18) who live within the Washington, DC Metropolitan Region (screened for using zip codes).

TABLE 2 Full range of survey attributes and levels. Travel time and price are mode-specific

Attribute	Levels
Mode	Ride-hailing, Shared ride-hailing, Bus, Rail
Automated	Yes/No
Attendant Present	Yes/No
Travel time (minutes)	
Ride-hailing	15, 20, 25, 30, 35
(Shared ride-hailing travel time set at between 80-120% of ride-hailing time)	
Bus	20, 25, 30, 35, 40
Rail	15, 20, 25, 30, 35
Price ($)	
Ride-hailing	5, 7, 10, 12, 15
(Shared ride-hailing set at 50-80% of the associated ride-hailing price)	
Bus	1, 2, 3, 4, 5
Rail	2, 3, 4, 5, 6

Model specification

We model choice using a random utility framework, which assumes that individuals will select the alternative that maximizes an underlying random utility model. The utility model is comprised of the observable attributes, $u_{ij} = f_i(x_j)$, as well as an error term, ε_{ij}, that captures unobservable attributes. Using this model, we can calculate the probability, P_{ij}, of an individual choosing a given alternative as the probability that the utility of one alternative *j* is greater than the utilities of the other alternatives. We assume that the error term follows a Gumbel extreme value distribution, yielding the following convenient closed-form expression that an individual will choose option *j* from the choice set J_c,, cf. Train [25]:

$$P_{ij} = \frac{e^{v_j}}{\sum_{k \in J_c} e^{v_k}} \quad \forall_C \in \{1, 2, 3, \dots C\},\ j \in J_C \tag{1}$$

In equation 1, *c* indexes a set of *C* choice sets with v_j capturing the observed portion of the utility model. The standard multinomial logit model (MNL) assumes that the error term is independently and identically distributed. Given that the survey collected several consecutive observations per respondent (often referred to as having a "pseudo-panel" structure), it violates this assumption of independence. To account for this pseudo-panel effect, we instead estimate mixed logit (MXL) models, a widely-used extension of the MNL model [10]. The MXL model allows for flexible substitution patterns and relaxes the assumption of independence of the error term [26]. For this study, we assumed that the parameters are drawn from independent normal distributions across the respondent population.

The general utility model yields coefficient estimates in the "preference space" in which coefficients represent the respondent utility for marginal changes in attribute values. We instead specify a "willingness-to-pay" (WTP) space utility model in which coefficient estimates have units of dollars and represent the valuation for marginal changes in attribute values. This has several advantages, in particular the ability the directly interpret the coefficients independent of one another and across different models; in contrast, utility coefficients must be interpreted relative to one another within each model as each model could have a different error scaling [27], [28]. The general WTP space utility model is as follows:

$$u_j = \lambda(\boldsymbol{\omega}' x_j - p_j) + \varepsilon_j \ , \qquad (2)$$

where p_j is price, λ is a scale parameter, x_j is all non-price attributes*,* and $\boldsymbol{\omega}$ is a vector of WTP coefficients for non-price attributes. For mixed logit models, directly estimating WTP provides greater control over how WTP is assumed to be distributed across the population and has been found to yield more reasonable distributions of WTP compared to WTP computed from preference space model coefficients [27]–[29]. Equation 3 shows the full model used in the study, with explanations of the variable names below:

WTP model for **Mode**, **Automated Mode**, and **Automated Mode + Attendant**
(Relative to non-automated rail)

$$u_j = \lambda \left(\begin{array}{c} \beta_1 x_j^{travelTime} \\ + \beta_2 \delta^{bus} + \beta_3 \gamma \delta^{bus} + \beta_4 \tau \gamma \delta^{bus} \\ + \beta_5 \delta^{RH} + \beta_6 \gamma \delta^{RH} + \beta_7 \tau \gamma \delta^{RH} \\ + \beta_8 \delta^{sharedRH} + \beta_9 \gamma \delta^{sharedRH} + \beta_{10} \tau \gamma \delta^{sharedRH} \\ -p_j \end{array} \right) + \varepsilon_j \qquad (3)$$

$\mathbf{p}_j$ = Price in US dollars
$\mathbf{x}_j^{\mathbf{travelTime}}$ = Total trip travel time in minutes
$\boldsymbol{\delta}^{\mathbf{bus}}$ = Dummy coefficient for bus mode type {1: yes, 0: no} (base level is rail)
$\boldsymbol{\delta}^{\mathbf{RH}}$ = Dummy coefficient for ride-hailing mode type
$\boldsymbol{\delta}^{\mathbf{sharedRH}}$ = Dummy coefficient for shared ride-hailing mode type
$\boldsymbol{\gamma}$ = Dummy coefficient for whether the mode is automated {1: yes, 0: no}
$\boldsymbol{\tau}$ = Dummy coefficient for whether there is an attendant present {1: yes, 0: no}

All models were estimated using the *logitr* R package which uses maximum simulated likelihood estimation to estimate mixed logit models [30]. The package includes the ability to appropriately account for data with a pseudo-panel structure by computing the probability that a respondent will make a sequence of choices when calculating the log-likelihood following equation 6.2 in Train [25]. Given the non-convex nature of WTP space log-likelihood functions, we use a randomized multi-start search to identify multiple local minima in a search for a global solution.

RESULTS

Sample description

The final sample consisted of 2,023 respondents who completed the survey between October 4 and October 17, 2021. Respondents who answered all choice questions the same, whose total survey response times or conjoint question response times were too short, who incorrectly answered a simple attention check question, or who were missing demographic information necessary for the model were removed. After filtering the data based on these criteria, the final sample size was 1,736 respondents for a total of 13,888 CBC responses. The final sample closely matched the demographics of the Washington, DC Metropolitan

Region, as reported by the National Capital Region (NCR) Transportation Planning Board's 2017/2018 Regional Travel Survey [31]. The most significant difference between our sample and the reference sample was the over-representation of individuals who self-identified as male. Our results are robust with and without weights to account for this gender imbalance (weighted model results are available in Appendix B). **Table 3** presents descriptive statistics of the final survey sample.

Effects of adding automation and an attendant

Table 4 presents the estimated coefficients from the multiple models we estimated. Standard errors are clustered at the individual level to account for the pseudo-panel data structure. Using the coefficients from the MXL model, we compute the WTP for automating modes and adding a vehicle attendant for the bus, ride-hailing, and shared ride-hailing modes. Using non-automated rail as the baseline, **Figure 2** displays individuals' WTP for the three other modes, *all else equal* (e.g., same travel time). A negative WTP can be interpreted as requiring a discount relative to a rail trip for an individual to be ambivalent between choosing a specific mode over rail. In the status quo (not automated) case, individuals have a slightly positive WTP for the ride-hailing mode and negative WTPs for the bus and shared ride-hailing modes. Adding automation does not drastically alter mode preferences. The addition of an attendant to the automated modes, however, does result in a significant shift to positive WTPs for automated buses and automated ride-hailing services. In the discussion section, we hypothesize about the interpretation of this result.

Subgroup Analyses

We perform subgroup analyses to investigate potential preference differences based on income, race, and gender. To do so, we directly estimated mixed logit WTP models for different subgroups. Since WTP-space estimation is independent of scale, we can directly compare the results from models for different groups, as opposed to estimating a single model with dummy parameter interactions. Prior studies have demonstrated that income, race, and gender impact attitudes towards conventional transportation modes and AVs [14]. No consistent differences emerged in our results regarding racial differences, though we are limited by our sample which was mostly white. Higher income individuals expressed a higher WTP for automation and an attendant, perhaps due to their overall lower price sensitivity. A gender-based[1] subgroup analysis revealed that although women and men shared similar baseline preferences for non-automated modes, men expressed significantly higher WTPs for automated modes and automated modes that also include an attendant (**Figure 3**). Even with the addition of the attendant to the automated modes, women only demonstrated a positive WTP for the automated ride-hailing mode. The gender subgroup analysis revealed that the positive WTPs from the whole-group analysis stemmed primarily from the men in our sample.

[1] We grouped individuals who self-identified transgender/gender non-conforming with respondents who identified as female. Alternative groupings did not change the reported results in aggregate.

TABLE 3 Summary statistics of survey sample compared to reference sample

Characteristic	N = 1,736[1]	Reference Sample
Gender		
Female	690 (40%)	52.3%
Male	1,013 (58%)	47.7%
Transgender/Gender Non-conforming	33 (1.9%)	-
Age		
18-24	108 (6.3%)	7.8%
25-34	359 (21%)	17.8%
35-44	580 (34%)	20.1%
45-54	256 (15%)	17.3%
55-64	150 (8.7%)	17.7%
65-74	198 (11%)	13.4%
75-84	68 (3.9%)	4.7%
85+	4 (0.2%)	1.3%
Unknown	13	-
Annual Household Income		
Less than $15,000	64 (3.7%)	3.0%
$15,000 - $24,999	45 (2.6%)	2.7%
$25,000 - $34,999	77 (4.4%)	3.2%
$35,000 - $49,999	128 (7.4%)	6.4%
$50,000 - $74,999	213 (12%)	12.9%
$75,000 - $99,999	196 (11%)	15%
$100,000 - $149,999	268 (15%)	24.8%
$150,000 or more	723 (42%)	31.9%
Unknown	22	-
Education		
No High school or High School	148 (8.6%)	-
Some College/Associate's	356 (21%)	-
Bachelor's degree	569 (33%)	-
Graduate or Professional Degree	651 (38%)	-
Unknown	12	-
Disability		-
None	1,038 (60%)	-
Intellectual	54 (3.1%)	-
Physical	545 (31%)	-
Visual	94 (5.4%)	-
Physical and Visual	5 (0.3%)	

[1]n (%)

TABLE 4 Discrete choice model coefficients in WTP space

Attribute	Coef.		MXL	MXL Male	MXL Female
Lambda			0.132 (0.008) ***	0.107 (0.010) ***	0.167 (0.013) ***
Travel time	β_1	μ	-0.438 (0.031) ***	-0.402 (0.045) ***	-0.453 (0.043) ***
		σ	0.542 (0.040) ***	0.670 (0.072) ***	0.498 (0.051) ***
Bus *(base = Rail)*	β_2	μ	-3.587 (0.445) ***	-4.047 (0.722) ***	-2.982 (0.526) ***
		σ	8.120 (0.687) ***	-9.644 (1.169) ***	6.311 (0.687) ***
Bus - Automated	β_3	μ	-0.385 (0.609)	1.898 (0.975)	-2.837 (0.807) ***
		σ	-7.426 (0.919) ***	-10.280 (1.633) ***	4.820 (1.425) ***
Bus - Attendant present	β_4	μ	6.350 (0.888) ***	11.907 (1.755) ***	4.295 (0.918) ***
		σ	-12.608 (1.315)***	23.572 (2.971) ***	4.868 (1.813) **
Ride-hailing (RH)	β_5	μ	1.034 (0.546)	0.776 (0.845)	1.573 (0.692) *
(base = Rail)		σ	13.441 (0.847) ***	13.992 (1.500) ***	11.854 (1.001) ***
RH - Automated	β_6	μ	-2.365 (0.791) **	2.587 (1.105) *	-4.147 (1.095) ***
		σ	-13.871 (1.118)***	-9.700 (2.287) ***	-12.416 (1.421) ***
RH – Attendant present	β_7	μ	9.442 (1.033) ***	12.884 (2.066) ***	3.274 (1.297) *
		σ	-19.070 (1.650)***	29.705 (3.706) ***	-12.221 (2.233) ***
Shared RH	β_8	μ	-3.861 (0.601) ***	-5.517 (1.085) ***	-4.363 (0.766) ***
(base = Rail)		σ	11.345 (0.831) ***	13.832 (1.534) ***	-9.411 (0.854) ***
Shared RH - Automated	β_9	μ	-2.755 (0.795) ***	2.716 (1.114) *	-3.427 (0.910) ***
		σ	-11.329 (0.950)***	-10.790 (1.365) ***	-6.614 (1.008) ***
Shared RH, Attendant present	β_{10}	μ	5.432 (0.918) ***	7.068 (1.447) ***	5.956 (1.072) ***
		σ	-14.539 (1.411)***	-26.278 (3.482) ***	6.958 (1.576) ***
Log-Likelihood:			-16,484.5	-9,538.0	-6,721.5
Null Log-Likelihood:			-19,252.9	-11,234.5	-8,018.3
AIC:			33,011.0	19,117.9	13,485.1
BIC:			33,169.3	19,264.9	13,625.0
McFadden R2:			0.1	0.2	0.2
Adj McFadden R2:			0.1	0.1	0.2
Number of Observations:			13,888	8,104	5,784
Number of Respondents:			1,736	1,013	723

Standard errors of estimates are presented in parentheses. Coefficient units are in USD \$. * $\leq$ 0.05. ** $\leq$ 0.01. *** $\leq$ 0.0001.

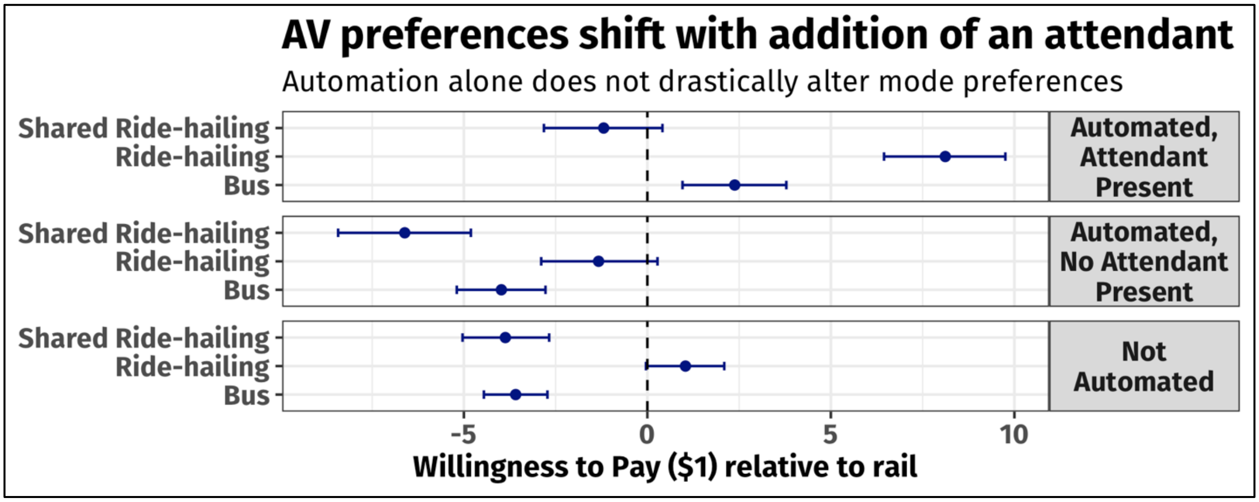

Figure 2 Average willingness-to-pay (WTP) values with 95% confidence interval bounds for the bus, ride-hailing, and shared ride-hailing modes relative to non-automated rail

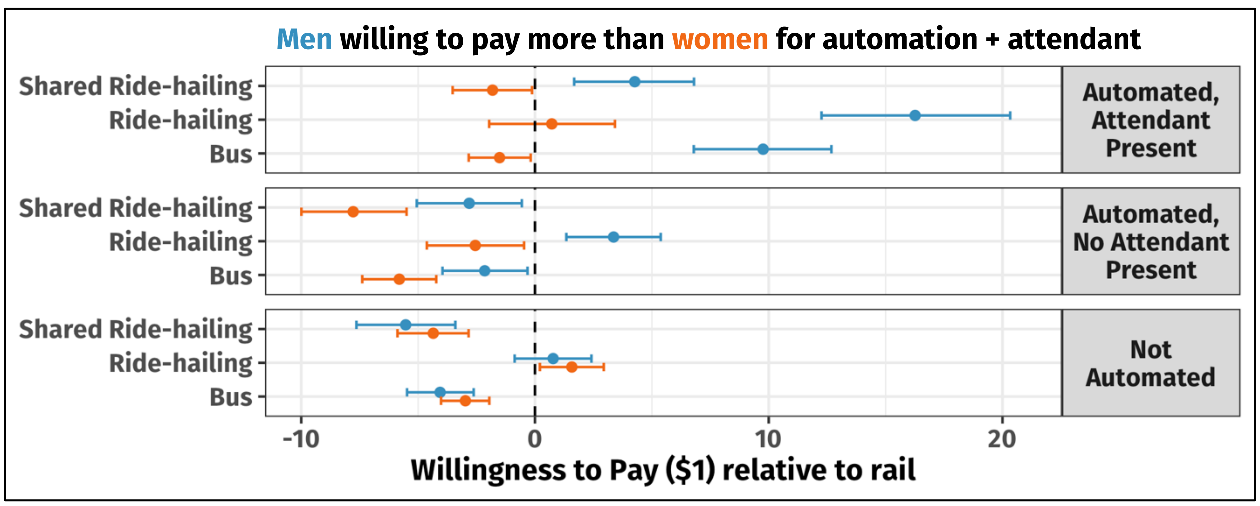

Figure 3 Gender differences in average willingness-to-pay (WTP) values with 95% confidence interval bounds

Scenario analysis

The WTP estimates provide insights into preferences for the different modes, *all else equal*. In reality, any one trip is a combination of mode, price, and travel time. To understand respondent preferences for the joint combination of these attributes, we use the estimated MXL model to simulate how AVs might compete with transit. We explore six scenarios of characteristic trips across Washington, DC (**Table 5**). Considering the status quo times and prices as the baseline, we modeled how demand for each mode (evaluated in terms of predicted market share) might change in response to automating ride-hailing and shared ride-hailing services. Given that automation is expected to decrease the cost of these modes, we also added in a 30% price decrease for the automated ride-hailing and shared ride-hailing modes. We limited the price decrease to 30% based on the current operating budgets for Uber and Lyft, which dedicate only 20% of their annual operating expenses to paying for drivers [32], [33]. These scenario analyses should not be interpreted as forecasts but rather as illustrative examples of the substitution patterns that our estimated choice model predicts for the limited respondent pool from our survey. The exercise reflects respondent preferences for the joint set of attributes associated with real trips individuals might take, as opposed to the *all else equal* context of WTP coefficients [16], [34]. Real-world forecasts would need to consider preferences of a much broader population and (ideally) include revealed preference data when they become available.

TABLE 5 List of scenarios used in scenario analysis and associated attribute values

			Bus		Rail		Ride-hailing		Shared Ride-hailing	
Scenario	**Trip Type**	**Distance (mi)**	**Price**	**Time (min)**	**Price**	**Time (min)**	**Price**	**Time (min)**	**Price**	**Time (min)**
1	Long trip	10.8	$2.00	80	$4.15	31	$35	25	$28	30
2	Pro-rail	3.8	$2.00	27	$2.00	15	$13	15	$10	20
3	Rail with transfer	3.8	$2.00	40	$2.25	28	$15	25	$12	30
4	Pro-bus	1.3	$2.00	17	$3.00	45 (bus to rail transfer)	$13	15	$10	20
5	Trip from lower income area	4	$2.00	40	$2.29	18	$11	10	$9	15
6	Bad transit options	5	$2.00	44	$3.00	46 (bus to rail transfer)	$17	15	$14	20

The six scenarios we developed aim to capture various trips individuals might take, including those who might travel to the city from the outer-lying regions via one mode (e.g., personal vehicle or train) and then travel within the city using additional modes. We once again based the travel times and prices for the scenarios on standard values for the region. We selected scenarios that matched the median trip length (distance) for non-commute trips within the region [20], as well as edge case scenarios in which we expected certain modes to be considered generally preferable. The scenario names indicate their archetypal trip type. For example, “Pro-Metro” indicates a trip in which the rail system (Metrorail) has a direct route between the trip start and end points. **Figure 4** illustrates the results of the scenario analyses. Status quo indicates current travel times and prices. As we move across the x-axis, we introduce automation, a discount, and having an attendant present for the **ride-hailing** and **shared ride-hailing** modes.

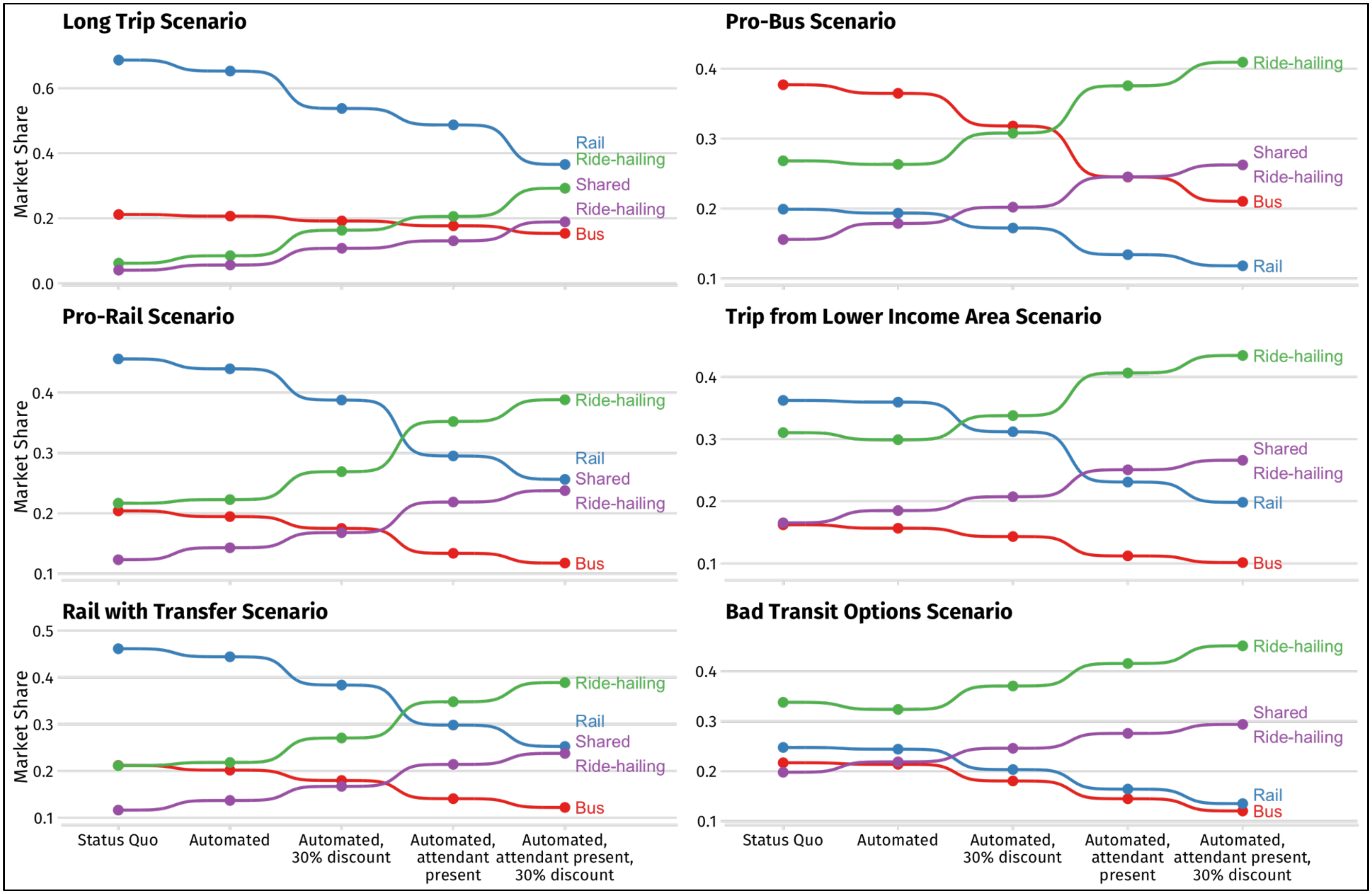

Figure 4 Mean estimated values for predicted market share based on introducing automation, an attendant, and price discounts for six trip scenarios. As one moves left to right across the x-axis, additional features are added to the *ride-hailing* and *shared ride-hailing modes*. "Status Quo" indicates that none of the modes are automated or have an attendant, and that the modes' prices reflect current prices. A version with 95% confidence interval error bars is available in Appendix C.

The following observations emerge from the scenario analysis:

1. Competition between transit modes and automated ride-hailing services (shared or not) stems more from price discounts than an inherent interest in automation.
2. For trips where rail dominates preferences in the status quo, it remains competitive even against discounted ride-hailing services that are automated and have an attendant.
3. Shared ride-hailing services largely remained unpopular, even with additional features and discounts.
4. For trips where people were already likely to use ride-hailing services, that likelihood increases with the addition of automation, an attendant, and a price discount. This supports the idea that automated ride-hailing could help to fill existing transportation gaps.

DISCUSSION

The results of the study indicate that fears of a mass transition away from transit to AVs may be limited by people's willingness to use AVs, at least in the short term. Respondents to our survey on average were only willing to pay a premium for automated modes when a vehicle attendant was also present, limiting the potential cost savings that AV operators might achieve by removing the driver. Nonetheless, attendant presence may be a critical feature for early AV adoption. Even without a discount, respondents demonstrated a positive willingness-to-pay for automated modes with an attendant onboard.

In many respects, an AV with an attendant onboard is fairly equivalent to current non-automated ride-hailing modes with a human driver. It is then perhaps counterintuitive that individuals would pay more for this feature. One potential explanation is that respondents may perceive computer-driven vehicles as safer or more reliable than those operated by human drivers. Indeed, some prior public focus group research has found evidence of this type of reasoning [35]. Nonetheless, people may not be fully comfortable ceding total control to automated systems, hence the desire for an attendant. Though our survey specified that the attendant's role was not to operate the vehicle, survey respondents may still have considered the attendant as a safety backup in case of emergency. Future qualitative studies could further explore perceptions of AV attendants and the multiple roles they might be expected to fill.

The presence of an AV attendant appears especially critical for women. Women only became ambivalent towards automated buses and automated shared ride-hailing services when the modes included an AV attendant. These results perhaps indicate that the presence of an attendant is an essential feature for women to consider using either of these modes, even at costs equivalent to rail. Overall, competition with public transportation may remain limited by the types of individuals who currently express the greatest willingness-to-pay for AVs: men and higher income individuals. These two groups make up a smaller share of current public transportation users in the United States [36], thus ridership losses among those two demographic groups would yield smaller impacts on overall ridership numbers. Nevertheless, the authors recognize that siphoning even small portions of riders away from public transportation modes could still negatively impact the system.

Although the Washington, DC Metropolitan Region has featured some AV pilots and testing [37], we expect that the majority of survey respondents had minimal (if any) experience with an automated vehicle. Approximately 62% of our sample reported having prior experience with ride-hailing services. Individuals' attitudes towards AVs might change as automated transportation modes become more widespread and they gain either exposure to or experience with using automated modes, as has been found with other emerging transportation technologies. This study provides a valuable data point of preferences as they currently stand—a snapshot of the market that both AV developers and transportation planners must face as they plan for an automated future.

CONCLUSIONS

In this study, we investigated the previously unexplored question of the extent to which automated ride-hailing services might compete with public transit modes in the United States. Using data from an online choice-based conjoint survey fielded in the Washington, DC Metropolitan Region, we estimated discrete choice models and used them to simulate choice probabilities for a variety of trips. We find that public interest in automated ride-hailing services stems primarily from the potential to achieve lower prices rather than an inherent interest in automation. Given the current business models for ride-hailing companies, potential competition of automated ride-hailing and shared ride-hailing services with transit modes will likely be limited, since driver costs only account for approximately 20% of ride-hailing companies' current operating budgets [32], [33]. Furthermore, for trips where desirable transit modes are available (i.e., low cost and relatively low travel time), transit modes remain competitive even against discounted and automated ride-hailing modes. Thus, investment in improving transit options could also stem future competition with AVs.

Our results also suggest that a vehicle attendant is important for increasing AV use. Individuals primarily expressed a positive willingness-to-pay for automated modes only when an attendant was also present. Gender differences also play a role, with men expressing a greater average WTP for automated modes than women. On average, women only expressed a positive WTP for automated ride-hailing services when an attendant was also onboard.

Gaining a greater understanding of public preferences for automated and non-automated modes enables transportation planners to begin designing future transportation systems that account for shifting preferences while still providing critical public transit services. Automated mobility providers can also use this information when making important design and service decisions, such as whether to include an onboard attendant and setting prices. At present, keeping attendants onboard appears critical for both men and women, though these preferences could change as AV deployment expands and users gain more experience with these systems.

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AUTHOR CONTRIBUTIONS

The authors confirm contribution to the paper as follows: study conception and design: L. Kaplan and J.P. Helveston; data collection: L. Kaplan; analysis and interpretation of results: L. Kaplan and J.P. Helveston; draft manuscript preparation: L. Kaplan. Both authors edited and approved the final version of the manuscript.

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