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Undercutting Transit? Exploring Potential Competition Between Automated Vehicles and Public Transportation in the United States

Leah Kaplan[1] and John Paul Helveston[1]

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 significant 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 used responses from an online choice-based conjoint survey fielded in the Washington, D.C. metropolitan region (N = 1,694) in October 2021 to estimate discrete choice models of public preferences for different automated (ride-hailing, shared ride-hailing, bus) and nonautomated (ride-hailing, shared ride-hailing, bus, rail) modes. We used 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. Scenario analysis additionally 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 the presence of an AV attendant as a critical feature for early AV adoption.

Keyword

innovative public transportation services and technologies, autonomous vehicles, stated preference, discrete choice, ridesharing

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 (*1–3*). 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 (*4*). If vehicle automation enables significant price decreases and increased availability of ride-hailing services, some fear that it could undercut public transit, which could have significant implications for the environment and transportation equity (*5*, *6*). Public transit plays a critical role in reducing emissions from transportation (*7*), mitigating road congestion, and providing basic mobility for individuals with limited to no other transportation options. As

[1]Department of Engineering Management and Systems Engineering, The George Washington University, Washington, D.C

Corresponding Author:
Leah Kaplan, leahkaplan@gwu.edu

one U.S. Federal Highway Administration report highlights, over 90% of public assistance recipients lack access to a vehicle and rely on public transit (*8*).

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 (*9*, *10*), whereas others find that current transit users lack significant interest in automated modes (*11*, *12*). Furthermore, public attitudes toward 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 on the potential impacts of automation on the billions of annual public transportation trips taken in the United States each year (9.9 billion in 2019) (*13*). Prior U.S.-based studies have either focused on one mode or omitted transit, limiting the ability to compare preferences between different automated modes (*11*, *14–20*). This study aimed to fill this gap by investigating public preferences for transit and ride-hailing modes with and without automation. We centered our analyses on the following two research questions:

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

We addressed these questions using data from an online choice-based conjoint (CBC) survey fielded in the Washington, D.C. metropolitan region (N = 1,694) in October 2021. We estimated discrete choice models of public preferences for different automated and nonautomated transportation modes, and then we used the estimated models to simulate future marketplace competition across a range of trip scenarios.

Literature on AV Preferences

Several studies on preferences for AVs have focused on factors associated with private AV ownership, such as consumers' perceived comfort with riding in an AV and their willingness to pay for features associated with different levels of automation (*14*, *18*, *21*, *22*). These studies often employ Likert scales (typically ranging from 1 to 5) or other similar rating systems to assess attitudes toward different automated modes. Although these studies provide insights into general consumer perceptions of AVs, they lack the ability to gauge potential substitution patterns between automated and nonautomated transportation modes.

To address this, some researchers have used 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. Conjoint surveys offer unique advantages, including the ability to explore hypothetical products, present multiple choice sets to the same respondent, fix all attributes of a given option, and avoid multicollinearities (*23*). 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 nonautomated transportation modes. The majority of these prior studies compare automated modes with conventional, nonautomated private cars.

The general consensus across most of these studies is that conventional, nonautomated vehicles continue to dominate preferences. For example, in Krueger et al.'s conjoint study of 435 residents of major metropolitan areas in Australia, respondents chose an automated mode in only 28% of the choice situations (*9*). Haboucha et al. surveyed 721 commuters in Israel, the United States, and Canada and found that 44% of respondents preferred conventional vehicles over private or shared AVs (*15*). This preference was even more pronounced among North American respondents, with 54% preferring conventional vehicles. Yap et al. asked Dutch travelers about their interest in AVs as a transportation option for filling the last-mile trip between a train station and a traveler's final destination, and even in this limited context respondents mostly selected the individual vehicle alternative over all other transportation options (*24*). Etzioni et al. surveyed 1,669 individuals across six EU countries and similarly found strong preferences for conventional vehicles, with respondents selecting conventional vehicles in 70% of the choices (*25*). Respondents in Zhong et al.'s survey of U.S. residents in small and medium metropolitan areas in the United States preferred their current private vehicles over private AVs and AV ride-hailing options (*20*). These studies signal that individuals are not likely to relinquish their personal vehicles in favor of AVs in the near future.

The strong preference for conventional vehicles, however, may mask other potential substitution effects that could occur with the introduction of AVs. Several of the aforementioned studies restricted their survey sample to individuals who have a driver's license, with some also

Table 1. Summary of Modes Investigated in Prior AV Conjoint Studies

		Nonautomated					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. * (*9*)	Australia	X	X	X	X	X		X	X	
Yap et al. (*24*)	Netherlands	X			X	X		X	X	
Steck et al. (*10*)	Germany				X	X	X	X	X	
Ashkrof et al. (*26*)	Netherlands	X			X			X		
Winter et al. (*12*)	Netherlands	X	X		X			X		
Etzioni et al. (*25*)	Cyprus, UK, Slovenia, Montenegro, Hungary, Iceland	X					X	X	X	
Daziano et al. (*14*)	USA	X					X			
Haboucha et al. (*15*)	USA, Canada, and Israel	X					X	X		
Lavieri and Bhat (*17*)	USA							X	X	
Zhong et al. (*20*)	USA	X					X	X	X	
This study	Washington, D.C.		X	X	X			X	X	X

Note: AV = automated vehicle.
*Nonautomated modes were collected as a self-reported reference trip.

requiring that respondents drive a personal vehicle frequently (*15*, *20*, *26*). 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. Moreover, even individuals who typically use their private vehicles might use transit for specific types of trips (e.g., traveling within the city after commuting from the suburbs, trips where parking is expected to be difficult). Substitution of these trips with AVs, in conjunction with changing transportation patterns for frequent transit users, is likely to have a greater impact on transit ridership.

The existing literature on AV substitution with transit is limited and inconclusive. Some studies find a preference for AVs over transit modes, such as in Steck et al.'s survey of 173 Germans (*10*). In the study, respondents could select from among privately owned AVs, automated ride-hailing (both shared and nonshared), walking, biking, and public transit. Overall, respondents found the private AV option most attractive, followed by AV ride-hailing, and finally transit. Ashkrof et al. explored preferences for conventional cars, AV ride-hailing, and transit among a sample of 663 Dutch respondents (*26*). Individuals similarly preferred AVs over transit, especially when the choice question was framed as a long-distance trip. Yet other studies suggest more limited competition of AVs with transit. In Yap et al.'s 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 (*24*). Winter et al. identified different classes of users among a sample of 796 Dutch survey respondents and found that respondents who currently commute by public transport actually show the lowest preference for automated modes (*12*), affirming Krueger et al.'s finding that current transit users were not more likely to switch to an automated mode (*9*).

There are some mode features that are particularly relevant when considering an AV future. Ride-sharing (i.e., riding with a stranger who is traveling in a similar direction) is already available in some cities via services like UberPool and Lyft Shared (*27*, *28*). Though ride-hailing companies canceled these services during the COVID-19 pandemic, some are now starting to reintroduce them. 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 (*5*). Despite enthusiasm from environmental advocates, the public seems less interested in a future of shared rides. As of 2017, pooled rides comprised just 20% of all Uber rides and 40% of all Lyft rides (*29*), and current literature suggests that these preferences may persist in an AV future. In Lavieri and Bhat's conjoint study on automated ride-hailing with sharing and nonsharing options, respondents chose to ride alone in 48.3% of choice occasions with work trips and 54% of choice occasions for leisure trips (*17*). Over the past few years, greater exposure to ride-sharing services as well as the COVID-19 pandemic may have altered individuals' attitudes toward sharing. Thus, sharing as a feature of automated ride-hailing services warrants further investigation.

A second mode feature—the presence of an AV attendant—is associated with additional services 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 (SP) surveys and choice studies on AVs is that women appear less likely to use AVs than men (*30*, *31*), and some hypothesize that this hesitation toward AVs may stem in part from personal security concerns (*18*, *32*, *33*). Dong et al.'s survey of University of Pennsylvania employees found that only 13% of respondents would agree to ride an automated bus without an employee on board (*34*). Similarly, in their multicountry survey on potential AV use, Kyriakidis et al. asked respondents about their willingness to use an AV when a human operator was and was not on board (*35*). The study found that people were more willing to travel in an AV and to allow their children to travel in an AV with an operator present. These findings suggest that operator presence might be an important feature that might affect whether individuals would prefer AVs over traditional modes. Although some AV companies are already operating their vehicles with onboard attendants in small pilots (*36*), 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 several studies conducted only within the past 6 years. Few studies have considered the impacts of AVs on current transit use, and no conjoint studies have examined the 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 addressed these gaps by fielding a United States-based conjoint study on preferences for

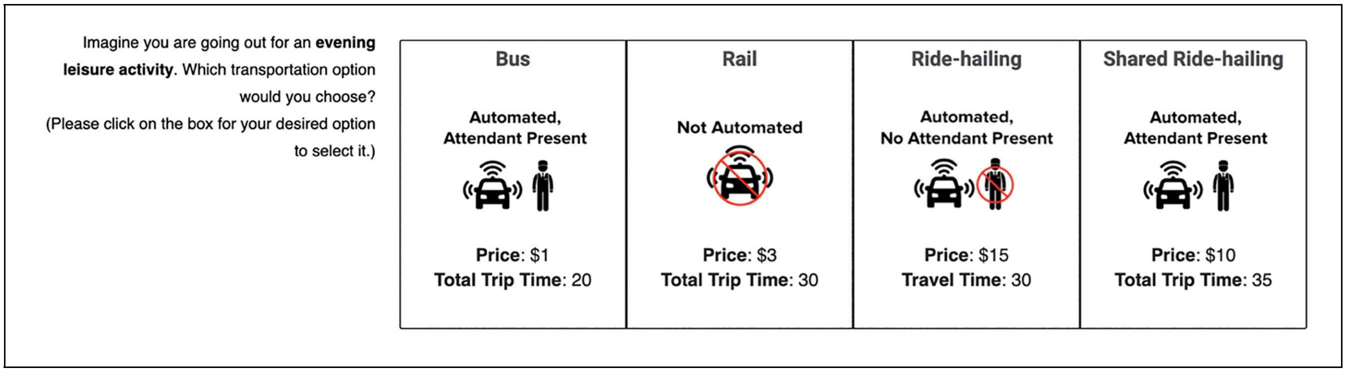

Figure 1. Sample choice-based conjoint question.

automated (ride-hailing, shared ride-hailing, bus) and nonautomated (ride-hailing, shared ride-hailing, bus, rail) modes.

Methods

AV services are primarily in the pilot and development phases, limiting the availability of revealed-preference (RP) data. In this study, we used an SP conjoint approach to measure public preferences for various automated modes. CBC analysis has a history of use in the automotive industry for evaluating preferences for both traditional vehicles and new vehicle technologies such as electric vehicles (*37*). It has also been used in several recent studies on automated driving (*9*, *14*, *15*, *20*, *24*, *38*). 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 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 for reasons such as social signaling and social adoption (*39*, *40*). 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 (*41*), and the full survey, data, and code used 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 (*42*). The survey was fielded within the Washington, D.C. metropolitan region to situate decision tradeoffs within a local context. The survey included three main parts: 1) background information and current transportation routines, 2) CBC questions, and 3) demographic questions. The background information section included a video clip describing the six levels of automation as defined by the Society of Automotive Engineers (*43*, *44*). We defined automated modes as Level 5 vehicles with the following description: "Vehicles that are automated would be operated by computer systems with no assistance from a human driver. No option to take control of the vehicle would be available." We also provided pictures and brief descriptions for how an automated bus, ride-hailing service, and shared ride-hailing service are expected to function.

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 noncommuting trips. The majority of prior AV preference studies have focused on commuting journeys, yet noncommuting trips account for approximately 78% of trips within the Washington, D.C. metropolitan region (*45*, *46*). We additionally hypothesized that focusing on evening trips would increase any potential value of having an attendant on board, per the aforementioned discussion about personal security. Future

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 (shared ride-hailing travel time set at between 80% and 120% of ride-hailing time)	15, 20, 25, 30, 35
Bus	20, 25, 30, 35, 40
Rail	15, 20, 25, 30, 35
Price ($)	
Ride-hailing (shared ride-hailing set at 50% to 80% of the associated ride-hailing price)	5, 7, 10, 12, 15
Bus	1, 2, 3, 4, 5
Rail	2, 3, 4, 5, 6

studies might investigate the extent to which time-of-day framing affects individuals' responses.

The five attributes investigated in this study were mode, automation (yes/no), attendant (yes/no), total trip time, and price. Although other attributes, such as wait time, have been found to affect individuals' mode choices (*9*, *24*), the respondents of initial pilot surveys reported feeling overwhelmed by the complexity of choice questions that included more attributes, including wait time. Balancing design complexity with showing realistic choices remains a challenge with the CBC method, and as Cherchi and Hensher note, the acceptable level of design complexity can vary among contexts, with some researchers recommending inclusion of no more than six different attributes (*47*). During the first pilot test of our survey, respondents reported feeling similarly overwhelmed by the complexity of the choice questions, which included wait time as an additional attribute. We subsequently chose to decrease the number of attributes to focus on identifying the potential impacts of attendant presence for automated modes, which has received less attention in the literature. We acknowledge this narrower focus as a limitation of our study.

To ensure that the price and time levels shown were calibrated to local market conditions in the Washington, D.C. metropolitan region, we determined ranges for the attribute values for each mode based on current travel times and prices as determined by GoogleMaps, the CityMapper transportation planning app, and ride-hailing price calculators (see Table 2) (*47–50*). 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% and 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% and 120% of the ride-hailing times. Although 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."

To design our choice experiment, we started by creating a full factorial design of experiment (DOE) matrix using all of the combinations of attributes for each individual mode but with the restrictions previously described (e.g., only automated modes could have an attendant), resulting in 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, with checks added to ensure that no one respondent saw a repeated choice question and that each choice question showed each of the four available modes. The use of random choice set assignment over other design strategies (such as D-optimal designs) was chosen as a tradeoff in parameter precision and the ability to observe potential interaction effects; a randomized design avoids confounding interaction and main effects at the expense of statistical precision (*23*). Rather than generate a single fractional factorial design, each respondent was shown a randomly generated set of choice sets drawn from the full set of possible combinations. This approach ensured sufficient variation across all combinations of attributes so as to be able to identify possible interaction effects. The primary disadvantage of this approach is that the resulting estimated standard errors may be larger than they otherwise could have been had we used a more efficient design. The researchers also checked to ensure that each respondent saw a variety of attribute levels and that no attribute level appeared to dominate. The final section of the survey collected demographic information including age, gender, race, education level, and household income. The survey also captured information that could help identify individuals who may face transportation barriers. These questions included whether the respondent has any type of disability, has a smartphone, and has access to a bank account (full survey available in Appendix A).

Before 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 Dynata, a market research firm, to recruit the full survey sample. Dynata recruits survey respondents using multiple types of incentives including cash and donations to charity. We limited the survey sample to adults (individuals over 18) who live within the Washington, D.C. metropolitan region (screened for using zip codes).

Model Specification

We modeled 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 assumed that the error term followed a Gumbel extreme value distribution, yielding Equation 1, a convenient closed-form expression that an individual will choose option j from the choice set, J_C (cf. Train [*51*]),

$$P_{ij} = \frac{e^{v_j}}{\sum_{k \in J_c} e^{v_k}} \; \forall \; c \; \in \{1, \; 2, \; 3, \; \ldots C\}, \; j \in J_C \quad (1)$$

where

c indexes a set of C choice sets,

J_C represents the cth choice set, and

v_j captures the observed portion of the utility model.

The standard multinomial logit (MNL) model 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 estimated mixed logit (MXL) models, a widely used extension of the MNL model (*20*). The MXL model allows for flexible substitution patterns and relaxes the assumption of independence of the error term (*52*). For this study, we assumed that the mode parameters are drawn from independent normal distributions across the respondent population. We also estimated separate travel time coefficients for each mode to capture how individuals may value their time differently when using different modes.

Table 3. Description of Model Variables

Variable	Description
p_j	Price in U.S. dollars
$x_j^{travelTime}$	Total trip travel time in minutes
δ^{bus}	Dummy coefficient for bus mode type {1: yes, 0: no} (base level is rail)
δ^{RH}	Dummy coefficient for ride-hailing mode type
$\delta^{sharedRH}$	Dummy coefficient for shared ride-hailing mode type
γ	Dummy coefficient for whether the mode is automated {1: yes, 0: no}
τ	Dummy coefficient for whether there is an attendant present {1: yes, 0: no}

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 specified 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 (*53*, *54*). The general WTP space utility model is shown in Equation 2,

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

where

p_j is price,

λ is a scale parameter,

x_j is all nonprice attributes, and

$\boldsymbol{\omega}$ is a vector of WTP coefficients for nonprice attributes.

For MXL 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 with WTP computed from preference space model coefficients (*53–55*). Equation 3 shows the full model used in the study, with explanations of the variable names in Table 3:

$$u_j = \lambda \begin{pmatrix} \beta_1 x_j^{time} + \beta_2 x_j^{time}\delta^{bus} + \beta_3 x_j^{time}\delta^{RH} + \beta_4 x_j^{time}\delta^{sharedRH} \\ + \beta_5\delta^{bus} + \beta_6\gamma\delta^{bus} + \beta_7\tau\gamma\delta^{bus} \\ + \beta_8\delta^{RH} + \beta_9\gamma\delta^{RH} + \beta_{10}\tau\gamma\delta^{RH} \\ + \beta_{11}\delta^{sharedRH} + \beta_{12}\gamma\delta^{sharedRH} + \beta_{13}\tau\gamma\delta^{sharedRH} \\ -p_j \end{pmatrix} + \varepsilon_j \quad (3)$$

All models were estimated using the *logitr* R package, which uses maximum simulated likelihood estimation to estimate MXL models (*56*). 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 using the equation below (*51*), where P_{nj} is defined by Equation 1,

$$L = \sum_n^N \sum_j^J y_{nj} \ln P_{nj}, \quad (4)$$

Given the nonconvex nature of WTP space log-likelihood functions, we used a randomized multistart 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 the demographic information necessary for the primary model and subgroup analyses were removed. After filtering the data based on these criteria, the final sample size was 1,694 respondents for a total of 13,712 CBC responses. The final sample closely matched the demographics of the Washington, D.C. metropolitan region, as reported by the National Capital Region (NCR) Transportation Planning Board's 2017/2018 Regional Travel Survey, a once-in-a-decade survey that collected detailed demographic and travel behavior information from approximately 16,000 randomly selected area households within the Washington, D.C. metropolitan region (*57*). The most significant difference between our sample and the reference sample was the overrepresentation of individuals who self-identified as male. Our results were robust with and without weights to account for this gender imbalance (weighted model results are available in Appendix B). Table 4 presents descriptive statistics of the final survey sample.

Table 4. Summary Statistics of Survey Sample Compared with the Regional Travel Survey as a Reference Sample

Characteristic	N = 1,694[1]	Reference sample, %
Gender		
Female	668 (39%)	52.3
Male	989 (58%)	47.7
Transgender/gender nonconforming	37 (2.2%)	NA
Age		
18–24	120 (7.1%)	7.8
25–34	367 (22%)	17.8
35–44	577 (34%)	20.1
45–54	253 (15%)	17.3
55–64	133 (7.9%)	17.7
65–74	181 (11%)	13.4
75–84	51 (3.0%)	4.7
85 +	4 (0.2%)	1.3
Unknown	8	NA
Annual household income		
Less than $15,000	66 (3.9%)	3.0
$15,000–24,999	42 (2.5%)	2.7
$25,000–34,999	73 (4.3%)	3.2
$35,000–49,999	126 (7.4%)	6.4
$50,000–74,999	202 (12%)	12.9
$75,000–99,999	189 (11%)	15
$100,000–149,999	260 (15%)	24.8
$150,000 or more	736 (43%)	31.9
Education		
No high school or high school	142 (8.4%)	NA
Some college/associate's	342 (20%)	NA
Bachelor's degree	564 (33%)	NA
Graduate or professional degree	639 (38%)	NA
Unknown	7	NA
Bank account access		
No	28 (1.7%)	NA
Yes	1,537 (91%)	NA
Doesn't use regularly	129 (7.6%)	NA
Phone access		
No cellphone	28 (1.7%)	NA
No smartphone	290 (17%)	NA
Has smartphone	1,376 (81%)	NA
Disability		
None	993 (59%)	NA
Intellectual	61 (3.6%)	NA
Physical	537 (32%)	NA
Visual	99 (5.8%)	NA
Physical and visual	4 (0.2%)	NA

Note: NA indicates that information about this category was not available for the reference sample.
[1] *n* (%)

Effects of Adding Automation and an Attendant

Table 5 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 computed the WTP for automating the modes and adding a vehicle attendant for the bus, ride-hailing, and shared ride-hailing modes. Using nonautomated rail as the baseline, Figure 2 displays individuals' WTP for the three other modes, all things being 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. Since it does not make sense to consider a zero minute trip, we plotted mode preferences for a short trip and a long trip. The longer trip length did slightly increase the WTP values for the bus, ride-hailing, and shared ride-hailing modes, but it did not change the overall trends in how automation and the presence of an attendant affected mode preferences.

In the status quo (not automated) cases, individuals had negative WTPs for the bus, ride-hailing, and shared ride-hailing modes, with the exception of a slightly positive WTP for the ride-hailing mode for a long trip. Adding automation did not significantly change WTP for the three modes for either trip length. The addition of an attendant to the automated modes, however, did result in a significant shift to positive WTPs for automated buses, automated ride-hailing services, and automated shared ride-hailing services. In the discussion section, we hypothesize about the interpretation of this result.

Subgroup Analyses

We performed subgroup analyses to investigate potential preference differences based on income, race, and gender. The survey sample included 33 individuals who self-identified their gender identity as transgender male, transgender female, gender queer, or gender nonconforming. We grouped all of these individuals with respondents who identified as female, given the higher rates of violence and discrimination that transgender and gender nonconforming individuals face (*58*). We hypothesized that such experiences might affect their attitudes toward safety, especially in relation to sharing rides. Alternative groupings did not change the reported results in aggregate.

To perform the subgroup analyses, we directly estimated MXL WTP models for different subgroups. Since WTP space estimation is independent of scale, we could 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 affect attitudes toward conventional transportation modes and AVs (*18*, *21*, *31*). No consistent differences emerged in our results for racial differences, though we were limited by our sample, which was mostly white. Higher-income individuals expressed a higher WTP for automation and an attendant, perhaps owing to their overall lower price sensitivity. A gender-based subgroup analysis revealed that although women and men shared similar baseline preferences for nonautomated modes, men expressed significantly higher WTPs for automated modes and automated modes that also included an attendant for a long trip (Figure 3). For a short trip, gender differences only emerged when the automated modes also included an attendant.

Even with the addition of the attendant to the automated modes, women only demonstrated a positive WTP for the automated ride-hailing mode for a long trip. The gender subgroup analysis revealed that the positive WTPs from the whole-group analysis stemmed primarily from the men in our sample.

Scenario Analyses

The WTP estimates provided insights into preferences for the different modes, all things being 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 used the estimated MXL choice model to simulate how AVs might compete with transit. We explored six scenarios of characteristic trips across Washington, D.C. (Table 6). We used our "low-income model" to conduct the scenario analysis for Scenario 5 (trip from lower-income area), recognizing that individuals making those types of trips may be members of lower-earning households. Considering the status quo times and prices as the baseline, we modeled how demand for each mode (evaluated in relation to 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 (*59*, *60*). These scenario analyses should not be interpreted as forecasts but rather as illustrative examples of the substitution patterns that our estimated choice model predicted 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 things being equal context of WTP coefficients (*15*, *37*). Real-world

Table 5. Discrete Choice Model Coefficients in WTP Space

Attribute	Coef.	Mean / sd	MXL	Male	Female	Mid/high income	Low income
Lambda	λ		0.094 (0.006) ***	0.074 (0.008) ***	0.130 (0.011) ***	0.083 (0.007) ***	0.152 (0.018) ***
Travel time	β_1		−0.573 (0.049) ***	−0.684 (0.086) ***	−0.460 (0.053) ***	−0.647 (0.065) ***	−0.353 (0.060) ***
Bus travel time	β_2		0.062 (0.049)	0.133 (0.083)	−0.007 (0.056)	0.086 (0.063)	0.002 (0.067)
RH travel time	β_3		0.232 (0.053) ***	0.366 (0.090) ***	0.095 (0.061)	0.267 (0.067) ***	0.096 (0.082)
Shared RH travel time	β_4		0.203 (0.050) ***	0.426 (0.087) ***	−0.014 (0.057)	0.289 (0.064) ***	−0.055 (0.069)
Bus	β_5	μ	−6.665 (1.454) ***	−9.267 (2.463) ***	−3.870 (1.605) *	−8.845 (1.898) ***	−1.526 (1.905)
(Base = rail)		σ	−10.632 (0.835) ***	−13.032 (1.521) ***	−8.094 (0.858) ***	−12.299 (1.155) ***	−6.213 (0.926) ***
Bus, automated	β_6		1.220 (0.725)	5.489 (1.257) ***	−2.628 (0.907) **	2.739 (0.930) **	−2.118 (1.042) *
Bus, attendant present	β_7		9.822 (1.078) ***	14.478 (2.067) ***	5.072 (1.035) ***	11.615 (1.453) ***	4.595 (1.176) ***
Ride-hailing	β_8	μ	−7.193 (1.573) ***	−11.883 (2.762) ***	−2.504 (1.716)	−8.106 (1.972) ***	−4.082 (2.406)
(Base = rail)		σ	13.168 (0.886) ***	−14.424 (1.554) ***	11.830 (0.972) ***	−14.042 (1.158) ***	10.506 (1.180) ***
RH, automated	β_9		0.731 (0.802)	4.772 (1.360) ***	−2.855 (0.992) **	1.573 (0.992)	−1.775 (1.267)
RH, attendant present	β_{10}		10.931 (1.106) ***	16.180 (2.150) ***	5.412 (1.064) ***	12.456 (1.449) ***	6.590 (1.474) ***
Shared RH	β_{11}	μ	−11.535 (1.584) ***	−18.273 (2.957) ***	−4.819 (1.624) **	−14.461 (2.102) ***	−2.732 (1.981)
(Base = rail)		σ	−12.503 (0.913) ***	13.472 (1.513) ***	−11.212 (1.036) ***	13.479 (1.179) ***	−9.824 (1.258) ***
Shared RH, automated	β_{12}		2.903 (0.815) ***	8.047 (1.539) ***	−1.748 (0.974)	4.338 (1.034) ***	−1.113 (1.305)
Shared RH, attendant present	β_{13}		8.560 (1.011) ***	10.902 (1.720) ***	6.195 (1.162) ***	9.385 (1.276) ***	6.253 (1.533) ***
Log-likelihood			−16,798.2	−9,742.6	−6,780.3	−13,781.7	−2,942.9
Null log-likelihood			−18,787.1	−10,968.4	−7,818.7	−15,382.3	−3,404.7
AIC			33,630.3	19,519.3	13,594.6	27,597.4	5,919.9
BIC			33,758.1	19,637.9	13,707.4	27,721.7	6,018.6
McFadden's R^2			0.1	0.1	0.1	0.1	0.1
Adjusted McFadden's R^2			0.1	0.1	0.1	0.1	0.1
Number of observations			13,552.0	7,912.0	5,640.0	11,096.0	2,456.0
Number of respondents			1,694.0	989.0	705.0	1,387.0	307.0

Note: WTP = willingness-to-pay; Coef. = coefficient; RH = ride-hailing; MXL = mixed logit; AIC = Akaike information criterion; BIC = Bayesian information criterion.
Standard errors of estimates are presented in parentheses. Coefficient units are in U.S. dollars ($).
*$p \leq 0.05$; **$p \leq 0.01$; ***$p \leq 0.0001$.

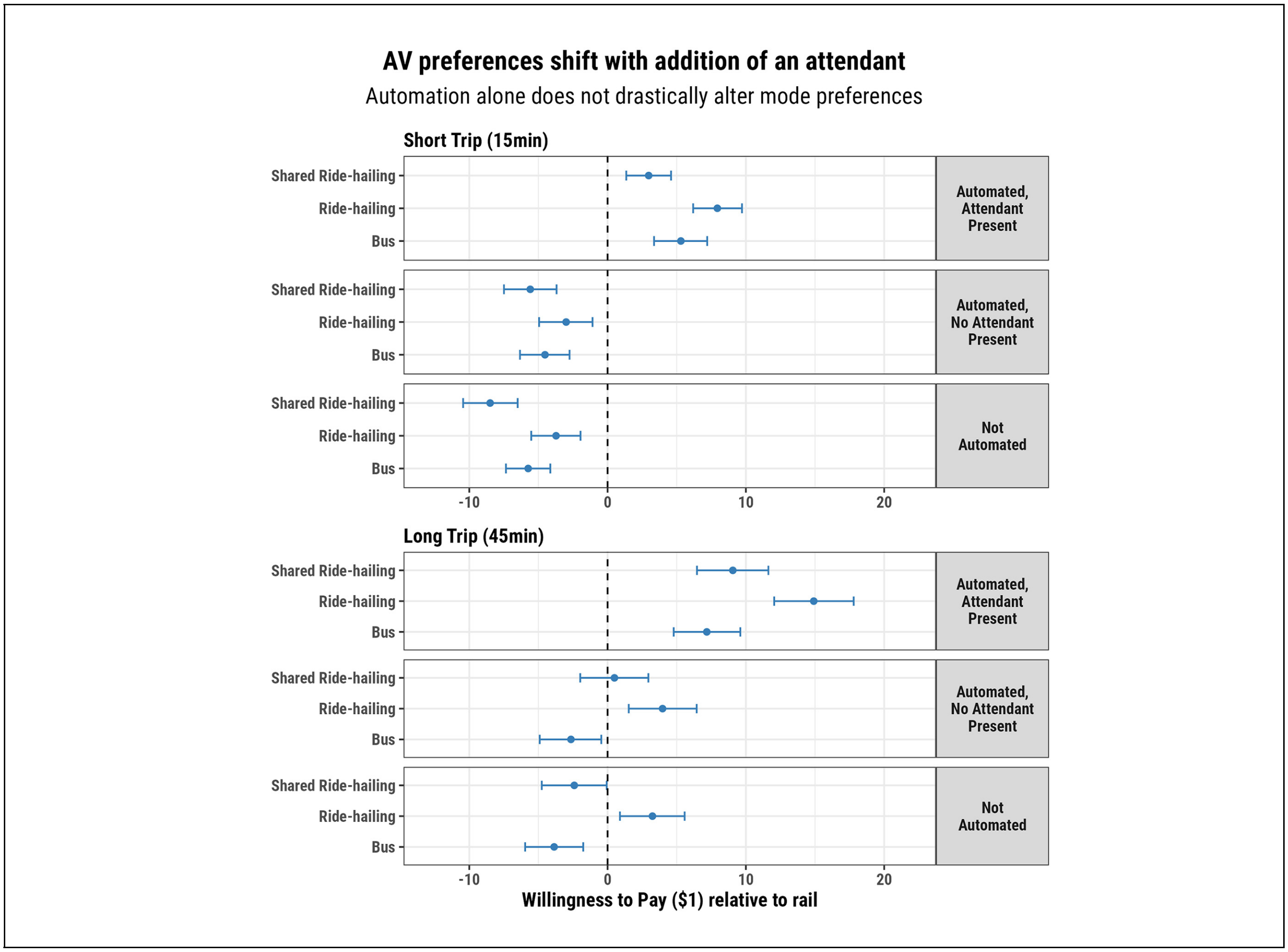

Figure 2. Average willingness-to-pay values with 95% confidence interval bounds for the bus, ride-hailing, and shared ride-hailing modes relative to nonautomated rail. Results shown for a short trip and a long trip.

forecasts would need to consider preferences of a much broader population and (ideally) include RP data when they become available.

The six scenarios we developed aimed to capture various trips individuals might take, including those who might travel to the city from the outlying regions via one mode (e.g., personal vehicle or train) and then travel within the city using additional modes. We based the travel times and prices for the scenarios on estimated values from Google Maps, Lyft's, and Uber's price estimators, the CityMapper travel planning app, and the Washington Metropolitan Area Transit Authority online price estimator (*48–50*, *61*, *62*). We selected scenarios that matched the median trip length (distance) for noncommute trips within the Washington, D.C. metropolitan region (*45*), 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.

The following observations emerged from the scenario analyses:

1. Competition between transit modes and automated ride-hailing services (shared or not) stemmed more from price discounts than an inherent interest in automation.
2. For trips in which rail dominates preferences in the status quo, it remained competitive even against discounted ride-hailing services that were automated, though was less competitive once an attendant was added to the automated modes.

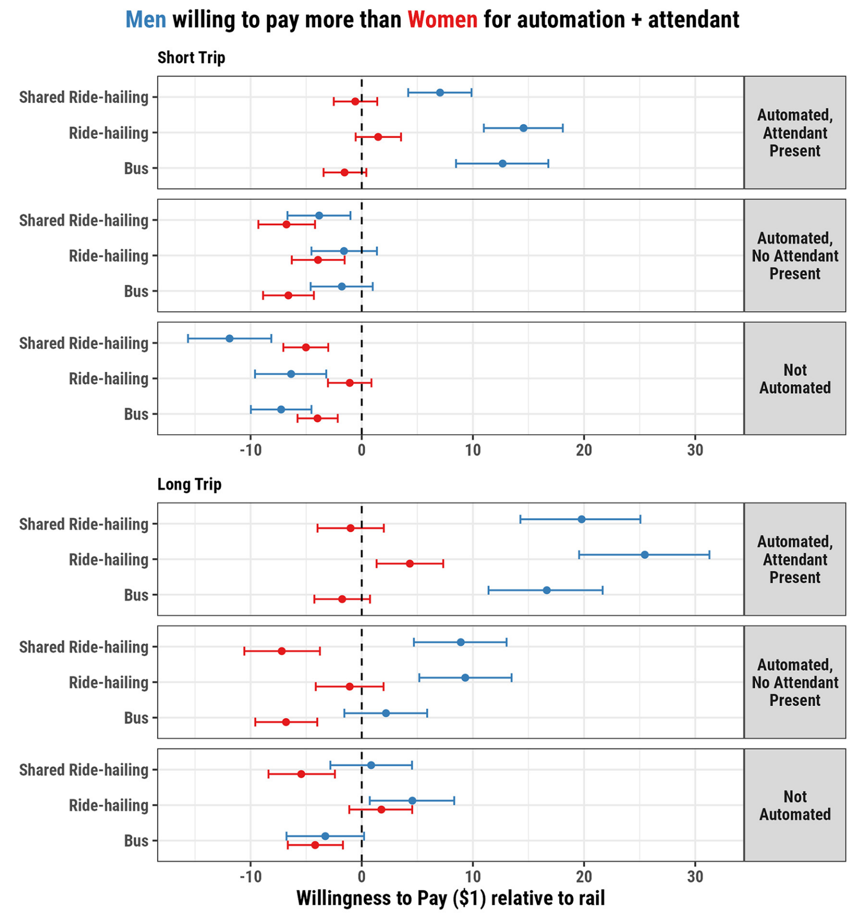

Figure 3. Gender differences in average willingness-to-pay values with 95% confidence interval bounds for a short trip and a long trip.

Table 6. 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	35.00	25	28.00	30
2	Pro-rail	3.8	2.00	27	2.00	15	13.00	15	10.00	20
3	Rail with transfer	3.8	2.00	40	2.25	28	15.00	25	12.00	30
4	Pro-bus	1.3	2.00	17	3.00	45 (bus to rail transfer)	13.00	15	10.00	20
5	Trip from lower-income area	4	2.00	40	2.29	18	11.00	10	9.00	15
6	Bad transit options	5	2.00	44	3.00	46 (bus to rail transfer)	17.00	15	14.00	20

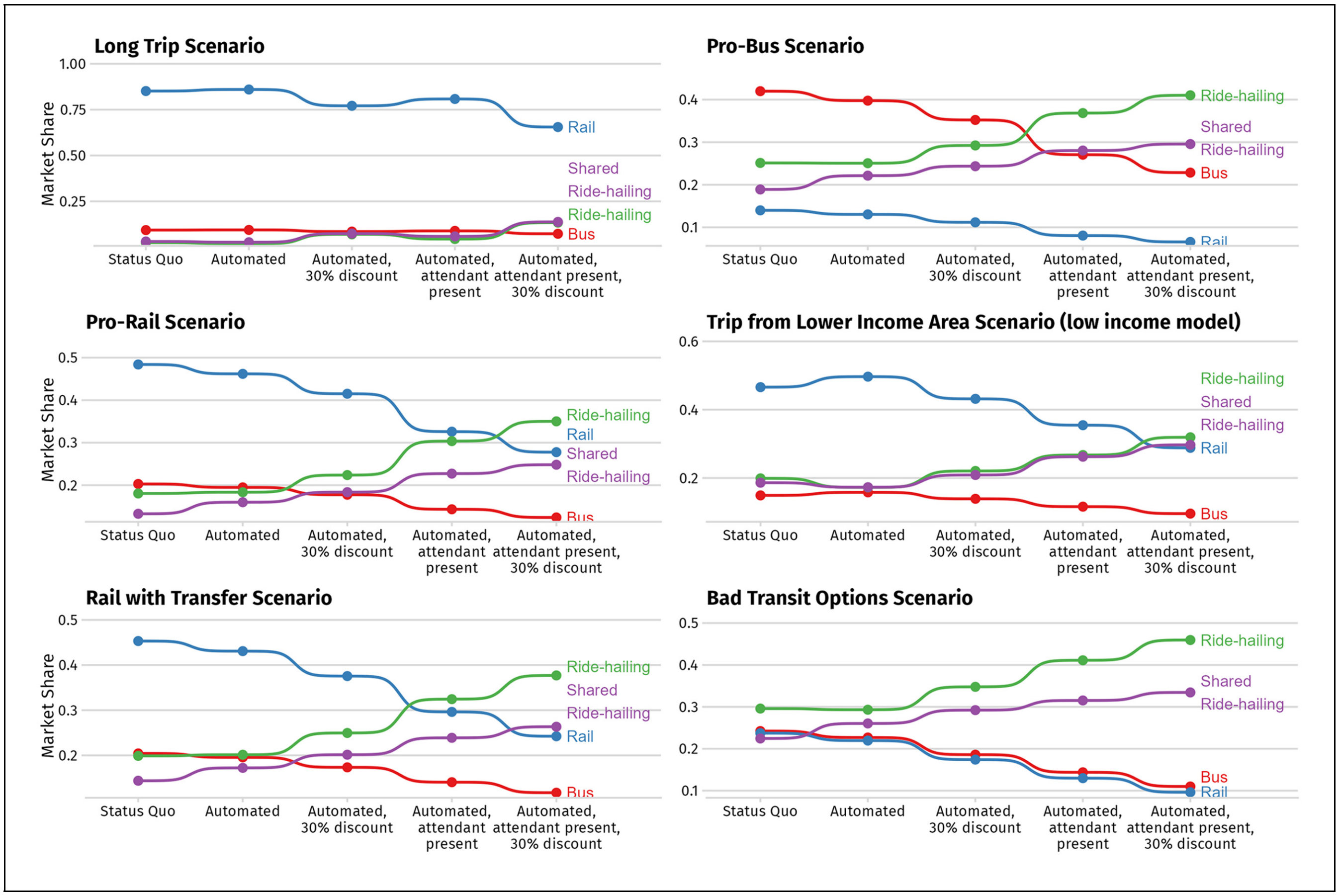

Figure 4. Mean estimated values for predicted market share based on introducing automation, an attendant, and price discounts for six trip scenarios. As one moves left to right across the *x*-axis, additional features are added to the ride-hailing and shared ride-hailing modes. "Status quo" indicates 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.

3. Shared ride-hailing services, though less popular in the status quo, became more attractive with additional features and discounts.
4. For trips in which people were already likely to use ride-hailing services, that likelihood increased 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.

We were not able to directly compare the status quo results of the scenario analyses with actual market shares since we did not have data on real market shares for these specific types of trips. We were, however, able to compare the status quo results with data on aggregate usage of these different mode types using data from the NCR Regional Travel Survey (also used as our reference demographic sample), which collected information on mode usage for trips within the entire region and within areas that are categorized as Equity Emphasis Areas (EEAs) (Appendix D). EEAs are defined as having higher concentrations of low-income individuals and/or traditionally disadvantaged racial and ethnic population groups. The "trip from lower-income area" fell into one of these EEAs. We found that the ordering of preferences in the status quo results of our scenarios generally matched those of mode use for noncommute trips in the region, with rail being typically most preferable. Bus and rail had more similar mode use within the EEAs in the region than our "trip from lower-income area" scenario estimates. This difference could have resulted from the specific trip that we selected for that scenario, which, based on the trip characteristics, favored rail. Although we acknowledge these differences, we emphasize that the focus of our study was on trying to understand the potential impact of automation on overall public transit use and feel that these minor differences do not detract from our overall study findings.

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 WTP for automated modes with an attendant on board.

In many respects, an AV with an attendant on board is fairly equivalent to current nonautomated 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 engagement research has found evidence of this type of reasoning. Stopher et al. conducted focus groups with participants of a recent AV pilot program between the AV ride-hailing company Waymo and the Valley Metro Regional Public Transportation Authority in Phoenix, AZ (*63*). Some focus group discussants expressed that they felt more comfortable with a computer driver than a traditional ride-hailing driver. Indeed, Waymo appears to be leveraging this perceived benefit with promotional advertisements asserting that, "You want a driver you can trust" (*64*). Yet people may not be fully comfortable ceding total control to automated systems, therefore 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. Some studies have already started to explore public attitudes toward different types of attendants, finding preferences for onboard attendants versus remote monitoring (*65*). In the meantime, some AV companies are already choosing—or may be required by state regulations—to launch their services with an onboard safety driver (*66*).

The presence of an AV attendant appears especially critical for women. Women only became ambivalent toward 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 WTP for AVs: men and higher-income individuals. These two groups make up a smaller share of current public transportation users in the United States (*67*), 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 have a negative impact on the system.

Although the Washington, D.C. metropolitan region has featured some AV pilots and testing (*68*, *69*), 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 toward 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. For instance, riding in an electric vehicle (EV) for just 3 to 5 min was found to significantly improve individuals' attitudes toward plug-in EVs (*70*). 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.

In the six aforementioned simulation scenarios, this study focused primarily on competition of automated ride-hailing services with transit. These scenarios did not, however, consider the potential benefits from automating buses. Given that buses are already typically the least expensive transportation option (at least in relation to user costs), automating buses is not expected to further decrease costs to consumers. Instead, the proposed benefits include decreasing operating costs, which could allow for increased service frequency and geographic coverage, or smaller AV shuttles could help fill gaps in the existing system (*71*, *72*). To avoid excessive cognitive burden of the CBC questions, our survey design did not include frequency, wait time, or reliability as choice attributes. Thus, the final model did not include sufficient information to explore scenarios in which buses benefit from automation. Future studies could further explore public interest in the potential enhancement of public transportation with automated modes, in addition to competition.

Finally, it is important to recognize some of the limitations of our findings. First, we framed our experiment around taking an evening leisure trip since noncommuting trips account for the majority of trips in the D.C. area. Results may differ for AV commuting scenarios, though we cannot conclude whether WTP would be higher or lower for commute trips since the relative value of each trip attribute may differ in these scenarios. We also selected a particular set of attributes that allowed us to focus on the potential impacts of automation and an attendant, but neglected other trip attributes such as wait time, which may influence individuals' choice preferences. Our sample included a large portion of higher-income and well-educated individuals who may not be as representative of general public transit users. Nonetheless, the sample was fairly representative of the study region, where costs of living are also higher than many other U.S. cities. Although residents in the study region may have higher incomes, it does not necessarily mean that they are any more or less price sensitive to travel costs than in other locations. Thus, although the study results may not generalize to all cities, they may reflect the preferences in other large cities that have similarly high costs of living, higher-earning households (on average), and multiple transit modes including buses and rail systems. Moreover, we attempted to highlight the preferences of lower-income individuals by specifically using our low-income model as part of our scenario analysis. Finally, the emergent nature of AVs means that we are unable to compare our results to actual market data, though "status quo" outputs of our scenario analyses generally reflect the relative usage of current rail, bus, and ride-hailing services.

Conclusions

With the continued development and gradual deployment of AVs, AV companies, mobility providers, and transportation planners will all need to understand how quickly and willing the public is to adopt AVs. In particular, potential competition between AVs and public transit systems could further detract from transit usage, yielding negative environmental and equity impacts. System-level impacts will largely depend on public uptake of automated transportation modes.

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 CBC survey fielded in the Washington, D.C. metropolitan region, we estimated discrete choice models and used them to simulate choice probabilities for a variety of trips. We found that public interest in automated ride-hailing services stemmed 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 is likely to be limited, since driver costs only account for approximately 20% of ride-hailing companies' current operating budgets (*59*, *60*). 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 suggested that a vehicle attendant is critically important for increasing AV use. Individuals primarily expressed a positive WTP for automated modes only when an attendant was also present. Gender differences also played 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 on board.

Gaining a greater understanding of public preferences for automated and nonautomated modes will enable 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 on board appears critical for both men and women, though these preferences could change as AV deployment expands and users gain more experience with these systems.

Author Contributions

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

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ORCID iDs

Leah Kaplan https://orcid.org/0000-0002-9710-2315
John Paul Helveston https://orcid.org/0000-0002-2657-9191

Data Accessibility Statement

The full survey, anonymized data, and code used in this study are available at: https://github.com/lkaplan25/AV_conjoint_survey_2022

Supplemental Material

Supplemental material for this article is available online.

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