



## Acceptance of driverless shuttles in pilot and non-pilot cities

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### ABSTRACT

Recently some US cities have launched pilot driverless shuttle programs, testing driverless shuttles on their roads. Using data collected in April 2020 from respondents in eight US cities, four with pilot driverless shuttle programs and four non-pilot control cities, we investigate the factors associated with residents' attitudes towards driverless shuttles. We use confirmatory factor analysis to construct four latent variables representing respondent attitudes: safety confidence, software security concerns, technology familiarity and interest, and preference for human control. Then, we estimate levels of adoption using a structural equation model-based multigroup analysis. We find that individuals in pilot cities not only demonstrate greater acceptance of driverless shuttle programs but also have different determinants of acceptance compared with those in non-pilot cities. Notably, the effects of local transit access on driverless shuttle acceptance vary between pilot and non-pilot cities. These findings provide early insight into how driverless shuttles may be accepted by the broader population and what factors may influence the effectiveness of driverless shuttles as public transportation over the long term.

### Introduction

Driverless technologies have received significant attention in the transportation industry, with researchers, mobility companies, and policymakers investigating and promoting benefits to safety, efficiency, and even sustainability (Lari et al. 2015). Driverless investment and development extend to public transportation, with driverless shuttles emerging as a driverless approach to providing multi-passenger public transit (Smolnicki and Sołtys 2016). Many cities across the world have tested or launched self-driving shuttles (Haque and Brakewood, 2020). However, it's still not clear whether the public will embrace driverless transportation (Hutson, 2017; Shin et al. 2015). Important concerns exist such as that of privacy, due to the large amount of personally identifiable data collected by the vehicle, and driverless ethics such as how the vehicles behave during potential crashes (Collingwood, 2017; Lin, 2016). Furthermore, transit operators, planners and researchers lack information on how driverless shuttles may be accepted. In this study, we seek to better understand these factors by examining whether increased exposure to driverless shuttles, via local pilot programs, changes the determinants of driverless vehicle acceptance.

Our study was conducted in April 2020 and consists of an online panel survey of four US cities with pilot driverless shuttle programs and four US cities without such programs. Through analyzing the online panel survey data, we investigate the factors associated with residents'

attitudes to driverless shuttles in the pilot and non-pilot control cities. We establish the qualitative dimensions of driverless shuttle attitudes through a confirmatory factor analysis using structural equation modeling (SEM). Then, we develop a multigroup analysis considering latent attitudinal variables as well as demographic and behavioral factors to estimate the determinants of residents' levels of adoption of driverless shuttles in pilot and non-pilot cities. We find significant differences in overall awareness and attitudes towards driverless shuttles between our pilot and non-pilot cities. In addition, those differences are associated with both demographic and behavioral factors, specifically current levels of transit use. The differences we observe in these two city groups may help planners and operators evaluate whether exposure to self-driving shuttles accelerates user acceptance, or qualitatively changes perceptions of the technology. The findings provide transit operators, planners, policymakers with new evidence of factors to address if this new technology is to be an effective part of urban public transportation.

### Background and Literature Review

#### Driverless Shuttles

Driverless shuttles are automated public transportation vehicles that facilitate multi-passenger travel on fixed routes or within a specified area, using artificial intelligence to navigate standard traffic. Fig. 1(a)

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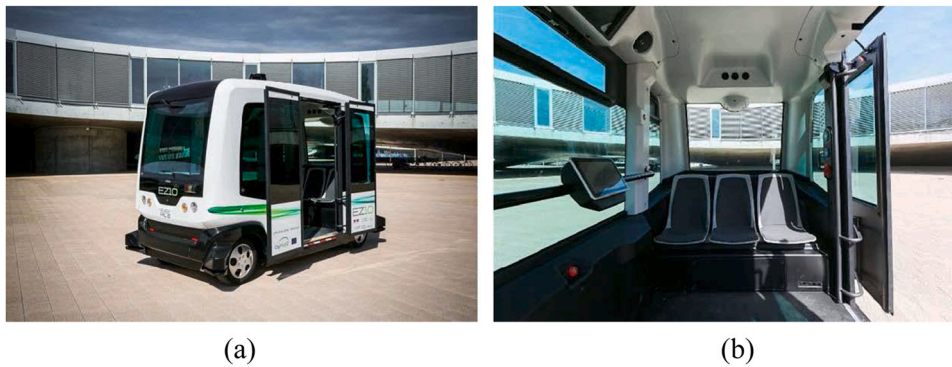


Fig. 1. EZ10 driverless shuttle vehicle photo. Image credit: Easymile (Easymile, 2015).

and (b) shows the exterior and interior of the EZ10, a widely adopted model produced by Easymile (Easymile, 2015). Driverless shuttles have the potential to reduce accident rates, ease congestion and travel times, improve passenger comfort, and reduce emissions (Bansal et al. 2016; Fagnant and Kockelman, 2015; López-Lambas and Alonso, 2019; Walker and Marchau, 2017). However, many in the public remain skeptical about the feasibility of driverless shuttles, citing passenger safety, data privacy, cybersecurity, and software bugs as major concerns (Roche-Cerasi, 2019; Liljamo et al. 2018; Walker and Marchau, 2017).

#### Attitudes to driverless transportation and driverless shuttles

Most research on attitudes to driverless transportation has focused on private or shared vehicles, rather than attitudes to automated transit or driverless shuttles. In the context of driverless vehicles generally, previous research has found that men are generally more likely than women to favor adoption of driverless technology (Hohenberger et al. 2016; Liljamo et al. 2018; Wang et al. 2020). Studies also find that adoption is positively associated with level of education, income, and proximity to urban areas (Kyriakidis et al. 2015; Lavieri et al. 2017; Liljamo et al. 2018). The effect of age on adoption tendencies had mixed results, with some papers claiming a negative relationship and others finding no statistical significance (Krueger et al. 2016; Lavieri et al. 2017; Liljamo et al. 2018; Nordhoff et al. 2017; Wang et al. 2020).

Attitudes specifically towards driverless shuttles have been less investigated, but some studies have been published in the past few years. Two studies ( $n = 197$  and  $44$ ) investigated the experiences of passengers of a driverless shuttle loop in Finland (Salonen, 2018; Salonen and Haavisto, 2019). They found that participants viewed traveling in driverless shuttles as safe, and exposure to driverless technology generally resulted in more positive attitudes. Nordhoff et al. (2018a) conducted a large cross-national survey of public perceptions of driverless shuttles. The study found that driverless shuttle acceptance is negatively correlated with gross domestic product (GDP), life expectancy, and motor density. However, most studies have concluded that potential users, such as those who ride conventional buses but have not yet ridden in a driverless shuttle, have positive attitudes towards driverless shuttles in general (Alessandrini et al. 2014; Azad et al. 2019; Eden et al. 2017; Nordhoff et al. 2018b; Wintersberger et al. 2018). The experience of riding in a driverless shuttle or living in a city where driverless shuttles operate can overall improve user acceptance and perceptions of this new public transportation technology (Alessandrini et al. 2016; Eden et al. 2017; Wintersberger et al. 2018).

Overall, the literature on attitudes towards driverless shuttles remains limited. Within the literature there are no recent examples of comparative analysis of how attitudes vary across the general population, particularly between locations with and without deployed driverless technology. Our research seeks to address this gap, establishing a multidimensional conceptualization of driverless shuttle attitudes and acceptance.

#### Research and survey design

Building on previous research and gaps in the literature, we pose two research questions:

- (1) Do individuals who have and have not been locally exposed to driverless shuttles accept and perceive driverless shuttles differently?
- (2) What are the factors which affect acceptance and attitudes toward driverless shuttles, and do those factors vary depending on local exposure to a driverless shuttle program?

Driverless shuttles are not yet a widespread part of public transit systems, so we take a quasi-experimental approach to comparing populations with differing levels of exposure to driverless shuttles. Our research splits respondents into test and control groups according to whether an individual resides in a city where driverless shuttle pilots have ever been deployed. We define exposure as a binary variable: whether the individual resides within a 6 km radius of a driverless pilot route.

In the pilot city category, we selected neighborhoods and sampled residents in zip codes within 6 km of driverless pilots in Phoenix, AZ, Boston MA, Arlington, TX, and New York, NY. For our second group - the non-pilot city category - we matched each city in the first group with a peer control city. To do this, we used the Peer City identification Tool which was developed by the Chicago Federal Reserve (Federal Reserve Bank of Chicago, 2020). The tool uses socioeconomic data and population demographics to find similar cities in the US. A summary table of our city groups is shown in Table 1.

The survey questionnaire (see Appendix A) captures individuals' 1) demographics, socioeconomic and current travel behavior characteristics; 2) attitudes and perceptions towards driverless technology and driverless shuttles; 3) latent reasons behind those attitudes and perceptions; 4) perceived benefits and risks; and 5) levels of shuttle acceptance. Some questions ask respondents to anticipate how likely or how often they might use driverless shuttles. For example, we ask respondents, "How often do you think you would use driverless shuttles when they become available?" Questions such as this are not intended to accurately predict future adoption of driverless shuttles. Instead, consistent with other studies of future technology acceptance, the question provides a cognitively tractable framework for respondents to consider holistically, the benefit they might glean from driverless shuttles.

#### Data and methods

##### Data source and study sample

Our survey was conducted in April 2020 via an online panel supplied by Qualtrics. Our survey respondents are residents of eight US

**Table 1**  
A summary of demographic and socio-economic characteristics for two city groups.

Pilot cities				Non-pilot cities			
City name	Total population <sup>1</sup>	Median household income <sup>2</sup>	Gini coefficient <sup>3</sup>	City name	Total population	Median household income	Gini coefficient
Phoenix, AZ	1,610,071	\$54,765	0.35	San Antonio, TX	1,486,521	\$50,980	0.35
Boston, MA	679,413	\$65,883	0.35	Seattle, WA	708,823	\$85,562	0.33
Arlington, TX	392,462	\$58,502	0.34	Nashville, TN	660,062	\$55,873	0.33
New York City, NY	8,443,713	\$60,762	0.37	Chicago, IL	2,718,555	\$55,198	0.36

<sup>1,2</sup>Data source: U.S. Census Bureau 2014–2018 American Community Survey (ACS) 5-year estimates.

<sup>3</sup>The Gini coefficient is a measurement of income inequality, which is calculated by comparing the cumulative wage income of all individuals across the sample with the overall cumulative wage income. Data source: Federal Reserve Bank of Chicago <https://www.chicagofed.org/>

cities: Phoenix, AZ, Boston, MA, Arlington, TX, New York, NY, San Antonio, TX, Seattle, WA, Nashville, TN, and Chicago, IL. After cleaning and controlling the quality of raw data, our dataset includes 1,800 responses in total, with each city having 225 respondents. While the sample was reasonably representative across demographic groups (Qualtrics, 2021), on-line panels are paid and can have potential biases such as a relatively smaller number of seniors (age > 70) and a more tech-savvy population that uses the internet.

*Analysis by socio-demographic and travel characteristics*

The summary statistics in Table 2 show respondents’ characteristics and the mean scores (the mean values on a scale from “1 = Never or almost never” to “5 = Daily”) of stated expected usage frequency of driverless shuttles, for each sample in the two city groups. In addition, we conduct Wilcoxon matched-pairs signed rank tests to show the statistical significance of differences between mean scores for different demographic groups (MacFarland and Yates, 2016). In the entire dataset, 52% of respondents are females and 48% are males. Although males in general are more likely to use driverless shuttles compared to females in both pilot and non-pilot cities, their reported likelihood of driverless shuttle usage is significantly different in the two city groups. Adults between the ages of 18 and 49 show much higher likelihood of usage of self-driving shuttles than older adults. Notably, pilot city respondents with annual household incomes over \$200,000 show a significantly greater interest in using driverless shuttles relative to their counterparts in non-pilot cities. People married or with children are significantly more likely to use driverless shuttles.

Table 2 also shows that transit usage and transit pass ownership are positively associated with driverless shuttle acceptance. Car users in the non-pilot city group are less likely to be adopters of the self-driving shuttles compared with car users in the pilot cities. Walking accessibility to transit is measured as the walking time to the nearest bus stop (in minutes). A majority of the respondents live in a neighborhood with good walking access to bus service, as 59% of the pilot city group and 73% of the non-pilot city group report needing 10 min or less to reach the bus service. When walking time increases to 30 min and over, interest in adopting driverless shuttles sharply declines in the pilot city group. Prior research suggests an association between driverless technology interest and neighborhood density, and walking distance to public transit nodes are associated with the intentions to switch to use shared self-driving services (Bansal et al. 2016; Lavieri et al. 2017; Martinez and Viegas, 2017). This study extends these findings by quantifying the influence of walking access to transit.

*Attitudes towards self-driving vehicles generally and self-driving shuttles*

Table 3 summarizes respondents’ attitudes towards driverless vehicles and technology. General awareness of both driverless technology and shuttles is significantly higher (about 15%) in pilot cities.

Respondents in pilot cities are more likely to indicate a positive attitude towards both driverless vehicles and shuttles, and also exhibit a greater degree of positivity. Compared to residents in non-pilot cities, residents in pilot cities predict faster widespread adoption of self-driving shuttles.

*Structural equation modeling*

We use Structural Equation Modeling (SEM) to examine relationships among variables across multiple inferential pathways. SEM has the capacity to simultaneously analyze both observed and unobserved (latent) variables, such as attitudes towards driverless shuttles. SEM has been widely used in different fields of study, including within transportation research (Carreira et al. 2014; de Oña et al. 2013). In this study, we use SEM to estimate the factors that most affect residents’ expected usage of driverless shuttles when they become available in their cities. Our analysis proceeds in two methodological steps.

*Step 1: Factor analysis*

In Step 1, we perform a factor analysis to identify attitudes towards driverless shuttles from a series of behavioral and attitudinal survey questions. The SEM measurement model is used to assess unobserved attitudinal dimensions (latent variables) as functions of a set of attitudinal variables (observed variables). The structural measurement model can be defined with the following basic equation:

$$x = \Lambda_x \xi + \delta$$

where

- $x$  is a vector of observed attitudinal variables,
- $\Lambda_x$  is a matrix of factor loadings,
- $\xi$  is a vector of latent variables, and
- $\delta$  is a vector of errors of measurement.

*Step 2: SEM-based multigroup analysis*

In Step 2, we build an SEM model that includes both latent variables constructed from the factor analysis and other independent variables, such as demographics, socioeconomic, and travel characteristics. A standard regression does not allow for the analysis of latent variables, while the SEM-based multigroup analysis combines the analysis of latent variables and regression analysis for our pilot and non-pilot city groups. This model identifies which inferential paths change significantly based on city group and which do not (Bowen and Guo, 2012).

**Results**

*Latent construct*

The factor analysis identifies four latent variables, which based on the survey questions contributing to each factor, we call (1) “confidence

**Table 2**  
Summary of characteristics of survey respondents in pilot cities and non-pilot cities.

Category	Variables	Residents in pilot cities (N = 900)			Residents in non-pilot cities (N = 900)			Mean difference p-value <sup>2</sup>
		N	%	Mean <sup>1</sup>	N	%	Mean	
Gender	Male	496	55%	3.613	360	40%	3.211	0.000 ***
	Female	404	45%	2.710	540	60%	2.719	0.853
Age	18–29	216	24%	3.130	247	27%	2.976	0.206
	30–39	272	30%	3.433	242	27%	3.112	0.007 ***
	40–49	222	25%	3.783	186	21%	3.118	0.000 ***
	50–59	104	12%	2.423	132	15%	2.629	0.373
	60–69	62	7%	2.276	66	7%	2.515	0.185
	70 and over	24	3%	1.667	27	3%	1.593	0.196
Income	Under \$25,000	136	15%	2.837	194	22%	2.696	0.383
	\$25,000 - \$50,000	219	24%	2.618	174	19%	2.845	0.105
	\$50,000 - \$100,000	246	27%	3.069	283	31%	2.869	0.081 *
	\$100,000 - \$200,000	225	25%	3.848	210	23%	3.143	0.000 ***
	\$200,000 or greater	74	8%	4.176	39	4%	3.436	0.000 ***
Education	High school or below	329	37%	2.690	337	37%	2.703	0.996
	Bachelors or above	571	63%	3.506	563	63%	3.043	0.000 ***
Household structure	Not married	445	49%	2.865	529	59%	2.824	0.635
	Married	455	51%	3.543	371	41%	3.046	0.000 ***
	No children	549	61%	2.880	636	71%	2.792	0.290
	Have children	351	39%	3.721	264	29%	3.212	0.000 ***
Transit use characteristics	Have an annual / monthly transit pass							
	No	554	62%	2.755	580	64%	2.614	0.112
	Yes	346	38%	3.934	320	36%	3.462	0.000 ***
	Transit use frequency <sup>3</sup>							
	Never or almost never	302	34%	2.344	290	32%	2.131	0.185
	Less than monthly	101	11%	3.178	135	15%	2.859	0.052 *
	1–3 days per month	127	14%	3.559	125	14%	3.320	0.093 *
1–3 days per week	209	23%	3.770	181	20%	3.365	0.001 ***	
Daily	161	18%	3.839	169	19%	3.527	0.034 **	
Car use characteristics	Have a valid driver's license							
	No	121	13%	3.058	134	15%	2.851	0.249
	Yes	779	87%	3.231	766	85%	2.927	0.000 ***
	Household vehicle number							
	0 vehicle	103	11%	2.913	127	14%	2.772	0.461
	1 vehicle	374	42%	3.216	480	53%	3.067	0.103
2 vehicles	300	33%	3.258	202	22%	2.827	0.000 ***	
3 or more vehicles	123	14%	3.309	91	10%	2.516	0.000 ***	
Walking access to transit	Walking time to the nearest bus stop (minute)							
	1–10 min	527	59%	3.089	653	73%	2.744	0.000 ***
	10–20 min	180	20%	3.511	132	15%	3.129	0.003 ***
	20–30 min	76	8%	3.921	76	8%	3.539	0.110
	> 30 min	117	13%	2.812	39	4%	3.846	0.000 ***

<sup>1</sup>The mean values are calculated based on the expected frequency of usage of driverless shuttles when they become available: 1 = Never or almost never; 2 = Less than monthly; 3 = 1–3 days per month; 4 = 1–3 days per week; 5 = Daily or almost daily. We ask respondents, “How often do you think you would use driverless shuttles when they become available?”

<sup>2</sup>p-value: Wilcoxon matched-pairs signed rank tests are conducted for the difference between means.

<sup>3</sup>This variable is about the transit use (bus / rail / subway) frequency for short trips (less than 50 miles).

\*\*\*Significant at the 99% level; \*\*significant at the 95% level; \*significant at the 90% level.

in the safety of driverless shuttles”, (2) “software security concerns”, (3) “technology familiarity and interest”, and (4) “preference for human control when traveling.” They are shown in Table 4. Furthermore, we checked the correlation among latent variables in the measurement model to ensure there is no multicollinearity issue.

Table 4 indicates factor loadings and Composite Reliabilities (CR) in which all CR values are greater than 0.6 as the suggested minimum level (Bagozzi and Yi, 1988). Overall, the loadings of the four factors are all acceptable (Hair, 2010), with loadings greater than 0.4.

*Comparison of positive attitudes, expected usage, and attitudinal factors towards driverless shuttles for pilot and non-pilot cities*

We compare the positive attitudes, expected usage, and attitudinal factors towards driverless shuttles for respondents in the pilot and non-pilot cities. As shown in Table 5, respondents in the pilot cities express

much more “very positive” attitudes towards the driverless shuttles, are more willing to use the driverless shuttles when they become available, have higher confidence in their safety, reduced software security concerns, and more familiarity and interest in technology. In both city groups, the rates of “somewhat positive” attitudes to driverless shuttles are similar. The difference in preference for human control when travelling is also not significant.

*Multi-group analysis for pilot and non-pilot cities*

The results are shown in Table 6. The independent variables of the final SEM model include the four latent variables and nine variables representing socio-demographics and travel characteristics, as shown in Table 5. All independent variables are either significant to one city group or significant to both city groups. Additionally, two visualization plots of the SEM models are shown in Appendix B.



**Table 3**  
Attitudes towards driverless vehicles generally and driverless shuttles specifically.

Category	Response	Residents in pilot cities (N = 900)		Residents in non-pilot cities (N = 900)		
		N	%	N	%	
Driverless vehicles	Awareness	628	70%	487	54%	
	General attitudes	Very negative	60	7%	56	6%
		Somewhat negative	85	9%	121	13%
		Neutral / No opinion	162	18%	176	20%
		Somewhat positive	280	31%	304	34%
	Technology development vision <sup>1</sup>	Very positive	313	35%	243	27%
		Never	86	10%	92	10%
		More than 50 years or never	37	4%	51	6%
		25–50 years	181	20%	155	17%
		10–25 years	304	34%	366	41%
Fewer than 10 years		292	32%	236	26%	
Driverless shuttles	Awareness	569	63%	425	47%	
	General attitudes	Very negative	77	9%	78	9%
		Somewhat negative	96	11%	144	16%
		Neutral / No opinion	173	19%	194	22%
		Somewhat positive	283	31%	293	33%
		Very positive	271	30%	191	21%
	Frequency of expected usage of driverless shuttles when they become available	Never or almost never	176	20%	203	23%
		Less than monthly	117	13%	161	18%
		1–3 days per month	165	18%	192	21%
		1–3 days per week	228	25%	197	22%
Daily or almost daily		214	24%	147	16%	

<sup>1</sup>This is based on the survey question “How soon do you believe driverless vehicles will replace all other forms of ground transportation?”

**Demographics**

We find that, controlling for other factors including attitudinal dimensions, gender is not a statistically significant variable in affecting the expected usage in either group. Thus, when fitting the final model, gender is removed. Interestingly, this finding contrasts the results of previous literature that consistently found males are more likely to express interest towards autonomous vehicles in general (Hohenberger et al. 2016; Liljamo et al. 2018). With respect to age, we find younger people being more likely to adopt driverless shuttles in non-pilot cities. Elderly people are less likely to adopt shuttles in non-pilot city group.

Education level is significant and positively associated with usage only for non-pilot cities. We find a contrasting relationship of income to likelihood of usage in the two groups: low-income individuals in non-pilot cities are more likely to be adopters of the driverless shuttle, however, in pilot cities, higher-income individuals show stronger willingness to use it, suggesting that pilot projects may attract a different demographic group to be future transit users. In terms of household structure, having children positively affects expected usage in pilot cities.

**Table 4**  
Standard factor loadings and reliability of latent structure.

Attitudinal attribute	Latent variable	CR	Factor loading
I believe that driverless shuttles will be safe and reliable under severe weather conditions (e.g. snow, heavy rain, fog).	Factor 1 “confidence in the safety of driverless shuttles”	0.908	0.879
I would feel safe riding in a fully driverless shuttle with no steering wheel or brake.			0.831
I believe that driverless shuttles will reduce the accident rate.			0.860
I would feel safe as a pedestrian / bicyclist crossing a street with driverless shuttles.	Factor 2 “software security concerns”	0.742	0.800
I am concerned that driverless shuttles are prone to malfunction / software bugs.			0.781
I am concerned that driverless shuttles are prone to software hacking.			0.735
I am concerned that driverless shuttles are sharing location data with other vehicles / companies.			0.573
It is fun for me to use new electronic devices.	Factor 3 “technology familiarity and interest”	0.789	0.836
I rapidly and intuitively learn to handle unfamiliar electronic devices.			0.778
Although driverless shuttles can operate without human supervision, I would still prefer having some level of human supervision.	Factor 4 “preference for human control when traveling”	0.644	0.774
I would not use a driverless shuttle because technology can sometimes fail.			0.548
I would prefer driving my personal vehicle over riding in a driverless shuttle.			0.504

N = 1,800.

Note: CR = composite reliability

**Table 5**  
Summary of general attitudes, expected usage, and attitudinal factors towards driverless shuttles.

Category	Variables	Residents in pilot cities (N = 900)	Residents in non-pilot cities (N = 900)	p-value <sup>1</sup>
General attitudes <sup>2</sup>	Very positive	N = 270 (30%)	N = 191 (21%)	0.000 ***
	Somewhat positive	N = 283 (31%)	N = 293 (33%)	0.614
Frequency of expected usage <sup>3</sup>	Daily or almost daily	N = 214 (24%)	N = 147 (16%)	0.000 ***
Attitudinal factors <sup>4</sup>	Factor 1: confidence in the safety of driverless shuttles	Mean <sup>5</sup> = 0.207	Mean = 0.116	0.000 ***
	Factor 2: software security concerns	Mean = 0.325	Mean = 0.360	0.030 **
	Factor 3: technology familiarity & interest	Mean = 0.535	Mean = 0.488	0.007 ***
	Factor 4: preference in human control when traveling	Mean = 0.333	Mean = 0.361	0.137

<sup>1</sup>p-value: Wilcoxon tests are conducted for testing the difference between the two groups.

<sup>2</sup>This is based on the survey question “What is your general opinion regarding driverless shuttles?”

<sup>3</sup>This is based on the survey question “How often do you think you would use driverless shuttles when they become available?”

<sup>4</sup>The four attitudinal factors are conducted from the factor analysis.

<sup>5</sup>This mean value is calculated based on the normalized scores ranging from -1 to 1.

\*\*\*Significant at the 99% level; \*\*significant at the 95% level; \*significant at the 90% level.

choose to actively change their transit method if they do not have a favorable view towards driverless shuttles, or believe they are unsafe to ride in. Software security concerns are a significant factor only in non-pilot cities. Exposure to driverless technology may establish more confidence in data security. In both groups of cities, technology familiarity and interest is significantly associated with expected usage, in line with the findings of previous research (Lavieri et al. 2017). The significance of preference for human control is also supported by literature (Roche-Cerasi, 2019).

**Conclusion**

This study investigates expected adoption of driverless shuttles from a survey of residents in pilot cities and non-pilot cities in the United States. Our approach, using individuals from pilot and non-pilot cities as quasi-experimental test and control groups, enables us to examine how attitudes to driverless shuttles are changing and may change further as pilots and implementation expand. Our study builds on the limited number of prior general population driverless shuttle acceptance surveys that could only represent shuttles as a prospective future mode. Other research has explored the attitudinal determinants of self-driving technology acceptance, including a variety of personal factors such as general attitudes and intents, willingness to pay, and modal preference. However, this approach is still limited for studies focused on automated transit, and driverless

shuttles in particular. Our contributions specifically include: (1) the underlying factors that affect attitudes towards the use of driverless shuttles; and (2) how acceptance may change when general exposure to the technology increases. The exploratory factor analysis extracts a set of attitudinal and behavioral dimensions that significantly explain general attitudes to driverless shuttles. We find that confidence levels in the safety of driverless shuttles and familiarity with and interest in technology are positively related to the levels of intent to use, while software security concerns and preferences in human control when traveling are negatively associated with adoption.

The survey confirms that individuals in pilot cities demonstrate a greater awareness and a more positive perception of self-driving shuttle programs, compared with those in control cities. Furthermore, the motivations for accepting self-driving shuttles are different in pilot cities, including demographic broadening of support from frequent transit users and low-income individuals. We also find that pilot programs for driverless shuttles are associated with increased confidence in data security and reduced software security concerns. These findings may provide early evidence as to how driverless shuttles may be accepted by the broader population and what factors must be addressed if this new technology is to be an effective, sustainable part of urban public transportation.

The model suggests that software security concerns become less of an issue for travelers in pilot cities, perhaps indicating that pilot programs can help build confidence in software stability and data security.

**Table 6**  
Factors influencing the expected usage of driverless shuttles in pilot and non-pilot cities.

Variable	Residents in pilot cities		Residents in non-pilot cities	
	Coeff.	SE	Coeff.	SE
Age	-0.036	0.028	-0.076 ***	0.026
Education background (base case: less than bachelor's degree)				
Bachelor's or graduate degree	-0.125	0.081	0.147 *	0.084
Income	0.067 **	0.031	-0.055 *	0.033
Have children (base case: no children)	0.139 *	0.080	0.050	0.085
Own annual / monthly public transit pass ownership (base case: no ownership)	0.116	0.092	0.193 **	0.088
Number of vehicles in a household	-0.097 **	0.039	0.022	0.043
Frequency of using public transit for trips less than 50 miles	0.142 ***	0.029	0.207 ***	0.029
Residential location accessibility to bus services				
Walking time to the nearest bus stop > = 20 min	-0.138 *	0.083	0.122	0.110
Level of positivity towards driverless vehicles generally	0.309 ***	0.032	0.298 ***	0.032
Factor 1: driverless shuttle safety confidence	0.501 ***	0.047	0.381 ***	0.050
Factor 2: software security concerns	0.084	0.114	-0.180 *	0.104
Factor 3: technology familiarity & interest	0.140 **	0.066	0.157 ***	0.056
Factor 4: preference in human control when traveling	-0.147 ***	0.051	-0.165 ***	0.062

N = 1,800.

Note: Coeff. = coefficient; SE = standard error.

\*\*\*Significant at the 99% level; \*\*Significant at the 95% level; \*significant at the 90% level.

The models show significant, contrasting relationships between income and driverless shuttle acceptance in pilot and non-pilot cities: low-income individuals in non-pilot cities are more likely to state their willingness to adopt driverless shuttles, while in pilot cities, higher-income individuals show a stronger willingness to use it. This finding may suggest that driverless shuttle pilot may reduce many of the attitudinal barriers to future use, but it is also cause for concern that driverless shuttles are more appealing to a higher-income demographic that does not necessarily rely on transit, rather than meeting the basic mobility needs of low-income populations.

Current transit usage is a significant factor affecting prospective driverless shuttle usage in both city groups. However, unlike in non-pilot cities, in pilot cities good walking accessibility to bus stops increases expected driverless shuttle usage. The positive relationship of both “the frequency of public transit usage” and “walking access to bus service” to the dependent variable implies that travelers understand driverless shuttles to be public transit and part of a transit network that must itself be useful if they are to consider adopting driverless shuttles. Overall, the results highlight the heterogeneity between pilot and non-pilot cities and suggest that driverless shuttles may become more attractive to the public as deployment increases.

This study has several limitations. Notably, the quasi-experimental design implies that the difference in attitudes in pilot cities are due to the introduction of the pilot program. However, it is also possible that the difference in attitudes as well as public/private decisions to deploy a pilot program are due to other, unmeasured factors, such as political or cultural outlook. Even in this case, the results show that attitudes are not consistent across US cities and can be used by transit planners and advocates to observe a divergence in attitudes within the US. Another limitation of this study is that our survey only captures stated preferences from responses, instead of the actual behaviors of taking driverless shuttles. At this stage, the service provided by pilots is limited, and actual users are small, self-selected groups compared to the broader population in pilot cities. However, when more deployments are operational, it will be important to return to these cities to determine how general attitudes as well as attitudes of regular driverless shuttle users vary. Future research should explore what aspects of driverless shuttle technology are attractive to specific demographics served by transit, as well as the deterrents preventing acceptance.

### Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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### Appendix. Supporting information

Supplementary data associated with this article can be found in the online version at [doi:10.1016/j.jpubtr.2022.100018](https://doi.org/10.1016/j.jpubtr.2022.100018).

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