frontiers | Frontiers in Built Environment

TYPE Original Research
PUBLISHED 25 June 2025
DOI 10.3389/fbuil.2025.1613232

OPEN ACCESS

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RECEIVED 16 April 2025
ACCEPTED 04 June 2025
PUBLISHED 25 June 2025

CITATION
Etminani-Ghasrodashti R, Patel RK, Pamidimukkala A, Kermanshachi S, Rosenberger JM and Foss A (2025) Young adults' acceptance of shared autonomous vehicles in an urban-university setting. *Front. Built Environ.* 11:1613232. doi: 10.3389/fbuil.2025.1613232

Young adults' acceptance of shared autonomous vehicles in an urban-university setting

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Introduction: This study focuses on a shared autonomous vehicle (SAV) demonstration implemented in Downtown Arlington and university campus to provide a representation of individuals' experiences with autonomous vehicles. We aim to understand how younger, better-educated individuals and students usually assumed to be early adopters of new technologies would accept SAVs.

Methods: This study utilized the survey data to investigate the factors that affect the individual's inclination to use and adopt the SAVs. Using a structural equation model (SEM), this study tested the effects of factors shaping individuals' acceptance of SAVs, including attitudes and travel modes.

Results and discussion: The study findings revealed that younger individuals and individuals with lower income are more prone to adopt SAVs. The findings demonstrated that favorable perceptions regarding SAVs markedly affect individuals' willingness to utilize the service. Car users, those with more dependency on cars and fewer ridesharing experiences, are less interested in riding in SAVs, which portends that integrating SAVs and on-demand rideshare services will enhance the accessibility of individuals who already take advantage of ridesharing opportunities. These findings offer a clearer understanding of the potential market for SAV service providers and deepen knowledge about SAV adoption among young people who are more receptive to new technologies.

KEYWORDS

self-driving vehicles, young adults, technology adoption, attitudes, structural equation modeling

1 Introduction

Self-driving vehicles are a promising technology that can reduce urban mobility and accessibility barriers by providing effective transportation options (Kittusamy and Bryan, 2004; Almaskati et al., 2024; Pamidimukkala et al., 2024). Rapid advances in technology and self-driving shuttles offer shared rides to citizens who have limited access to transportation, such as senior citizens, individuals with disabilities, and individuals with lower income (Krueger et al., 2016). By providing first/last mile rides on low-demand routes, shared autonomous vehicles (SAVs) can be a complimentary option to existing public transportation services.

Currently in the United States, 41 states and DC have enacted AV legislation, 6 states have issued executive orders, and 5 states have passed laws and executive orders related to autonomous driving, allowing testing or deployment of autonomous vehicles on public roads (NCSL, 2020). The SAV pilot projects are usually begun by a public-private partnership (Kerlin, 2019) and when integrated with existing on-demand rideshare have the potential to expand accessibility to individuals with different mobility needs. Accordingly, public inclination, attitudes, preferences, and adoption of AV and SAV technology can result in the successful implementation of pilot projects (Etminani-Ghasrodashti et al., 2021; Hassan et al., 2021; Patel et al., 2021).

Understanding public acceptance and adoption of such vehicles is essential; consequently, the number of studies on this topic is rapidly growing (Acheampong and Cugurullo, 2019; Etzioni et al., 2021; Shabanpour et al., 2018; Wang and Akar, 2019; Yuen et al., 2020). Although empirical evidence of the association among factors such as attitudes and preferences towards AV technology and acceptance of this new mobility mode has been substantiated, several gaps in the literature exist (Etminani-Ghasrodashti et al., 2021a; Khan et al., 2022; Tian et al., 2021).

Research on the acceptance of AVs in public transit highlights several factors influencing user adoption that are especially pertinent to SAVs, which operate as shared, on-demand services (Khan et al., 2023). One key factor is in-vehicle privacy, which is more complex for SAVs as passengers must share rides with others, raising privacy concerns not as prevalent with private AVs (Nazari et al., 2019). Studies show that privacy is a central issue for users of public transit, and this concern is likely amplified in SAVs where passengers may share close quarters with strangers (Acheampong and Cugurullo, 2019).

Travel time and cost are also critical considerations. While personal AVs focus on convenience, SAVs are typically designed to be cost-effective, encouraging users who prioritize affordability. Low costs significantly influence public transit acceptance, suggesting that SAVs could attract riders by offering a similarly economical alternative to private vehicles (Hulse et al., 2018). Additionally, service reliability is crucial for both public transit and SAVs, as users expect consistent availability, short wait times, and timely arrivals. For SAVs, however, shared routes can add pickup and drop-off stops, which may affect perceived reliability (Yuen et al., 2020).

First, most studies explore the individual's interest in vehicle technology based on survey data (Haboucha et al., 2017; Krueger et al., 2016; Bansal et al., 2016; Lu et al., 2017), and they simulate and evaluate the integration of AVs into an existing public transit system (Shen et al., 2018; Wen et al., 2018; Levin et al., 2019). However, it is still uncertain whether the results and findings associated with the acceptance of SAVs through simulation methods will be consistent when autonomous vehicles operate on the road in the near future.

Second, most of the existing literature is based on the researchers conducting an investigation into the acceptance of SAV technology by collecting data from people who has no ridership experience (Dichabeng et al., 2021; Hossain and Mahmudur, 2022). This is inevitable, due to the limited number of AVs and SAVs on the road, which means that due to the intangibility of this new technology.

Third, most studies on the adoption of SAVs were developed in metropolitan areas that provide access to a variety of transportation modes (Soltani et al., 2021). However, there is an essential need to understand how an SAV service can improve the mobility, accessibility, and equity of those who live in distant and sprawling areas with limited or no access to fixed-route transit.

Given the importance of SAV acceptance and adoption, this research aims to understand the differences between users and non-users of self-driving vehicles and the factors that ultimately affect their acceptance of SAVs.

2 Literature review

The emergence of app-based transportation has remodeled travel supply and demand. The opportunities arising from the growing rate of technology-based transportation can be challenged, however, by factors such as behavioral differences, travel patterns, and sociodemographic characteristics across different segments of communities that influence their acceptance and adoption. A systematic review of 71 empirical studies identified several categories of factors influencing the adoption of autonomous vehicles including "psychological and behavioral factors, technological factors, social factors, environmental factors, security and privacy concerns, and AV-specific attributes, risky and negative perceptions, conditional factors, and monetary considerations" (Al Mansoori et al., 2024). Patel et al. (2023) found that users' inclination to use SAVs was enhanced by their ease of use and the user-friendliness. The authors identified that a lack of knowledge about AVs had detrimental effects on people's attitudes and opinions.

The influence of subjective factors—such as individual attitudes, preferences, and travel behaviors—can be effectively interpreted through socio-psychological frameworks. Two widely recognized theories in this domain are the Value-Belief-Norm (VBN) theory (Stern et al., 1999) and the Theory of Planned Behavior (TPB) (Ajzen, 1991), both of which offer a foundational understanding of how beliefs and attitudes translate into behavioral intentions, particularly in transportation decision-making contexts. Complementing these, the Technology Acceptance Model (TAM) (Davis, 1989) is particularly relevant when examining the adoption of emerging technologies like shared autonomous vehicles (SAVs). TAM posits that an individual's intention to use new technology is shaped primarily by their perceptions of its ease of use and usefulness. The model has since been extended to incorporate additional constructs such as trust and perceived risk (Pavlou, 2003), both of which are highly pertinent in the context of AVs. For instance, Xing et al. (2020) found that factors including trust, perceived risk, perceived usefulness, and ease of use significantly influence users' willingness to ride in autonomous vehicles (Xing et al., 2020). Their study emphasized concerns about data privacy, shared rides, and general interaction with self-driving systems.

The literature on AV and SAV adoption may also be related to attitudes and perceptions towards technology and transportation. Subjective norms, attitudes, and perceived behavioral control & conditions can significantly impact individuals' intentions to use self-driving vehicles (Yuen et al., 2020). For instance, individuals who are more inclined to take risks tend to accept autonomous vehicles (Hulse et al., 2018; Wang et al., 2020), and technology adept adults are more likely to have positive attitudes towards integrating AVs into public transport (Song et al., 2021). Exploring public opinion towards AVs revealed that people from developed countries are more concerned about AV-related issues like software hacking and data misuse. The study revealed that concerns about data privacy such as the collection, storage, and use of personal data by AV system can create hesitancy among potential users. People worry about the security of their personal information, such as travel patterns and location history, which AV systems may track and share with third parties for various purposes. These concerns are amplified in shared AV settings, where the collection of data may be more frequent and could include multiple users per vehicle, increasing the perceived risks associated with data misuse or breaches (Kyriakidis et al., 2015). Some studies mentioned that personal characteristics such as environmental concern, risk preference, and personal innovativeness significantly affect individuals' intentions to adopt SAVs (Si et al., 2024).

Those belonging to different cohorts and segments might have different perceptions and attitudes towards technology, as age, gender, prior knowledge and personality can significantly impact individuals' attitudes towards it (Charness et al., 2018). Males, young people, and those who live in highly populated places are likely to have more positive attitudes and trust in the integration of AVs into existing transportation services than females, the elderly, and people who live in rural areas (Deb et al., 2017). High income individuals are concerned about liability issues related to AVs, while lower-income individuals are more prone to concern about SAV safety and control (Howard and Dai, 2014). Females are said to be more skeptical about the benefits of AVs and more likely to believe that they negatively affect people's safety and security (Acheampong and Cugurullo, 2019).

Travel behavior and daily trip patterns are another predictor of an individual's adoption and usage of SAVs (Haboucha et al., 2017). A study by (Rahimi et al., 2020) indicated that user behaviour or attitude towards AVs varies according to individual subgroups, e.g., private car users are less probable to share a car with other users, while transit users are comfortable sharing rides. Kassens-Noor et al. (2020) found that 27% of regular public transit users and 14% of occasional or non-users tend to use an autonomous bus service. In comparison, 53% of both regular and non-regular users of public transportation services are less probable to use an AV transit service. Users of public transportation services tend to share a ride in an SAV than non-users. Furthermore, individuals who utilize rideshare services are more interested in SAVs than non-users (Wang and Akar, 2019). Hamadneh and Esztergár-Kiss (2023) found that participants favored personal AVs over SAVs and conventional automobiles over personal AVs.

While the existing research on individuals' decision-making on autonomous vehicles has contributed to the knowledge of SAV adoption, there are still some questions that require deeper investigation. Earlier empirical research mainly explored the willingness to ride SAVs by surveys designed to reveal general public population perceptions and attitudes. Only a few studies have been developed to understand how younger and better educated adults and students that are usually assumed as early adopters of new technology would accept this new technology. For instance, Soltani and his colleagues surveyed a sample of students at the University of South Australia, Adelaide, to explore how their perceptions and concerns can affect AV acceptance (Soltani et al., 2021). The study results revealed that the younger male students are positive about AV technology than female students. Researchers have found that younger individuals with higher education level are more likely to accept and adopt emerging technologies and are less likely to be concerned about SAV safety due to their high-risk preference (Gangadharaiah et al., 2023; Si et al., 2024). The systematic literature review of 107 studies focusing on SAVs' effects on total travel demand, mode choice, and in-vehicle time use demonstrate that there are mixed findings regarding the impact of education level on AV adoption (La Delfa and Han, 2025). While some studies suggest that university students are more likely to adopt SAVs compared to other population segments (Alhajyaseen et al., 2021), others find no significant effect (Aasvik et al., 2024). In addition, Fu and colleagues recently surveyed the University of Alabama students in Tuscaloosa to understand their knowledge and attitudes about SAVs. The study results indicated that awareness of AV companies and ride-hailing services positively correlates with students' willingness to pay for SAV services (Fu et al., 2021).

The concentration of this study on the adoption of emerging mobility services by university students, particularly in small urban areas, can provide new insights to the area of knowledge through the following:

1. Help the US and state DOTs to manage available financial sources more reasonably for the implementation of Mobility Innovation projects,
2. Offer a more precise perspective about the potential market and ridership of new technologies for service providers technologies, and
3. Provide transportation researchers with a piece of more accurate knowledge about the adoption of SAV by early adopters and youngsters that are more open to new technologies.

The main contribution of this study would be investigating this new technology in a community in which an SAV is an available mobility mode. We explore individuals' enthusiasm towards using self-driving service, and by analyzing data from an SAV demonstration, which provides a practical perspective of individuals' interests and experiences using self-driving technology, we explore the actual differences between users and non-users.

3 Methodology

This study addresses the literature gaps by answering the following research questions: Who will be an early adopter of SAVs? And how do different factors shape people's acceptance of SAVs? We attempt to provide explicit and actual insights into the contribution of attitudes, travel patterns and sociodemographic status on individuals willingness to ride SAVs.

3.1 Study area and sample

This research focuses on the Rideshare, Automation, and Payment Integration Demonstration (RAPID), a pilot project that operates self-driving shuttles in Arlington, Texas. The Federal

Transit Administration is funding the Arlington RAPID initiative, which will connect an existing on-demand rideshare service (Via) with SAV service in the city. The on-demand rideshare service began operations in a limited region of Arlington in December 2017 and later took the service all over the city in January 2021. It is an app-based on-demand ridesharing service that provides rides to customers in 6 passenger vans anywhere inside the service boundaries (City of Arlington, 2019). The major stakeholder in the RAPID SAV pilot project were May Mobility, Via Transportation, and the University of Texas at Arlington (UTA) and the city of Arlington. The service boundaries cover an area with a 39% poverty rate and 11% households without private vehicle to align with the transportation equity and accessibility goals of the project.

The SAVs used in the RAPID pilot project were operated by May Mobility and included four Lexus RX 450h hybrid vehicles and one Polaris GEM vehicle equipped for wheelchair accessibility. These vehicles functioned at SAE Level 4 automation, meaning they were capable of performing all driving tasks within a defined operational design domain (ODD) without human intervention. However, for safety and regulatory compliance, a trained onboard operator was present during service hours. The vehicles operated at a maximum speed of 25 mph and provided fully on-demand rides within the service area. The survey targeted individuals who live, work, or study within the RAPID pilot service area in Arlington, Texas, which includes Downtown Arlington and the University of Texas at Arlington (UTA) campus. This area was selected due to its significant transportation needs, including a high poverty rate (39%) and a notable proportion of households (11%) without access to private vehicles (Etminani-Ghasrodashti et al., 2021b). The survey was disseminated online via the QuestionPro platform and distributed through institutional channels such as UTA email lists and outreach efforts by project stakeholders. This approach ensured the majority of responses came from individuals familiar with or directly exposed to the SAV system, minimizing potential bias. A random sampling method was applied to gather responses, aligning with standard practices for exploratory studies focused on emerging transportation technologies. The survey questionnaire was designed to collect data from current and potential SAV users who live and work/study in Arlington. The Institutional Review Board (IRB) at UTA examined and approved it. An online survey was developed, utilizing the QuestionPro platform. The survey received 259 completed responses. The sample size ($259 > 21^{*}10 = 210$) required for this study was found to be suitable based on the recommendation of scholars for a desired level of 5–10 observations per item variable for applying structural equation modelling (SEM) (Hair et al., 2015; Kline, 2015). Figure 1 presents the RAPID SAV service area and distribution of survey respondents.

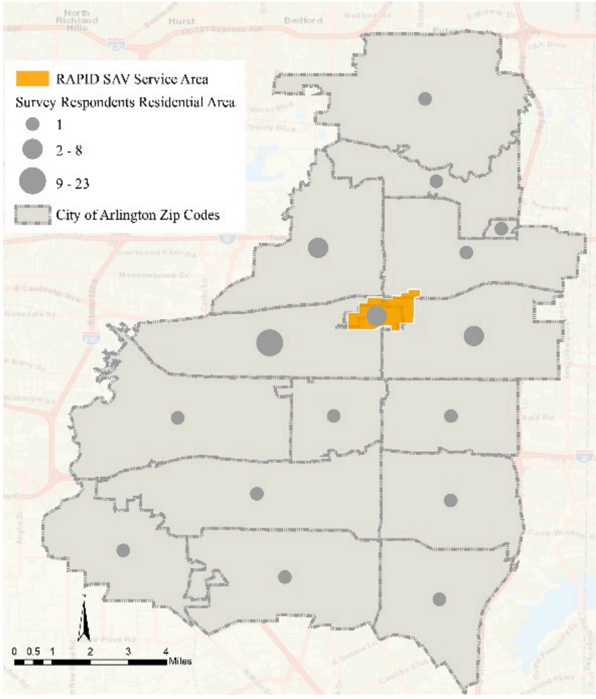

FIGURE 1
RAPID SAV service area and distribution of survey respondents.

3.2 Data and variables

The survey consisted of multiple sections, such as SAV ridership characteristics, views, and opinion on SAVs, personal travel characteristics, and demographic characteristics. The dataset of the study was compiled based on the reviewed literature and the factors that may determine the potential users' adoption of AVs and SAVs.

The first section of the survey collected data related to SAV ridership, wherein respondents were asked whether they had ridden the SAV RAPID service. This question is identified as the "SAV ridership experience" variable, and only 34% of the respondents responded that they had ridden in it. Another part of the survey explored respondents' acceptance of self-driving shuttles by asking them about the likelihood of their riding the RAPID SAV (Xing et al., 2020). Responses were presented in a five-point Likert-type scale from very unlikely to very likely (see Table 1). This question is identified as "willingness to ride SAVs" in the future, and a majority of respondents said that they are likely to ride an SAV in the future.

Given the significant effect of "attitudes" toward willingness to use and adopt the AVs and SAVs (Haboucha et al., 2017; Acheampong and Cugurullo, 2019; Song et al., 2021). We included eight attitudinal statements in the survey to measure the individuals' attitudes regarding the AV technology. (See Table 2). Responses were given on a five-point Likert-type scale (where 1 = "strongly disagree" to 5 = "strongly agree").

Earlier studies pointed to the importance of daily travel patterns and modality styles in predicting individuals' preferences towards the acceptance of SAVs (Wang and Akar, 2019; Krueger et al., 2016). For instance, the literature suggests that people using public transit and car-sharing services are more likely to adopt self-driving technology than those who drive their privately-owned cars (Wang and Akar, 2019). Therefore, respondents were asked about their usage of different "travel modes," Responses were provided based on the frequency of usage on a seven-point Likert scale (where 1 = "never" to 7 = "more than three times per week.")

Another part of the survey queried about local "residential accessibility" in terms of travel distance to different destinations. Respondents were asked to indicate the approximate distance (in minutes) from home that their errand destinations, such as grocery

TABLE 1 Demographic characteristics of survey respondents (N = 259).

Variable	Descriptive of the variable	Frequency	Percent
SAV ridership experience	RAPID SAV user	87	33.6
	RAPID SAV non-user	172	66.4
Willingness to ride SAV	Very unlikely	5	1.9
	Somewhat unlikely	2	0.8
	Neither unlikely nor likely	8	3.1
	Somewhat likely	74	28.6
	Very likely	170	65.6
Sociodemographic			
Age	18–24	164	63.3
	25–34	65	25.1
	35–44	11	4.2
	45–54	9	3.5
	55–64	3	1.2
	65+	4	1.5
	Missing	3	1.2
Race	Asian	121	46.7
	White	71	27.4
	Black or African American	38	14.7
	American Indian or Alaska Native	6	2.3
	Other	20	7.7
	Missing	3	1.2
Education			
	Prefer not to answer	5	1.9
	Some grade/high school	2	0.8
	High school/GED	37	14.3
	Some college/technical school	61	23.6
	Associate degree/technical school	40	15.4
	Bachelor's degree	48	18.5
	Graduate/professional degree	65	25.1
	Missing	1	0.4
Household income	Less than $20,000	130	50.2
	$20,000-$34,999	44	17.0

(Continued on the following page)

TABLE 1 (*Continued*) Demographic characteristics of survey respondents (N = 259).

Variable	Descriptive of the variable	Frequency	Percent
	\$35,000-\$49,999	26	10.0
	\$50,000-\$74,999	20	7.7
	\$75,000-\$99,999	13	5.0
	\$100,000 or more	16	6.2
	Missing	10	3.9
Vehicle Ownership	0 vehicles	69	26.6
	1 vehicle	92	35.5
	2 vehicles	59	22.8
	3 and more vehicles	36	13.9
	Missing	3	1.2

stores, shopping malls, restaurants or fast-food places, drugstores, healthcare providers, and places to exercise (gym or park) are by car.

The final section asked questions related to the riders' "socio-economic characteristics," such as age group, race, household income, vehicle ownership, and education. Table 1 presents the demographic characteristics of survey respondents.

3.3 Conceptual method

To answer the research questions, we developed a conceptual framework for this study that consists of two main methods. The outcomes and results of the methods are presented in Section 4. In the first step, the survey data was analyzed to identify who was riding in SAVs. Using the survey dataset, cross tabulations were employed as a quantitative research method to analyze the relationship between being an SAV user/nonuser and sociodemographic attributes.

Secondly, to understand the latent structure behind the observed variables an exploratory factor analysis (EFA) was conducted on the survey dataset. Factor analyses help us to reduce observed data to a smaller set of variables and recognize the underlying theoretical framework of a phenomenon (Costello and Osborne, 2005). We employed EFA for four sets of variables, including SAV ridership experience, willingness to ride in an SAV, attitudes, and residential accessibility, and used IBM SPSS Statistics 27 to run the factor analysis. The EFA identified the number and nature of the factors.

Finally, a structural equation model (SEM) was employed to study how different factors shaped the respondents' acceptance of SAVs. The SEM is usually evaluated by performing covariance (structure) analysis, in which the variance and covariance of the parameters suggested by the model system are nearly equal to the variance and covariance of the observed sample data. To develop the SEM, a confirmatory factor analysis (CFA) was performed based on the latent variables responsible for the covariance of the data extracted from the EFA. The outcome of this step was the "measurement model" for the SEM. The CFA determined the relationships between the latent and observed variables, and we developed a structural model to test the causal (theoretical) associations between the key variables and the hypotheses related to the relationships among observed and latent variables in the model. The SEM was composed of three sets of equations: (1) a measurement model for the "acceptance of the SAV" as an endogenous variable; (2) a measurement model for including attitudes, travel mode, and residential accessibility as exogenous variables; and (3) a structural model. All were tested simultaneously. In comparison to other linear statistical techniques, SEM has several advantages, including the capacity to identify effects from both dependent and independent variables, the ability to model the mediating variables, and the ability to determine the structure of latent construct, etc. (Golob, 2003).

4 Results

4.1 Sociodemographic differences between SAV users and non-users

To test if there were statistical differences between SAV users and non-users, we first conducted chi-square tests on key categorical variables. The analysis revealed significant differences in household income ($p < 0.05$), education level ($p < 0.05$), and vehicle ownership ($p < 0.01$), indicating that individuals with lower incomes, fewer vehicles, and higher education levels were more likely to use SAV services. Additionally, we examined SAV usage patterns alongside sociodemographic characteristics. Given that the variables were categorical (both ordinal and nominal), cross-tabulation analysis was employed to explore how these attributes varied between users and non-users, highlighting distinct differences in their profiles (See Figure 2) This helped identify how the SAV ridership experience varies among different population segments. Although

TABLE 2 Factor loadings for attitudes, travel patterns and residential accessibility.

Attitudes	Loading factors	
Factors	Positive Attitudes towards SAV	Negative Attitudes towards SAV
V1: AVs can enhance the travel convenience	0.735	
V2: AVs can simplify my trips since I will not have to worry about finding parking	0.737	
V3: Cyber security concerns are an issue		0.847
V4: There is likely to be confusion between human drivers and AVs on the roads		0.855
V5: AVs can improve the transportation safety	0.839	
V6: I would recommend AVs to my family and friends	0.850	
V7: I am in favor of AV technology	0.831	
V8: I would prefer to ride in an AV rather than drive myself	0.679	
Travel modes	**Loading Factors**	
Use of the following modes of transport?	**Rideshare riders and active travelers**	**Car users**
V9: Car		−0.500
V10: Via on-demand rideshare service	0.795	
V11: Uber/Lyft	0.613	
V12: UTA transportation services	0.712	
V13: Biking/walking	0.597	
Residential accessibility	**Loading Factor**	
The approximate duration (in mins) from your residential location to the following locations	**Residential accessibility**	
V14: Closest grocery store or department store	0.738	
V15: Nearest shopping mall	0.570	
V16: Nearest restaurant or fast-food place	0.798	
V17: Nearest drugstore	0.786	
V18: Nearest healthcare provider	0.667	
V19: Nearest place to exercise	0.668	
Acceptance of SAV	**Loading Factor**	
	SAV acceptance	
V20: SAV ridership experience	0.670	
V21: Willingness to ride SAV	0.900	

the respondents were mostly young students, the proportion of older adults was higher among SAV non-users. The discrepancy of users' and non-users' annual incomes may have resulted from the propensity of university students with less than $20,000 annual income to request rides. According to the stacked plots, SAV tend to be more educated than non-users and often have limited or no access to a personal vehicle, while a majority of the non-users have two or more vehicles.

It should also be noted that the proportion of Asian SAV users is higher than that of other races. These results are reasonable because the RAPID SAV service area encompasses the university campus and downtown to target the mobility improvement of low-income people as the primary goal of the RAPID demonstration.

4.2 Identifying the latent factors

The nature and structure of the latent factors behind the observed variables can be identified by employing an exploratory factor analysis (EFA) and can then be used to develop the SEM. We conducted the EFA for three sets of variables: attitudes, travel modes and residential accessibility. We conducted an EFA for the factors belonging to individual attitudes. Two main factors were extracted through factor analysis: maximum likelihood, 65% variance explained, KMO = 0.848. One factor was loaded based on the variables that represent a positive perception towards AV technology, such as convenience, ease, and safety of AV trips; another factor was extracted based upon the disadvantages of AV trips. Therefore, the EFA of attitudes indicates two latent factors: "positive attitudes towards SAVs" and "negative attitudes toward SAVs". Table 2 presents the extracted factors and associated statements.

To classify the travel patterns, we examined individuals use of different transportation modes including Car, Via on-demand rideshare service, Uber/Lyft, UTA transportation services, Biking/walking. We applied EFA to reduce the dimensionality of the travel mode data and uncover underlying patterns in travel behavior.

Results from the EFA revealed two main factors that showcased individuals' travel behavior, including "maximum likelihood, 40% variance explained, KMO = 0.622". Table 2 shows the statements regarding loaded factors. The factor (component) scores for the Via, uber/Lyft, university transportation, and walking/biking were positive, while it was negative for private vehicle ownership. This factor indicates a negative correlation between owning a private vehicle and the loaded factor. Accordingly, the extracted factor represents "non-car users." (See Table 2).

We also analyzed travel distances from the respondents' homes to different destinations and loaded the latent factor. One main factor was extracted for observed travel distance variables titled as the "residential accessibility factor" (maximum likelihood, 50% variance explained, KMO = 0.800).

Acceptance of SAVs was explored through two variables: SAV ridership experience and willingness to ride in an SAV. (See Table 1.). We applied the EFA to combine these two variables into one dependent variable, and one latent factor for the two observed variables was extracted as "SAV acceptance" (maximum likelihood, 56% variance explained, KMO = 0.500).

4.3 SEM: acceptance of shared autonomous vehicles

This section explores how individuals' acceptance of riding in SAVs is influenced by the key variables of the study through SEM. We developed the SEM based on the four latent factors determined through the EFA shown in Table 2, including positive attitudes, negative attitudes, car users, and residential accessibility. All these factors were treated as continuous variables since they were extracted from the factor analysis. A confirmatory factor analysis (CFA) was run in SEM and shaped the measurement model for the exogenous variables. In addition, the SEM included the five sociodemographic variables listed in Table 1: age, race, education, income, and vehicle ownership. The model contained two endogenous dependent variables: SAV ridership experience and willingness to ride in an SAV. To combine the two response variables into one dependent factor, a CFA was applied through the SEM (following the results from EFA) and the measurement model extracted the final dependent endogenous variable as "SAV acceptance." This dependent variable is a continuous factor and was suitable for use as the final exogenous variable in our model.

Figure 3 demonstrates the structure of the SEM and measurement models, the structural relationships between the exogenous and endogenous variables, and the standardized loading factors for the measurement model. The values in the ovals represent the load factors of the associated variables from the CFA in the SEM. It is worth noting that the values here are different from those in Table 2, because Table 2 was the first step in identifying the latent factors behind the observed variables by conducting an EFA. The values in the ovals in Figure 3 show the loading factors based on the CFA of the measurement model in SEM. Based on Figure 3, the final SEM includes five sets of latent factors determined by CFA: positive attitudes towards SAVs, negative attitudes towards SAVs, car users, residential accessibility, and SAV acceptance. In addition, our SEM model contains observed sociodemographic variables, including vehicle ownership, age, education, household income, and race.

The model explores the effects of negative attitudes, positive attitudes, car users, destination accessibility, and sociodemographic information on SAV acceptance. Simultaneously, it tests the effects of sociodemographic characteristics (income, education, vehicle ownership, and age) on positive attitudes towards AV technology, as well as the effects of positive attitudes of car users. Exploring these mediating relationships deepens our understanding of the differences in SAV users and non-users. Table 3 illustrates the results of SEM model.

Table 3 shows the coefficients (estimates) and associated p-values (significance) and indicates the significant relationships between individuals' attitudes as a latent variable and SAV acceptance. When a positive attitude is increased by one unit, SAV acceptance increases by 0.36. Individuals with better attitudes about the benefits and advantages of AVs are more likely to accept SAVs. In contrast, individuals with negative attitudes towards AV technology are less likely to accept SAVs in the future. When negative attitudes go up by one, acceptance goes down by 0.167.

Car users are less likely to accept SAVs. When car use increases by one, SAV acceptance goes down by 0.392. This result suggests that individuals' travel patterns have a significant

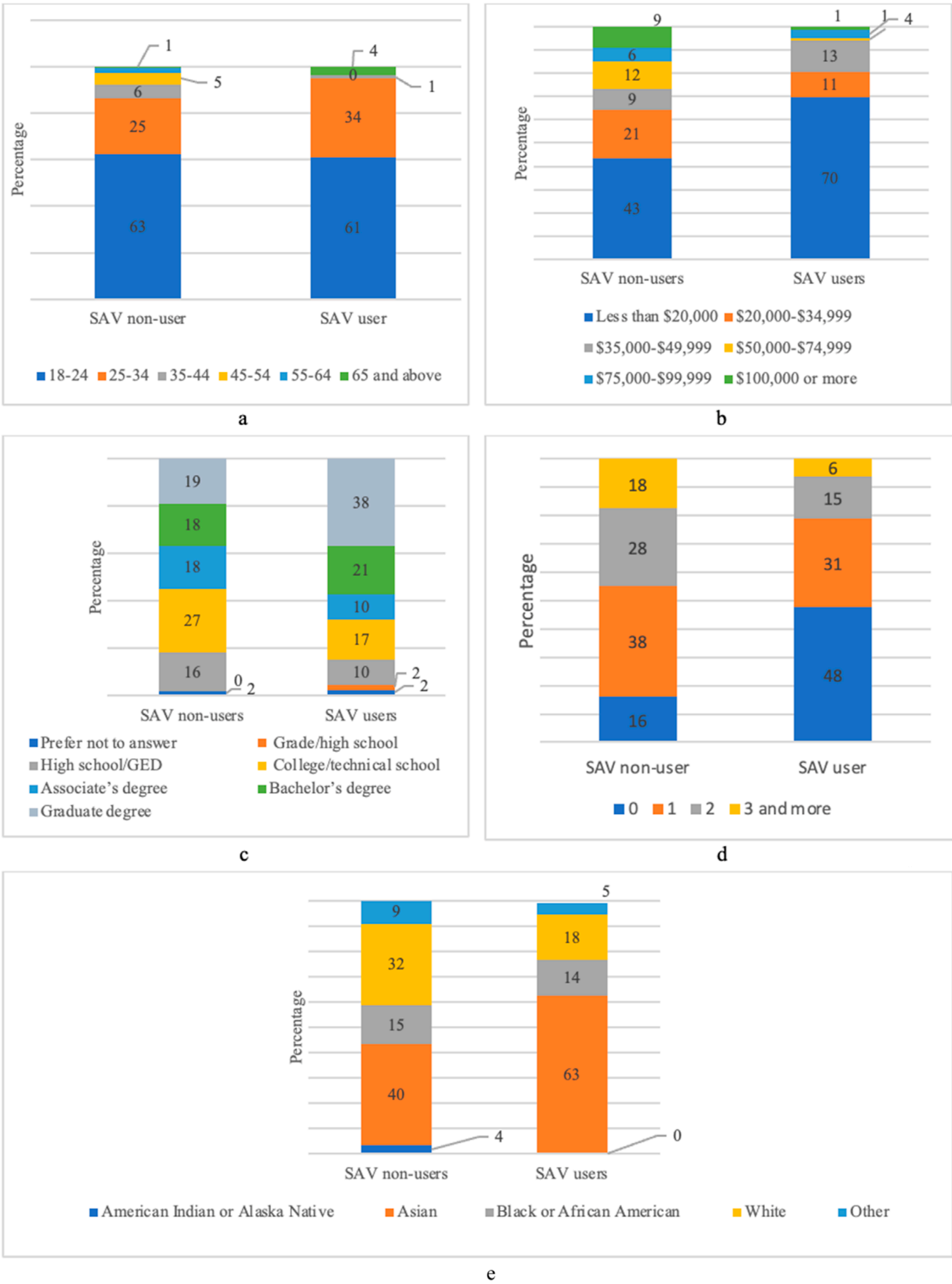

FIGURE 2
Sociodemographic differences between SAV users and non-users **(a)** SAV users' and non-users' age categories. **(b)** SAV users' and non-users' household incomes. **(c)** SAV users' and non-users' eduaction levels. **(d)** SAV users' and non-users' vehicle ownership. **(e)** SAV users' and non-users' race.

effect on SAV acceptance and individuals using public transit, ridesharing services, and walking or biking are more likely to accept them. Sociodemographic attributes income and race also have a significant impact on SAV acceptance, as those with higher incomes are less interested in SAVs, and Asians are more likely to accept them.

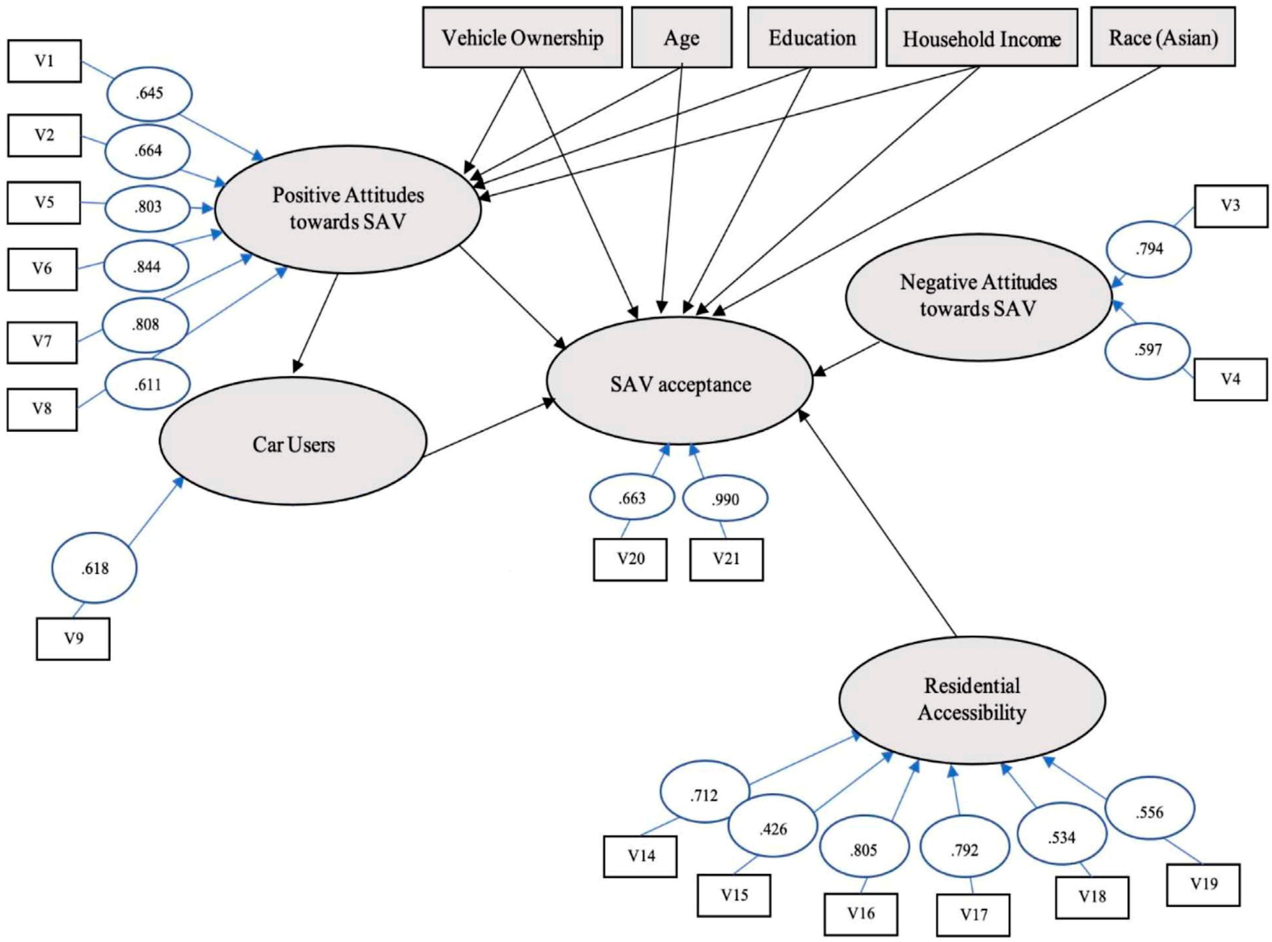

FIGURE 3
Structural equations for SAV acceptance.

In addition to direct effects from key variables on SAV acceptance, our model evaluates the effects of sociodemographic characteristics on positive attitudes and the effects of positive attitudes on car users. The results indicate that age negatively impacts attitudes towards AV technology, as older adults seem less likely to have positive perceptions towards the advantages of AVs. In contrast, education significantly impacts positive attitudes as highly educated individuals are more likely to be positive about the benefits of AV technology. Individuals with a positive attitude towards AV benefits are less likely to use private vehicles as their main mode of transportation.

We also tested the validity and reliability of the measurement model, using different types of goodness-of-fit indices, such as the non-significant chi-square statistic, with particular statistical functions. We evaluated the model's goodness-of-fit based on three indicators: the χ^2/df, RMSEA, and CFI, calculated the indicators based on widely acknowledged standards. Table 4 displays the results for the model's goodness-of-fit and shows that the reliability of the model is acceptable.

5 Discussion

5.1 Key findings and relation to existing literature

This study examines factors influencing SAV acceptance and rejection, analyzing collected survey data. Through a self-reported online survey, we analyzed attitudinal, travel pattern, and sociodemographic differences among those who have ridden the service, potential riders, and those unlikely to use the service. Notably, the survey population was dominated by students, which likely influences the findings and limits generalizability to a broader population.

Several findings align with existing research on SAV adoption trends among younger adults, who tend to be more receptive to new mobility technologies (Dong et al., 2019; Wang et al., 2020). In this study, the RAPID service's proximity to a university and free access likely encouraged student ridership, reinforcing the association between age and SAV acceptance. Additionally, low-income students

TABLE 3 Direct standardized effects of the key variables.

Effects from → on ↓		Estimate	P
Positive Attitudes towards SAV	Age	−0.160	0.018**
Positive Attitudes towards SAV	Vehicle Ownership	−0.013	0.846
Positive Attitudes towards SAV	Education	0.170	0.012**
Positive Attitudes towards SAV	Household Income	−0.043	0.523
Car Users	Positive Attitudes towards SAV	−0.247	0.008**
SAV acceptance	Age	−0.020	0.444
SAV acceptance	Vehicle Ownership	−0.035	0.185
SAV acceptance	Education	−0.020	0.242
SAV acceptance	Household Income	−0.030	0.072*
SAV acceptance	Car Users	−0.392	0.000**
SAV acceptance	Race (Asian)	0.094	0.073*
SAV acceptance	Positive Attitudes towards SAV	0.360	0.000**
SAV acceptance	Residential accessibility	0.059	0.143
SAV acceptance	Negative Attitudes towards SAV	−0.167	0.005**

Note: *Significant α = 0.10, **Significant α = 0.05.

TABLE 4 Fitness of SEM.

Model fit	χ^2/df (<3)	RMSEA (<0.1)	CFI (>0.95)
	2.6	0.081	1

-$\frac{\chi^2}{df}$; that is recommended to be equal to or less than 3 (Chi square test values/model's degrees of freedom).
-Comparative fit index (CFI) (should be ≥0.95).
-The root-mean-square error of approximation (RMSEA) (is suggested to be <0.10).

without private vehicle access comprised a significant portion of the SAV user group, aligning with research showing that individuals with limited transportation options are more probable to use shared mobility (Lim, 2021; Kodransky and Gabriel, 2014). This student-dominated sample may reflect a context-specific demographic rather than a generalized trend, as SAV acceptance might vary in a more demographically balanced sample.

The data also showed that most early adopters of SAVs in this sample were Asian students. While race can offer insights into social inclusion or exclusion in transportation access, our study cannot conclude that this finding applies beyond this specific setting, as the racial representation in the literature on SAV acceptance remains limited (Janatabadi and Ermagun 2022). Future studies with more diverse samples are necessary to avoid biases and to better understand the role of race in SAV acceptance.

One of the most substantial findings from the SEM is the central role of individual attitudes in predicting SAV acceptance. Positive attitudes toward SAVs were strongly associated with a greater likelihood of adoption, while negative attitudes showed a significant deterrent effect. These results align with socio-psychological models such as the Technology Acceptance Model (TAM), which emphasize the influence of perceived usefulness and ease of use—both reflected in the attitudinal constructs captured in our study. These findings underscore the importance of public education and targeted communication strategies aimed at improving perceptions of SAV safety, convenience, and trustworthiness.

Additionally, our model revealed a strong negative relationship between car usage and SAV acceptance, indicating that individuals who rely more heavily on private vehicles are significantly less inclined to adopt SAVs. This result is particularly relevant for transportation planners aiming to encourage modal shift. It suggests that without specific strategies to reduce car dependency, such as improved integration of SAVs with transit systems, incentives for non-car use, or disincentives for driving; SAV adoption may remain concentrated among existing non-drivers or rideshare users. As such, efforts to maintain SAVs should not only promote the technology itself but also address entrenched patterns of automobile reliance.

The SEM results revealed that trust in AV technology significantly influenced willingness to ride SAVs. Positive perceptions of reliability and functionality enhance acceptance (Xing et al., 2020; Tussyadiah and Inversini, 2015). However, SEM findings in this study may be inherently shaped by the high representation of students, who generally have more favorable views toward technological advancements than older or more diverse populations. This suggests a need to interpret these results within the context of this sample.

5.2 Limitations and generalizability

This research provides insights into SAV acceptance patterns, especially within a college-centric deployment. However, it is essential to recognize that the findings are likely influenced by the student-heavy sample. For example, the association of younger, lower-income, and car-free individuals with SAV acceptance reflects student-specific characteristics and should not be generalized to the broader population.

The study's limitations highlight the importance of additional research with broader, more representative samples to better understand how sociodemographic factors influence SAV acceptance in various contexts. Future studies could provide valuable insights by analyzing SAV adoption trends across more diverse demographic groups and settings. Despite these limitations, the study offers a foundation for policymakers and transportation planners, providing early insights into user characteristics and travel patterns that affect SAV adoption, particularly in university areas or similar environments.

5.3 Policy and practical implications

The findings of this study suggest several important policy considerations for the implementation of SAV services. First, local governments and transit agencies aiming to promote the adoption of SAV should focus the community outreach and public engagement to enhance the awareness about the service availability in areas with a high concentration of younger adults, lower-income, and individuals with no access to private vehicles, as these groups are more receptive to new mobility technologies.

Second, SAV integration should be prioritized alongside existing fixed-route and demand-responsive transit services to enhance accessibility for individuals already familiar with these modes. Current public transit users are more likely to accept integrated new mobility services compared to those who do not regularly use public transit.

Additionally, policy initiatives should consider investing in educational campaigns to improve public attitudes toward autonomous vehicle safety and benefits, particularly among more car dependent population. Planners should consider integrating SAVs more efficiently with existing public transit networks to offer continuous multimodal options. Incentive programs that reward SAV usage such as discounts, fare integration, or loyalty points could further encourage shifts away from car ownership.

Finally, the demographic profile of the sample, also emphasizes the importance of planning SAV initiatives that are inclusive and representative. Future SAV pilot programs should aim to engage a wider range of participants across different age groups, income levels, and racial backgrounds to make sure that the services are equitable. This method is particularly important considering that race and social inclusion remain overlooked in SAV research, despite their significance in wider transportation equity discussions.

6 Conclusion

This study explored the factors affecting acceptance of shared autonomous vehicles, using survey data largely drawn from a student population. The findings highlight the strong role of individual attitudes in predicting SAV adoption. Positive attitudes about SAVs particularly regarding safety, convenience, and trust significantly increased the likelihood of use, while negative opinions acted as barriers. The analysis revealed that individuals who have access to private vehicles are less likely to adopt SAVs. The results also revealed that most SAV users in this study were younger, low-income students, often without private vehicles and their higher acceptance of SAVs aligns with existing research. The outcomes of this research aid transportation planners and policymakers in improving the technology, and also on changing public perceptions and travel behavior specifically in individuals who are less likely to adopt emerging technologies.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Ethics statement

The studies involving humans were approved by Institutional Review Board at UTA. The studies were conducted in accordance with the local legislation and institutional requirements. The ethics committee/institutional review board waived the requirement of written informed consent for participation from the participants or the participants' legal guardians/next of kin because As no identifiable information was collected.

Author contributions

RE-G: Writing – original draft. RP: Writing – original draft. AP: Writing – original draft. SK: Supervision, Writing – review and Editing. JR: Supervision, Writing – review and Editing. AF: Writing – review and Editing.

Funding

The author(s) declare that no financial support was received for the research and/or publication of this article.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

The author(s) declared that they were an editorial board member of Frontiers, at the time of submission. This had no impact on the peer review process and the final decision.

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Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fbuil.2025.1613232/full#supplementary-material

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