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Article

Identification of Contributory Factors That Affect the Willingness to Use Shared Autonomous Vehicles

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Abstract: Shared autonomous vehicles (SAVs) aspire to change not only vehicles but also the way people and goods move in urban areas. However, the promotion of such services, that is, whether travelers are willing to share their trips with other service users, is still a challenge. This study aims to examine the contributory factors that influence the willingness of individuals to use shared autonomous vehicles by simultaneously identifying the differences in terms of preferences with conventional competitive transport modes, namely, private cars and public transport. A stated preference experiment combined with perception ratings was designed and conducted in Athens, Greece. Based on the collected responses, a multinomial logit model was estimated. The results show that the flexibility of SAVs and, particularly, the possibility of performing door-to-door trips has a serious added value that travelers are willing to pay. Compared with public transport, additional waiting time does not increase the disutility. Furthermore, people who belong to high-education and -income groups expressed a higher willingness to use SAVs and socialize while traveling. The familiarity of each potential user with technology is a necessary precondition. Lastly, it is confirmed that environmentally conscious people are more positive about using these new services.

Keywords: shared autonomous vehicles; willingness to use; stated preference experiment; logistic regression; choice modeling

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1. Introduction

An autonomous vehicle can be defined as a vehicle that is capable of sensing its environment and navigating without human input [1]. Based on the amount of drivers' attention and intervention that is required, vehicle automation can be classified into six different levels, starting from SAE level 0, no automation, to SAE level 5, full automation. In level 5, none of the longitudinal and lateral movements of the vehicle are controlled by the user [2]. This means that automated driving systems (ADS) fully perform the dynamic driving task (DDT) without any limitation, supervision, or condition.

Automation aspires to change not only vehicles but also the way people move in urban areas. The latter is related to the concept of shared autonomous vehicles (SAVs), which combines automation with ridesharing to provide flexible, on-demand, and door-to-door travel services [3]. SAVs may be publicly or privately owned and can provide successive trips performed for single passengers or several passengers taking overlapping trips [4]. Sharing strategies can reduce CO_2 emissions by 17% or 19% in a mid-sized city, which is a prerequisite for the successful operation of SAVs, and it is anticipated that they will also lead to reductions in energy consumption, traffic congestion, and travel costs [5]. According to Stead et al. [6], the operation of shared mobility services will lead to lower car ownership and, consequently, lower parking supply needs. Therefore, SAVs are seen as a concept that may transform urban road environments [7] and support efficient and sustainable transportation systems. Considering an inclusive science map developed for SAVs and shared mobility services, car sharing, collaborative consumption, the adoption of new services, operational constraints, and technological advancements are some of the main themes that are being investigated by researchers today [8]. Regarding the first two themes, it is still questionable whether travelers are willing to use and share these vehicles in their daily trips.

Various studies have dealt with the previously mentioned challenge through stated preference experiments. Older travelers [9,10], females [4], lower-income people [11], and residents of non-urban areas [12] are among those groups that have displayed a relatively low willingness to use SAVs in previous surveys. Nevertheless, in Arlington, Texas, USA, a comparative analysis between users and non-users of a self-driving pilot service indicated that Asian individuals from low-income groups and with limited access to private transport were early adopters compared with other groups [13]. In general, well-educated men tend to be more open to using on-demand mobility services that are comparable with SAVs [9]. A lack of private vehicle ownership due to several reasons, except affordability, can be characterized as a key driver in adopting SAVs according to Patel et al. [13]. The familiarity of potential users with smart mobility applications and technology comprises additional factors, which are, in turn, correlated with sociodemographic characteristics [14]. Furthermore, supporters of measures for a more sustainable transport system are more likely to accept new technologies, like SAVs [15]. Surprisingly, the study by Xiao and Goulias [16] observed a positive association between the proximity of a home location to an electric vehicle or hydrogen fueling station and the willingness to use SAVs. The last findings show the positive attitudes of some communities toward more sustainable, flexible, and innovative transport services.

An individual's decision to adopt shared mobility services (and, therefore, SAV potential users) can be based on other motives, such as environmental awareness and cultural socialization [17–19]. Multiple psychological factors have been examined in this context, namely, privacy-sensitivity, time-sensitivity, interest in the productive use of travel time inside the shared automated vehicle, trust, reciprocity, etc. [3]. In SAVs, a passenger can utilize his/her travel time to be more productive or perform more enjoyable activities; this is a hypothetical benefit that is difficult to examine in a survey [20]. On the other hand, safety and security comprise a discouraging factor, especially for females and elders [21]. Lavieri et al. [4] found that, when commuting to work, people are less sensitive to the presence of strangers compared with leisure-activity trips. Concerns have also been expressed regarding the technical issues of automation and driverless cars. Trust not only in the service provider but also in the autonomous vehicle seems to be a very critical factor according to many previous studies [15,22,23]. Still, perceived risks are interrelated in social groups, particularly the familiarity of individuals with technological advancements [24].

It is questionable whether or not SAVs can be classified somewhere between private cars and public transport in terms of flexibility [25]. The extra travel time to detour and serve other travelers can be a very serious obstacle that may influence the efficiency of these services and future demand [26]. Considering the value of travel time savings, the study by Gkartzonikas et al. [27] proved that the majority of future users will prefer a single-occupancy SAV to a shared one. However, multiple pick-up or drop-off points are expected shortly; this means a short access/egress trip to/from the collection point, which may boost the attractiveness of SAVs compared with conventional public transport services. SAV users will not have to worry about finding a parking spot; this comprises a significant advantage concerning private transport modes [28]. Regarding trip costs, some studies have shown that the introduction of a discount to service prices leads to a higher willingness to share a trip [17,26]. According to König and Grippenkoven [26], a reduced travel cost, which will also be split between passengers, will be the major motive for using shared autonomous vehicle services.

This study attempts to examine all these factors by conducting a stated preference experiment combined with perception ratings. At the same time, it aims to identify the differences in terms of preferences for conventional transport modes that will be competing with SAVs in the future, namely, private cars and public transport, so that the role of SAVs in future urban transport systems can be clarified. Based on the collected responses, choice models were developed that take into consideration sociodemographic characteristics and user perceptions. In the next section, the design of the stated preference experiment is described. In Section 3, descriptive statistics and the developed logistic regression models are presented. In Section 4, the results are discussed concerning the literature before exporting valid conclusions in the last section of this paper.

2. Experimental Design

The methodology is based on a stated preference survey conducted in Athens, Greece. Stated preference experiments are formulated based on a particular methodology that consists of seven steps: selection of variables, identification of measurement unit, determination of variable levels, survey design, translation of designed scenarios into a set of questions, selection of appropriate estimation procedure, and model estimation [29,30].

2.1. Selection of Variables and Variable Levels

In this experiment, respondents have to choose the best transport mode per scenario among three different options, namely, private car (CAR), public transport (PT), or shared autonomous vehicles (SAVs). Therefore, the dependent variable is the choice of each respondent; it is a discrete variable that does not have metric information. To model choices, choice scenarios are developed in the next steps, which display a wide range in terms of flexibility. Private cars can serve door-to-door trips at any desired time, while public transport follows a fixed route with specific stops and schedules. Figure 1 classifies the examined transport modes, taking into account two dimensions: on-demand (y-axis) vs. door-to-door (x-axis). According to this definition, a door-to-door service ensures less walking time or distance from the stop location to the destination [31,32]. On the other hand, on-demand services aspire to quickly respond to a request and, therefore, minimize the waiting time [33]. We hypothesize that SAV services will be somewhere in the middle in terms of flexibility. Based on this consideration, all choice options seem to be independent. This is valid, as SAVs can be considered to be a replacement for taxi services, which exhibit distinct differences from public transport [34].

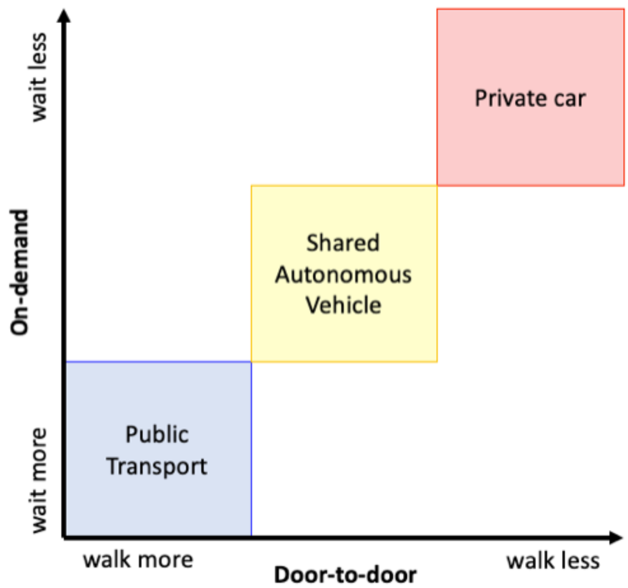


Figure 1. Classification of examined transport modes based on their flexibility.

Regarding independent variables, several potential contributory factors have been explored in the literature to explain sharing behavior, leading to complex choice models that cannot be straightforwardly utilized in practice. Table 1 summarizes notified factors and underlined findings from previous studies that explored the attractiveness and associated factors of flexible transport services. These were also referred to in the problem description in the first section. The goal is to use existing knowledge to select a set of contributory factors that have to be further examined in this stated preference experiment.

Table 1. Summary of notified factors and underlined findings from previous studies.

Study	Data Collection/ Analysis Method	Noticed Factors and Underlined Findings
Schoettle et al. [14]	Online survey	-Most respondents were unaware of connected-vehicle technology but had a positive initial opinion. -Respondents expressed high concern about security and performance issues. -Safety was considered the most important aspect of connected vehicles. -Integration of personal communication devices and internet connectivity in connected vehicles was deemed important.
Amirkiaee et al. [3]	Online scenario-based survey	-High transportation anxiety increases the likelihood of people participating in ridesharing when they trust the service providers and participants.
Lavieri et al. [4]	Revealed and stated choice data analysis obtained using a web-based survey	-Users are less concerned about the presence of strangers during a commute trip than during a leisure-activity trip. -The additional travel time required to accommodate other passengers may pose a greater obstacle to the adoption of shared services. -High-income individuals may be more willing to embrace shared services despite the potential travel time increase.
Fraedrich et al. [9]	Mixed method: in-depth interviews and a quantitative survey	-Skepticism regarding the compatibility of autonomous vehicles (AVs) with existing transport and urban-planning objectives.
Carteni et al. [21]	Discrete choice experiment	-Male individuals aged 18–40 years old have 53% more reluctance to use driverless transit services compared with female individuals. -Individuals who commonly use onboard automation features show a positive willingness to pay for driverless vehicles.
Chng et al. [22]	Self-reported online survey	-Concerns about SAVs exist regarding technical issues and legal liability. -Acceptance linked to perceived benefits, regardless of concerns or sociodemographic backgrounds.
Paddeu et al. [23]	Three-stage stated preference experiment	-Trust had statistically significant relationships with each independent variable, whereas perceived comfort did not have significant relationships with either variable. -A strong correlation was observed between comfort and trust, suggesting that trust in the shared autonomous vehicle (SAV) is a crucial predictor of perceived comfort.
König et al. [26]	Household stated preference survey	-The primary motivation for utilizing shared autonomous vehicle services is expected to be the reduced travel cost, which will be shared between passengers.
Maeng et al. [15]	Conjoint stated preference experiment	-Consumer satisfaction increases with higher SAV automation and provider liability. -Higher-income individuals prefer provider liability, while older individuals, drivers, and lower-income individuals prefer manufacturer liability.
Xiao et al. [16]	Structural equation modeling with survey data	-Perceived usefulness influences behavioral intention toward AVs. -Young, well-educated males perceive AVs as more useful. -Access to infrastructure like EV charging and hydrogen fueling stations enhances positive AV perception. -Young, educated households with more regular riders are inclined toward AV-sharing services rather than owning AVs.

Table 1. *Cont.*

Study	Data Collection/ Analysis Method	Noticed Factors and Underlined Findings
Patel et al. [13]	Comprehensive stated preferences survey	-SAVs should target young Asian individuals and low-income students who lack private vehicle access.
Etminani-Ghasrodashti et al. [24]	Online survey	-The ultimate adoption of SAVs will be determined by public attitudes toward technology and perceptions of associated risks.
Gkartzonikas et al. [27]	Online stated preference survey	-The shared autonomous vehicle (SAV) option is less preferred than single-occupant AVs across all market segments. -Value of travel time savings (VTTS) is lower for SAVs compared with single-occupant AVs.
Patel et al. [28]	Self-reported survey and post-implementation interviews	-The ease of using SAVs without worrying about parking positively impacted individuals' future willingness to use them. -However, concerns about potential confusion between human drivers and SAVs on the road decreased the willingness to use SAVs. -Qualitative interviews highlighted waiting time, pick-up and drop-off locations, and maneuverability at intersections as major concerns.

In this study, the variable identification process was organized based on four groups of variables (see Figure 2 and Equations (1)–(3)). The first group refers to sociodemographic characteristics: gender, age, education, and income are independent variables that are commonly used in choice models. Having a driving license and vehicle availability are considered too. The next group is related to perceptions that influence the willingness to use these new services. It is also related to some of the benefits SAV services will offer in the future. More specifically, SAVs aspire to become "green" transport modes since they will reduce vehicle kilometers covered in cities and, therefore, energy consumption, GHG emissions, etc. It is, therefore, hypothesized that respondents with environmental sensitivities are more positive about using them. Moreover, SAVs will provide the chance for users to socialize and meet new people while traveling. This can be a benefit for a group of people, though other commuters will prefer to use the in-vehicle travel time to work. Therefore, parameters related to the aforementioned choices of time utilization are also explored in this experiment. Additionally, familiarity with different technological innovations may be a necessary precondition so that a traveler will use these new services [4,35]. This is because their flexibility is based on smart mobile applications, which facilitate communication between service users and, therefore, sharing behavior. The frequency of using of PCs/laptops, smartphones, internet maps, telematics, taxis, and trip advisor applications is an indicator of the familiarity of each respondent with technologies that are required in SAV services.

The last group refers to exogenous trip parameters. Travel time and trip costs are common variables in choice models that influence mode and route choices. In this experiment, travel time is divided into in-vehicle travel time, waiting time, and walk time from/to the stop so that the flexibility of each transport mode can be parametrized [36,37]. To do so, zero walking or waiting time is assumed when using a private car. Higher waiting and walking times, yet lower costs, are set to public transport options rather than SAVs. The in-vehicle travel time levels of private cars present a wider range of values when considering the chance of traffic congestion and, consequently, delay when using a private transport mode [38]. The exogenous independent variable and the variable levels are presented in Table 2.

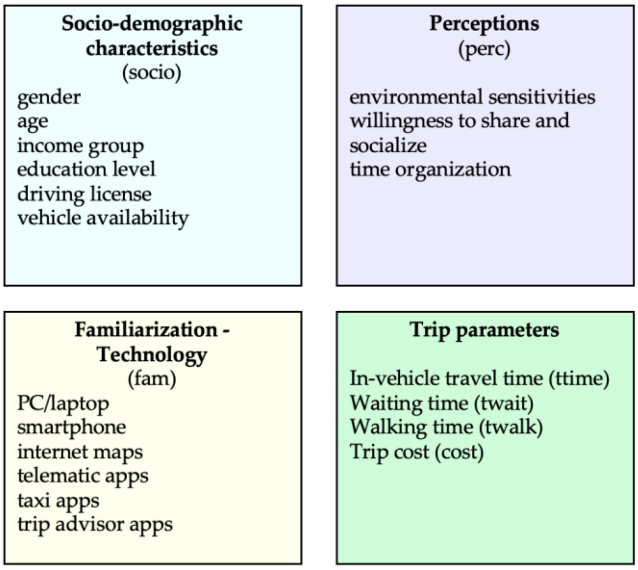


Figure 2. Selected independent variable and variable groups.

Table 2. Exogenous variables and variable levels.

	Transport Mode	Level 1	Level 2	Level 3
Trip cost in euros (*cost*)	car	4.50	6.00	7.50
	pt	0.70	1.20	1.70
	sav	1.50	3.00	4.50
In-vehicle travel time in minutes (*time*)	car	15	25	45
	pt	10	20	30
	sav	10	20	30
Walking time in minutes (*twalk*)	car	0	0	0
	pt	5	10	15
	sav	2	6	10
Waiting time in minutes (*twait*)	car	0	0	0
	pt	5	10	20
	sav	2	6	15

Based on the above, the utility functions for the three examined modes are formulated as follows:

$$U_{car,i,t} = \beta_{ttime,car} \times ttime_i + \beta_{cost,car} \times cost_{i,car} + \varepsilon_{car,t} \tag{1}$$

$$\begin{aligned} U_{pt,i,t} = ASC_{pt} + \; & \beta_{ttime,pt} \times ttime_{i,pt} + \beta_{cost,pt} \times cost_{i,pt} + \beta_{twalk,pt} \times twalk_{i,pt} + \beta_{twait,pt} \times twait_{i,\,pt} \\ & + \sum \beta_{socio_j,pt} \times socio_{j,t} + \sum \beta_{perc_j,pt} \times perc_{j,t} + \sum \beta_{fam_j,pt} \times fam_{j,t} + \varepsilon_{pt,t} \end{aligned} \tag{2}$$

$$\begin{aligned} U_{sav,i,t} = ASC_{sav} \; & + \beta_{ttime,sav} \times ttime_{i,sav} + \beta_{cost,sav} \times cost_{i,sav} + \beta_{twalk,sav} \times twalk_{i,sav} \\ & + \beta_{twait,sav} \times twait_{i,sav} + \sum \beta_{socio_j,sav} \times socio_{j,t} + \sum \beta_{perc_j,sav} \times perc_{j,t} \\ & + \sum \beta_{fam_j,sav} \times fam_{j,t} + \varepsilon_{sav,t} \end{aligned} \tag{3}$$

An explanation of all the symbols in the previous equations is provided in the nomenclature at the end of this paper. The units of these variables are also provided. Figure 2 and Table 2 match the symbols with the selected variables.

2.2. Survey Design

The choice experiment was designed based on the selected trip parameters and their levels, which are shown in Table 2. These variables can be controlled in the survey design process. Other groups include variables that refer to the respondents' characteristics or perceptions, which were unknown before distributing the survey. Considering the variable levels, the total number of all possible combinations is estimated to be 177,147. Formulating and sharing this number of scenarios is not feasible at all. To minimize the scenarios considered in the stated preference experiment, a fractional factorial design is first chosen, providing 27 scenarios. Fractional factorial designs are based on orthogonal tables, which ensure zero correlation between the independent variables that were imported into the design process. Yet, in the final choice set, there are scenarios with a dominant alternative; this means that a relatively high percentage of respondents (more than 90%) will prefer one transport mode over the others since the trip conditions are better.

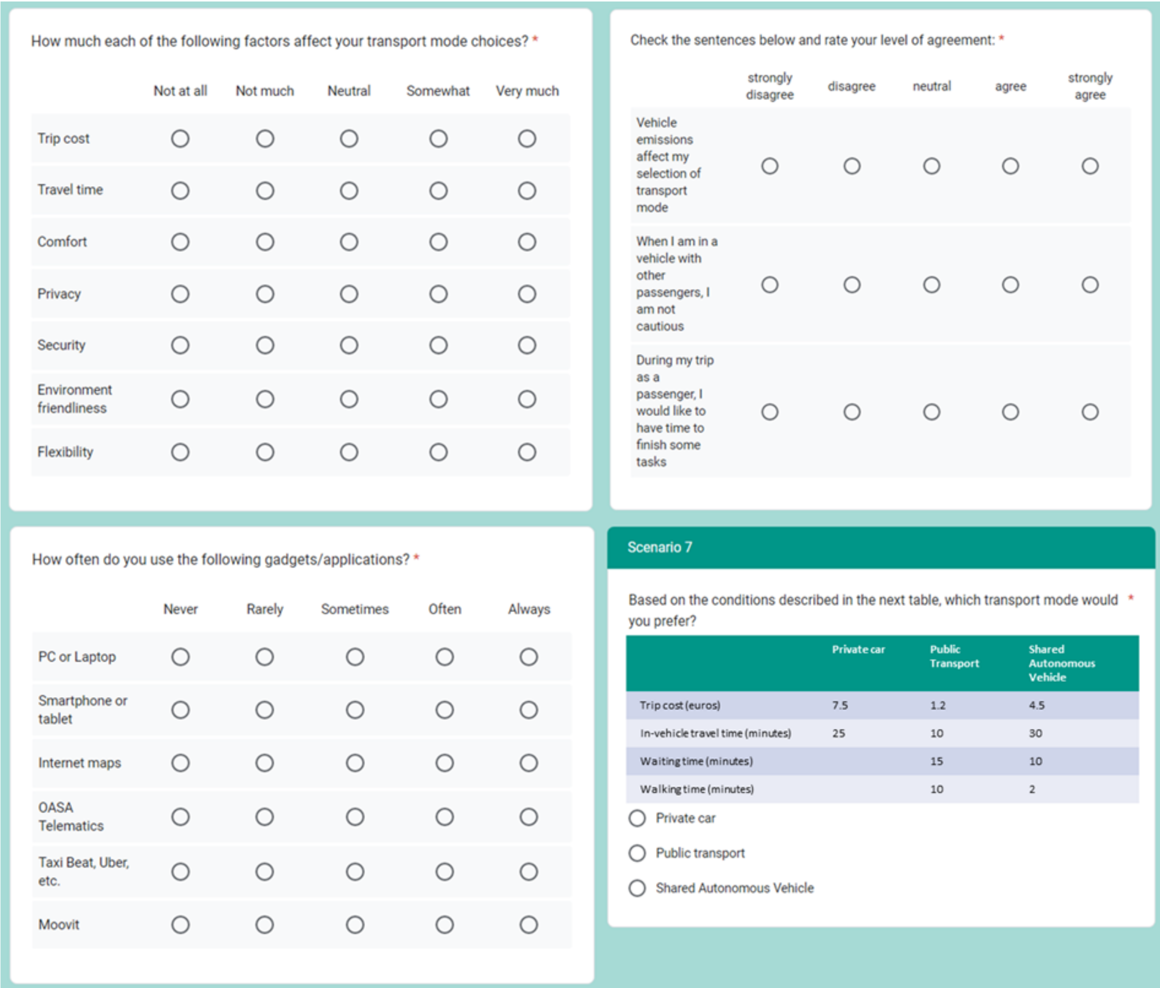
To eliminate these scenarios before developing the final survey form, a pilot study was undertaken. Ten transport planning experts evaluated the 27 scenarios of the orthogonal scenario subset. Based on the collected choices, prior beta parameters were calculated to estimate prior choice probabilities and, therefore, identify choice situations with a "dominant" option. An efficient design was applied to eliminate the identified scenarios, resulting in a choice set of 9 scenarios, which were integrated into the survey form and evaluated by the respondents together with additional questions related to sociodemographic characteristics and user perceptions. Of course, in the choice set, there were weak correlations between the independent variables, which were insignificant for a confidence interval of 95%.

The next step of the survey design process was the translation of these scenarios into a set of questions included in the survey form. In Figure 3, the survey form is presented; it consists of four different sections. The first section deals with questions about trip characteristics and familiarity with different technologies and their application. The purpose of this section is to find out some characteristics of respondents to help in the interpretation of the questionnaire. Hence, there are two more groups of questions about the factors that influence mode choice and familiarity with using smart devices and applications. These questions utilize a Likert scale, meaning that travelers must choose what represents them the best on a graded five-point scale. The second section explores user perceptions and attitudes considering the environment, safety, and productivity. The section consists of three statements that express perceptions around these three issues. Each sentence is accompanied by a Likert scale of five levels, "strongly disagree", "disagree", "neither agree nor disagree", "agree", and "strongly agree", and each respondent is asked to choose the level that best matches with three levels of agreement. Below, the statements that were added to the survey form are presented:

- Environmental sensitivities: "Vehicle emissions affect my selection of transport mode".
- Willingness to share and socialize: "When I am in a vehicle with other passengers, I am not cautious".
- Time organization: "During my trip as a passenger, I would like to have time to finish some tasks".

The stated preference experiment is introduced in the third section of the survey form. Scenarios are presented in tables, as shown in Figure 3. The fourth section collected sociodemographic data. This section includes 14 closed-ended questions about the social and demographic characteristics of the respondents. Also, the sociodemographic characteristics helped to conclude by combining these features with the questions in the previous sections.

The questionnaire form was created using Google Forms and was made available only online because of COVID-19 restrictions, which did not allow for in-person survey distribution. The time required to fill out the survey was not more than 15 min. This was indicated on the first page of the survey form, combined with information about SAV services. Images were also used for better interpretation. Students from the National Technical University of Athens and their parents were invited to fill out the survey. Invitations were also sent via personal messages on social media to control the sociodemographic characteristics of the sample. The sampling procedure resembled, partly, the snowball and convenience sampling methods.



How much each of the following factors affect your transport mode choices? *

	Not at all	Not much	Neutral	Somewhat	Very much
Trip cost	○	○	○	○	○
Travel time	○	○	○	○	○
Comfort	○	○	○	○	○
Privacy	○	○	○	○	○
Security	○	○	○	○	○
Environment friendliness	○	○	○	○	○
Flexibility	○	○	○	○	○

Check the sentences below and rate your level of agreement: *

	strongly disagree	disagree	neutral	agree	strongly agree
Vehicle emissions affect my selection of transport mode	○	○	○	○	○
When I am in a vehicle with other passengers, I am not cautious	○	○	○	○	○
During my trip as a passenger, I would like to have time to finish some tasks	○	○	○	○	○

How often do you use the following gadgets/applications? *

	Never	Rarely	Sometimes	Often	Always
PC or Laptop	○	○	○	○	○
Smartphone or tablet	○	○	○	○	○
Internet maps	○	○	○	○	○
OASA Telematics	○	○	○	○	○
Taxi Beat, Uber, etc.	○	○	○	○	○
Moovit	○	○	○	○	○

Scenario 7

Based on the conditions described in the next table, which transport mode would you prefer? *

	Private car	Public Transport	Shared Autonomous Vehicle
Trip cost (euros)	7.5	1.2	4.5
In-vehicle travel time (minutes)	25	10	30
Waiting time (minutes)		15	10
Walking time (minutes)		10	2

○ Private car

○ Public transport

○ Shared Autonomous Vehicle

Figure 3. Survey form (in English).

2.3. Data Processing and Analysis

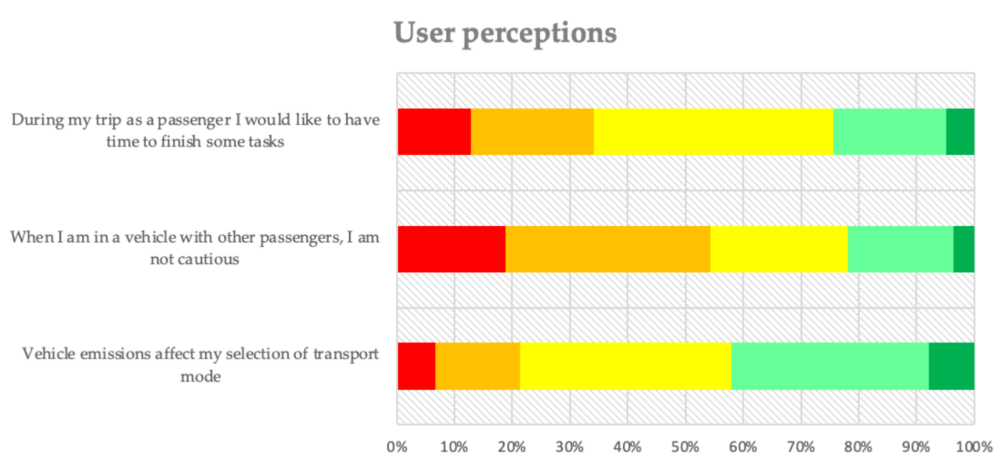
The collected responses were downloaded directly from the survey platform. Simultaneously with the survey distribution process, a tool to process the data was developed using the Python™ programming language. Therefore, sample characteristics and collected responses were continuously monitored to optimize data quality. Each respondent had a unique person ID, while the choice responses were organized based on scenarios.

To analyze the data, the R programming language was used, particularly the mlogit package. Descriptive statistics were estimated first; however, before developed models, a correlation analysis was performed to select the right set of variables, eliminating multicollinearities that are inevitable among sociodemographic characteristics and user perceptions (i.e., uncontrolled variables). To estimate the beta parameters of the utility function of each transport mode, the maximum likelihood estimation (MLE) method was implemented using the previously mentioned package. The significance of each variable was assessed based on t-tests, while the model quality was checked by calculating McFadden's rho-squared. It was hypothesized that the responses of each respondent would be independent of each other, as we attempted to describe the heterogeneity in preferences based on the selected sociodemographic and user perception variables. If this assumption was valid, a relatively high McFadden's rho-squared would be expected, which indicates that a considerably high proportion of unobserved heterogeneity was modeled more systematically. Finally, trip preferences, which we asked about in the first section of the questionnaire, were visualized to allow for qualitative comparisons with model results. In the next section, the outputs of the data analysis are presented.

3. Results

The survey distribution process lasted about two months; 164 respondents participated in this experiment, yielding a total of 1476 choice observations (164 respondents multiplied by nine scenarios). In total, 55% of the sample is female (according to the latest census, the proportion of women in the prefecture of Attica is 52%). The vast majority (e.g., 70%) of the survey respondents belong to age groups 18–25 and 26–35. The mean household income is estimated to be approximately EUR 1250 per month, while 65 out of the 164 respondents belong to a household of four members or more. Only 10 respondents live outside the metropolitan area of Athens, Greece. Considering the present mode choice, 56.4% use a private car to perform their daily trips (from home to work/school); 27.4% prefer public transport; and 16.2% use other urban transport modes, e.g., cycling, walking, and taxis. The high proportion of private car mode use is highly associated with the car ownership characteristics of the sample; 153 respondents have at least one private car available for traveling daily. In the stated preference experiment, private cars were selected in 37.47% of choice sets, public transport in 29.06%, and SAVs in 33.4%. Fifteen respondents selected private cars in all scenarios, irrespective of the different presented variable levels.

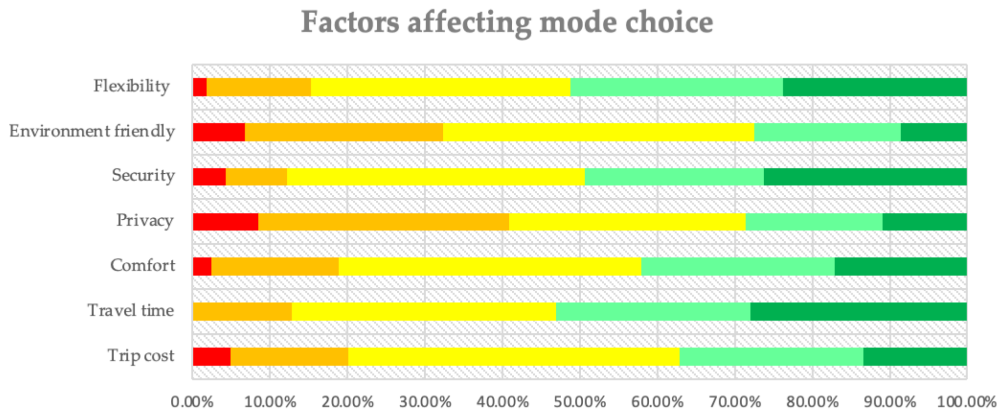
As the sample consists of young people, 68.29% of survey respondents use a laptop or smartphone continuously, and only 1.83% have never used one. Interestingly, smart mobility apps are rarely or sometimes used by 88.96% of the sample. The opposite is observed when speaking about internet maps, which are continuously utilized by 52.03% of the respondents. This is due to the absence of specialized and user-friendly smart mobility applications in Athens, Greece. Regarding user perceptions, Figure 4 presents the statement evaluation data collected from this survey. According to this, 42.07% of the sample argues that vehicle emissions can influence their travel behavior, making them to choose “greener transport modes”. On the other hand, 54.27% of the respondents feel uncomfortable when sharing a vehicle with other passengers. Various opinions were observed in the last argument about whether travel time can be utilized to finish some working tasks. Most of the responses concentrated around the neutral level.



	Vehicle emissions affect my selection of transport mode	When I am in a vehicle with other passengers, I am not cautious	During my trip as a passenger I would like to have time to finish some tasks
strongly disagree	6.71%	18.90%	12.80%
disagree	14.63%	35.37%	21.34%
neutral	36.59%	23.78%	41.46%
agree	34.15%	18.29%	19.51%
strongly agree	7.93%	3.66%	4.88%

Figure 4. Evaluations of user perceptions.

Focusing on the factors that affect respondent mode choices, travel time seems to be the most important factor, as 53.08% of respondents evaluate it as important or very important. A similar percentage appears in the flexibility factor. Security, comfort, and trip cost are the next factors, while privacy and environmental friendliness seem to be the less significant ones. Figure 5 presents the factors affecting mode choice.



	Trip cost	Travel time	Comfort	Privacy	Security	Environment friendly	Flexibility
not at all	4.88%	0.00%	2.44%	8.54%	4.27%	6.71%	1.83%
not much	15.24%	12.80%	16.46%	32.32%	7.93%	25.61%	13.41%
neutral	42.68%	34.15%	39.02%	30.49%	38.41%	40.24%	33.54%
somewhat	23.78%	25.00%	25.00%	17.68%	23.17%	18.90%	27.44%
very much	13.41%	28.05%	17.07%	10.98%	26.22%	8.54%	23.78%

not at all not much neutral somewhat very much

Figure 5. Factors affecting mode choice.

A correlation analysis was performed to identify potential statistical relationships between user perceptions, technology familiarity, and sociodemographic characteristics. Table 3 presents the output of this analysis. It was observed that males with high education levels express a higher willingness to share the vehicle with "strangers" and socialize. People with environmental sensitivities prefer to use in-vehicle time for organizing and performing some of their working tasks. Males with high income are associated with more frequent laptop and smartphone use, while females tend to use more internet maps and smart mobility applications to reach their destination. Overall, high correlations were observed between sociodemographic characteristics. An analysis of variance (ANOVA) was performed to select variables that strongly influence mode choices. These are the age group and the income level.

The model outputs are presented in Table 4. Starting with the constant parameter of the private car utility function, this is statistically significant for a confidence interval of 95% and positive. This indicates a strong preference for private cars over SAVs and public transport. Respondents belonging to high-income groups tend to prefer SAVs, as the beta parameter has a positive sign and is significant. Conversely, public transport is not a popular choice for high-income commuters. All user perception-related variables were found to be statistically significant with a confidence interval of 95%. One exception to this appears in the public transport utility function, where the chance to finish some working tasks during the trip does not influence the utility of this mode. Respondents with environmental sensitivities and those with the least concerns about sharing a vehicle with strangers are potential users of these services. Naturally, familiarity with smart mobility applications makes a statistically significant contribution to this, yet the differences in the beta parameter between PT and SAV are relatively small. The same happens when looking at the beta parameter of in-vehicle travel time; there is no actual difference. Yet, in private cars, in-vehicle travel time costs less. Additionally, any increase in the trip costs of public transport results in a higher decrease in the utility of this mode compared with SAV services. Indeed, the values of these parameters clearly distinguish these three modes, providing an extra economic value to the flexibility provided by each one. Flexibility was an important factor that substantially affects mode choices according to the previous analysis. Lastly, respondents are more willing to wait for an SAV than to walk to the closest collection point if the service is stop-based and not door-to-door. On the other hand, considering public transport, respondents prefer higher frequency than higher system coverage. This is illustrated through the estimated values of the beta parameters.

Table 3. Correlation analysis—Kendall rank correlation test (with * indicating significant collinearities considering a 95% confidence interval).

	Environmental Sensitivities	Willingness to Share and Socialize	Time Organization	PC or Smartphone	Smart Mobility Apps	Gender (1, if Male)	Age	Education Level	Income Group	Driving License	Vehicle Availability
Environmental Sensitivities		−0.10 *	0.33 *	0.08 *	0.00	–0.08 *	0.07 *	0.01	0.07 *	−0.02	–0.03
Willingness to Share and Socialize	–0.10 *		−0.03	0.00	–0.05 *	0.04	–0.03	0.28 *	–0.03	0.06 *	–0.07 *
Time Organization	0.33 *	−0.03		0.08 *	0.10 *	–0.07 *	0.05	–0.01	0.13 *	0.01	−0.04
PC or Smartphone	0.08 *	0.00	0.08 *		−0.05	0.10 *	0.04	–0.01	0.06 *	0.10 *	0.04
Smart Mobility Apps	0.00	–0.05 *	0.10 *	–0.05		–0.13 *	–0.06 *	0.04	0.10 *	–0.12 *	–0.11 *
Gender (1, if Male)	–0.08 *	0.04	–0.07 *	0.10 *	–0.13 *		0.03	–0.06 *	0.15 *	0.11 *	–0.07 *
Age	0.07 *	–0.03	0.05 *	0.04	−0.06	0.03		0.43 *	0.19 *	0.34 *	–0.02
Education Level	0.01	0.28 *	−0.01	–0.01	0.04	–0.06 *	0.43 *		–0.09 *	0.31 *	–0.19 *
Income Group	0.07 *	–0.03	0.13 *	0.06 *	0.10 *	0.15 *	0.19 *	–0.09 *		0.11 *	0.33 *
Driving License	–0.02	0.06 *	0.01	0.10 *	–0.12 *	0.11 *	0.34 *	0.31 *	0.11 *		0.23 *
Vehicle Availability	–0.03	–0.07 *	–0.04	0.04	–0.11 *	–0.07 *	–0.02	–0.19 *	0.33 *	0.23 *	

Table 4. Model results.

	Transport Mode	Estimate	Std. E.	t-Test	p (>|z|)
Alternative specific constant	car	4.000	0.628	6.369	<0.001
Sociodemographic					
Age in years	pt	0.006	0.006	0.914	0.426
	sav	0.006	0.004	1.457	0.072
Income group (1: less than EUR 900, 2: 900–1500, 3: 1500–2500, 4: 2500–3750, 5: 3750–5000, 6: more than EUR 500)	pt	–0.271	0.048	–5.634	<0.001
	sav	0.022	0.006	3.656	<0.001
Perceptions					
Vehicle emissions affect my selection of transport mode (from 1 to 5)	pt	0.393	0.078	5.032	<0.001
	sav	0.297	0.073	4.057	<0.001
When I am in a vehicle with other passengers, I am not cautious (from 1 to 5)	pt	0.210	0.069	3.043	0.002
	sav	0.164	0.065	2.527	0.013
During my trip as a passenger, I would like to have time to finish some tasks (from 1 to 5)	pt	0.102	0.066	1.541	0.122
	sav	0.145	0.063	2.291	0.022
Familiarity					
Laptop or smartphone (from 1 to 5)	pt	0.384	0.078	4.936	<0.001
	sav	0.153	0.070	2.173	<0.001
Internet maps and smart mobility applications (from 1 to 5)	pt	0.551	0.061	9.107	<0.001
	sav	0.547	0.060	9.147	<0.001

Table 4. *Cont.*

	Transport Mode	Estimate	Std. E.	t-Test	p (>|z|)
Trip parameters					
Trip cost in euros	car	−0.224	0.051	−4.358	<0.001
	pt	−0.559	0.155	−3.606	<0.001
	sav	−0.306	− 0.050	−6.083	<0.001
In-vehicle travel time	car	−0.053	0.005	−10.000	<0.001
	pt	−0.072	0.008	−8.819	<0.001
	sav	−0.073	0.008	−9.508	<0.001
Waiting time in minutes	pt	−0.080	0.011	−7.417	<0.001
	sav	−0.069	0.012	−5.831	<0.001
Walking time in minutes	pt	−0.057	0.016	−3.566	<0.001
	sav	−0.099	0.019	−5.124	<0.001
Number of observations	1476				
Number of respondents	164				
Null Loglikelihood	−2742.91				
Loglikelihood	−1282.15				
McFadden's R-squared	0.53256				

4. Discussion

The factors that were taken into account in the development of the new mode choice model were divided into four distinct groups: trip parameters, sociodemographic characteristics, user perceptions, and familiarity with technology. These models consider SAVs to be a major alternative to travel in urban areas. The main study hypothesis is that SAVs, as a new transport mode, can be placed somewhere in the middle between public transport and private cars offering (almost) on-demand and door-to-door trips, which can be shared with other travelers.

The main findings confirm the main study hypothesis. Indeed, additional walking time seems to highly increase the disutility of SAVs compared with public transport. The respondents prefer a more flexible solution that can perform door-to-door trips. A dense distribution of pick-up/drop-off points in the city is required. This result confirms the finding of the study by Patel et al. [28], which showed that travelers will exchange some access/egress walking meters for the additional time it takes to park in a private transport mode. Furthermore, extra waiting time seems to not seriously influence the demand for SAV services, while in public transport, it reasonably affects its attractiveness. This major difference shows that the role of this new transport mode has not been highlighted by previous studies. Most of them have focused on the necessity of an SAV performing detours to satisfy all demand needs [3,17,26]. This study also proves that potential users prefer to wait longer to take a single-occupancy SAV than share it and, therefore, detour. This can be proved by the value of the calculated beta parameters per travel time component; it is in line with the observations of Gkartzonikas et al. [27]. Compared again with conventional public transport, respondents expressed a higher willingness to pay for flexible transport services like SAV. It is promising that the elasticity of trip cost approaches the estimated one for private cars. This reinforces the belief that smart pricing policies in SAV services will seriously reinforce the attractiveness of the mode, increasing its demand [26].

The unwillingness of future users to share an autonomous vehicle is proved by the value of the beta parameter of in-vehicle time and by the high percentage of respondents who will feel uncomfortable inside. Indeed, in-vehicle time weighs the same both in public transport and SAVs according to the model outputs. This has also been mentioned in previous studies [4,21]. Nevertheless, respondents with environmental concerns are ready to accept it so that energy consumption and CO_2 emissions will be reduced. These positive attitudes are proved by the positive and significant beta parameters of environmental awareness in the utility function, both of public transport and SAVs. This confirms the findings of the study by Maeng and Cho [15]; some social groups are in search of alternative and more sustainable ways of traveling. High-income groups belong to this category. While they express more positive attitudes toward SAVs, a general unwillingness to use public transport services is reported. This was also observed in the study by Anspacher et al. [11]. Based on the correlation analysis, people with higher education levels are more open to socializing and meeting new people while traveling. Familiarity with technology does not have a special contribution to the willingness of using an SAV compared with public transport, as similar beta parameters were observed in public transport. Yet, their sign is positive, which proves that respondents who still prefer private cars are less familiar with smartphone applications, online platforms, and maps. This also underlines the necessity of these tools in guiding travelers when performing multimodal trips comprising first/last-mile legs.

Regarding the limitations of this study, the sample consists mainly of people who either belong to the community of the National Technical University of Athens or have a close relationship/friendship with a member of it. Therefore, most of them come from young age groups. On the other hand, these people will be the most active part of the population when SAV services are offered in the future, and as such, this age group is expected to be more relevant. Yet, opinions on new mobility technologies like SAVs coming from older or lower-income people would be interesting in scientific research covering multiple dimensions of the topic. Moreover, in this study, public transport and SAVs were considered two independent options: this hypothesis led to the development of an MNL model. The variations in preferences were systematically modeled by integrating factors related to sociodemographic characteristics, perceptions, and technology familiarity. The integration of random beta variables by developing mixed logit models would help uncover heterogeneity that exists in "tastes" (i.e., the influence of each beta parameter). This also implies the existence of dependencies between alternatives, especially when considering the dilemma of a car vs. no car. Additionally, this was a choice experiment, and the sample of respondents was rather small; however, the set of choice observations was large enough to export some significant results. This is not fully true since some significant dependencies in the choices of each respondent would be observed by including panel effects in the modeling practice. Another limitation is the existence of multicollinearities between sociodemographic and perception factors. This limited the number of factor combinations that could be used in the modeling part. An alternative technique was the creation of respondent clusters, which would refer to specific social groups. Yet, the complexity of the models would be increased, making the extraction of valid conclusions difficult.

5. Conclusions

The present study examined contributory factors that influence the willingness to use an SAV service over private and public transport by conducting a stated preference experiment in Athens. In terms of flexibility, SAVs were placed somewhere in the middle between public transport and private cars. Contributory factors coming from four distinct groups, i.e., trip parameters, sociodemographic characteristics, user perceptions, and familiarity, were explored.

By comparing the results with the literature and considering the study limitations, valid conclusions can be exported at this point. First, respondents are willing to walk less ($\beta_{twalk,\ SAV} = -0.099\ utils/minute$) and wait more ($\beta_{twait,\ SAV} = -0.069\ utils/minute$) for an SAV compared with public transport ($\beta_{twalk,\ PT} = -0.057,\ \beta_{twait,\ PT} = -0.080\ utils/minute$). This shows the difference between these two modes as they are currently perceived by travelers and the future role of SAVs. Yet, in-vehicle time increases with almost the same value (approximately –0.0072 $utils/minute$) as the utility of these two modes; private cars have a considerably lower value ($\beta_{ttime,\ CAR} = -0.053\ utils/minute$). The last factor underlines the general unwillingness of most respondents to share their trips with others since privacy is among the most significant factors that influence mode choice. Yet, the flexibility of this new mode has a value that users are willing to pay, showing higher elasticity. People with environmental sensitivities are more willing to use this new mode so that they will consume and pollute less. Males in higher educational groups think that the travel time in an SAV can be fully utilized to socialize and organize their time. Higher-income groups are willing to use SAVs, and they fully avoid public transport modes in Athens. SAV and public transport use require familiarity with the technology too.

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Abbreviations

Abbreviation	Explanation
ANOVA	Analysis of variance
AV	Autonomous vehicle
CAR	Private car as a transport mode option
CO_2	Carbon dioxide emissions from the transport system
COVID-19	Novel coronavirus disease 2019
DDT	Dynamic driving task
EV	Electric vehicle
GHG	Greenhouse gas emissions coming from the transport system
MLE	Maximum likelihood estimation
Mlogit	Multinomial logit package in R statistical programming language
OASA	Main public transport operator in Athens, Greece
PC	Personal computer
PT	Public transport as a transport mode option
SAE	International Society of Automotive Engineers
SAV	Shared autonomous vehicle as a transport mode option
VTTS	Value of travel time savings

Nomenclature

Symbol	Description	Units
ASC_m	Alternative specific constant of mode m; in private cars, it is set to zero	utils
$cost_{i,m}$	Trip cost in the scenario, i, using mode, m	EUR
$fam_{j,t}$	Technology familiarity variable, j, value of respondent, t	level (ordinal scale)
I	Set of choice scenarios in the stated preference experiment	
J	Set of sociodemographic/perception/familiarity variables	
M	Set of transport mode options, i.e., CAR, SAV, and PT	
T	Set of respondents	
$perc_{j,t}$	User perception variable, j, value of respondent, t	level (ordinal scale)
$socio_{j,t}$	Sociodemographic variable, j, value of respondent, t	level (ordinal scale)
$ttime_{i,m}$	Travel time in the scenario, i, using mode, m	minutes
$twait_{i,m}$	Waiting time (at the stop) in the scenario, i, using mode, m	minutes
$twalk_{i,m}$	Walking time (to/from the stop) in the scenario, i, using mode, m	minutes
$U_{m,i,t}$	Utility of mode, m, in the scenario, i, of respondent, t	utils
$\beta_{ttime,m}$	Alternative specific beta parameter of travel time of mode, m	utils/minutes
$\beta_{twait,m}$	Alternative specific beta parameter of waiting time of mode, m	utils/minutes

$\beta_{twalk,m}$	Alternative specific beta parameter of walking time of mode, m	utils/minutes
$\beta_{cost,m}$	Alternative specific beta parameter of trip cost of mode, m	utils/EUR
$\beta_{socio_j,m}$	Alternative specific beta parameter of sociodemographic variable, j, of mode, m	utils/level
$\beta_{perc_j,m}$	Alternative specific beta parameter of user perception variable, j, of mode, m	utils/level
$\beta_{fam_j,m}$	Alternative specific beta parameter of technology familiarity variable, j, of mode, m	utils/level
$\varepsilon_{m,t}$	Error term: mode, m; respondent, t	utils

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