Research Article

Transportation Research Record
1–16

DOI: 10.1177/0361198119843858
journals.sagepub.com/home/trr

Exploring Preferences for Transportation Modes in an Urban Air Mobility Environment: Munich Case Study

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Abstract

Urban Air Mobility (UAM) is a recent mobility concept with the potential to reduce travel time and change travel patterns. When evaluating the introduction of UAM, understanding the potential users' choice behavior regarding current available urban transportation modes and autonomous transportation services is essential to demand estimation. This preliminary research intends to gain insight into the travel behavior impacts of autonomous transportation modes, especially UAM, by deriving measures for transportation service attributes and identifying characteristics of potential users who might adopt autonomous transportation services, particularly the services of UAM. Thus, a stated preference questionnaire was designed and distributed in Munich metropolitan region. A main mode choice multinomial logit model and several sub-models, based on market segmentation, were estimated regarding four transportation alternatives: private car, public transportation, autonomous taxi, and autonomous flying taxi. The results indicate that travel time, travel cost, and safety may be critical determinants in autonomous transportation mode adoption. The potential consumers may be willing to pay more for using autonomous transportation modes, especially the service of UAM. Among different market segments, younger individuals, as well as older individuals with high household income, are more likely to adopt UAM. In addition, during the market entry stage, potential travelers may favor UAM particularly for performing non-commuting trips.

Rapid population growth and urbanization have imposed enormous strains not only on the environment, but also on urban transport (*1*). Meanwhile, mobility requirements are increasing. Consumers will demand forms of transportation which are faster, cheaper, cleaner, and safer than today (*2*). The contradiction between supply and demand may drive the contemporary transportation system to its limit. Therefore, new transport solutions are required and expected to be developed to fulfill future mobility needs.

The recent rapid technological development of autonomous vehicles (AVs) led to the current situation in which tests with driverless cars are being performed. With increasing autonomous driving assistance systems in cars, the shift toward a fully autonomous driving experience has already begun (*3*). The advent of autonomous technology lets manufacturers and technological companies see great potential in developing sky-bound transport systems. A novel concept, called urban air mobility (UAM), is proposed by introducing next-generation vertical take-off and landing (VTOL) aircraft for transport services, which can add a new dimension to the urban transport system and reduce time spent in daily travel (*4, 5*).

Under the influence of the sharing economy, new mobility services such as on-demand mobility (ODM) and mobility as a service (MaaS) have been pushed to the mainstream (*6*), which allows point-to-point transportation providing additional alternative transport options instead of consumers' private vehicles. It has been anticipated that the convergence of autonomous technology and the trend of sharing, forming the new term shared autonomous mobility, will likely happen more quickly and more dramatically in the urban environment (*2*).

Before introducing new transportation services, notably VTOLs and UAM, to the market, evaluating their demand drivers is a prerequisite (*7*). To predict usage rates, understanding choice behavior regarding several

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current existing urban transportation modes and new transport services is essential. No current research has been found that analyzes the potential behavior shifts among conventional transportation modes, AVs, and UAM. This study takes the first step to investigate urban transportation modes preferences in the case that AVs and UAM are accessible to all users, by estimating the independent influence of transportation service attributes and individual characteristics. For this purpose, a stated preference (SP) survey, incorporating a stated choice (SC) experiment, has been designed and conducted, based on which mode choice models were estimated.

The remainder of this paper is structured as follows: a review of the existing literature concerning the potential market feasibility barriers of AVs and UAM is given, followed by the applied methodologies including survey design and model development. For further model development, an exploratory analysis has been conducted based on gathered survey data. Then, estimated mode choice model results are presented along with main observations. Finally, the results are described and critically discussed. An outlook on further research concludes the paper.

Literature Review

Existing literature agrees that fully autonomous cars are to appear within the next decade and that a large number of fully autonomous vehicles will be on the road within the next 50 years (*3*). Although autonomous cars will not directly enable autonomous aircraft, their required technologies have a strong commonality (*4*).

The current discussion highlights several aspects where autonomous driving may offer several advantages, such as comfort and the possibility to pursue useful activities while traveling (*8*). Nevertheless, a contradictory effect may also exist among the increase in traffic capacity resulting from reduced crashes, redeveloped infrastructure, and improved traffic flow (*3*). Literature suggested that positive effects would only become apparent if AVs are used in a shared manner. One example of novel business models is shared autonomous vehicle (SAV), specifically in the form of autonomous taxi (AT) or driverless taxi, which could provide inexpensive on-demand services and could play an essential role in sustainable transportation systems (*9, 10*). Similar to a regular taxi, the AT could carry up to five passengers. Users could use, for example, smartphones to request vehicles, which—if so desired—would not be shared with group-external passengers (*11*). AT would be self-driving, and thus not require any driver input. Once arrived at a destination, the user would simply pay per ride and would not need to search for parking spots (*11*).

The challenges caused by population growth and urbanization lead to changes not only in transport demand, but also in infrastructure requirements and average travel distances (*7*). To enable transportation of people or goods around densely populated cityscapes within minutes, UAM could be implemented in the form of air taxis that can pick up passengers on request as part of an on-demand urban network (*5*).

The environmental impact of UAM has yet to be understood and analyzed. For this study, though, and to avoid possible confusion, a specific case of fully autonomous eVTOL or autonomous flying taxi (AFT) is assumed in which those vehicles are expected to be energy efficient, operationally emission-free, and substantially quieter than a traditional helicopter (*12*). AFT is envisioned to transport up to four passengers (the travel group the user is traveling with) within short ranges (10–50 km) in an urban area, and enable passengers to significantly reduce the in-vehicle travel times while experiencing comfortable traveling and being able to pursue other tasks during their travel (*13–15*). Different from the usage of AT, AFT can only be operated from dedicated AFT infrastructure, vertiports, which are expected to be distributed throughout a city.

Whereas the technology development of AVs seems to be swiftly progressing, the adoption of autonomous mobility services is just beginning. Besides potential technological restrictions, several other critical barriers need to be considered. Regarding the challenges of adopting AVs, one of the major aspects is legal issues, concerning who will take responsibility for damages or accidents. As for flying vehicles, new regulations and air traffic control systems are needed, with issues around how to allocate the use of the airspace considering the increasing number of flying vehicles (*12*). Another limiting factor is the existing infrastructure and required investment in infrastructure, which will have a substantial impact on how AVs will be used in the future. Similarly, lacking sufficient locations to place take-off and landing zones, parking lots, and vertiports is a great operational barrier to deploy eVTOL fleets in urban areas (*4*). As long as conventional ground-based, human-controlled vehicles remain the major form of transport, behavioral aspects are expected to have an inhibiting effect on the adoption of AVs and flying vehicles (*3*). Potential passengers may need to overcome psychological barriers to use autonomous modes. Therefore, safety plays a crucial role, as any failure can draw significant attention and can slow down the pace of adoption (*12*).

Transportation Mode Choice Factors

UAM and eVTOL are novel phenomena; current research concerning them mainly focuses on technological and operational aspects (*4, 16, 17*), although several UAM market research studies have been released recently. For example, Airbus conducted worldwide focus group studies and identified potential market segments (*18*), and Georgia Institute of Technology is currently conducting research predicting demand for eVTOL urban air trips in the United States (*19*). As dedicated mode choice studies including UAM are not yet available, a general review of factors affecting transport mode choice has been implemented of existing studies that have used discrete choice theory to model various aspects of AVs and SAVs, and of studies about public opinions on AVs and flying vehicles. The explanatory variables have been categorized into three groups.

Overall, cost- and time-related attributes have been most commonly considered in many transport mode choice studies (*20–22*). Meanwhile, among a few publications that include AVs or SAVs in discrete choice models, several other factors have been identified as relevant. For instance, a SP survey, which provides a practical way to collect data regarding potentially unavailable transportation alternatives (*23*), has been conducted in the Netherlands. To understand the independent influence of various factors on the decisions made by individuals facing a specific choice situation, an SC experiment featuring car, public transportation (PT), car-sharing, and SAV has been designed and logit choice models have been developed (*11*). The relatively complex choice tasks include trip cost, parking cost, travel time, walking time, and time for finding a parking spot as service attributes. Among the travel time-related attributes with significant impact, waiting time for SAVs has been found insignificant. In other research, examining the travel behavior impact of SAV in Australia, travel time and travel cost have proven to be significant determinants of SAV acceptance (*10*). A few studies (*9, 10*), analyzing the willingness to pay for AVs and SAVs, show an opposing view that waiting time is a critical service attribute of SAV operations.

The result of a general mode choice literature review indicates that socio-economic variables, such as gender, age, and income have effects on the propensity to travel by conventional car or PT (*24, 25*). However, as stated in an earlier study (*26*), "concerning the influence of personal and household characteristics on the choice to travel by AVs or SAVs, the findings of previous research do not provide consistent conclusions." For instance, assessing age as a factor, some studies claim that younger individuals have a higher interest in AVs and are more open to adopting them (*27, 28*). Another study stated that SAVs could constitute an attractive mobility option for the elderly or individuals too young to drive (*9*). Moreover, a positive relationship, between willingness to pay for an autonomous feature and income of the respondents, has been observed (*28, 29*). Besides socio-economic variables, other factors, such as an individual's current modality pattern, also strongly influence potential SAV adoption (*10*). Nevertheless, the results of the previous research indicate that the characteristics of potential SAV adopters are vague, because of a lack of theoretical or empirical evidence that can be considered to segment potential SAV users (*10*). Only a few survey results were found regarding public opinions on flying vehicles. A market study released by NASA found neutral to positive opinions of the U.S. respondents to the UAM concept (*30*). Other survey results present that younger and more educated respondents are more willing to use pilotless aircraft (*31*).

Attitudinal factors, such as the preference for convenience, comfort, and flexibility have been found to influence mode choice concerning conventional transportation modes (*32*). Regarding AVs, existing literature highlighted the impact of safety concerns (*33*). Respondents who are more likely to use AVs or SAVs also express greater concern for the environment (*33, 34*) and technology awareness (*28, 35*). These respondents also place higher importance on amenities and vehicle automation (*11, 34*). Similarly, safety has been recognized as one of the first psychological barriers of adopting flying vehicles (*12, 30*). Another critical finding is that piloted operations are generally preferred over the fully automated aircraft services (*30*).

Methodology

A SC experiment was conducted for data collection to estimate discrete choice models and measure individuals' transportation mode preferences, as shown in Figure 1.

Stated Preference Study

This research was conducted based on a case study of Munich. The online SP survey was completed by 248 respondents from the Munich metropolitan region, during the period of mid-February to April 2018.

The survey was executed following the respondent recruitment procedure (*36*), in order to overcome the potential value-of-time (VOT) bias, which may be caused by employing an online panel, in which the participants take time to answer the survey for a rather low monetary reward. To capture the actively commuting population, some printed survey flyers, containing survey links and instructions, were distributed at business campuses, universities, residential areas, and public transport stations. In addition, the online survey was disseminated via emails and social media. Considering the research scope and the extensive legal implications, individuals who were not frequent travelers within the Munich

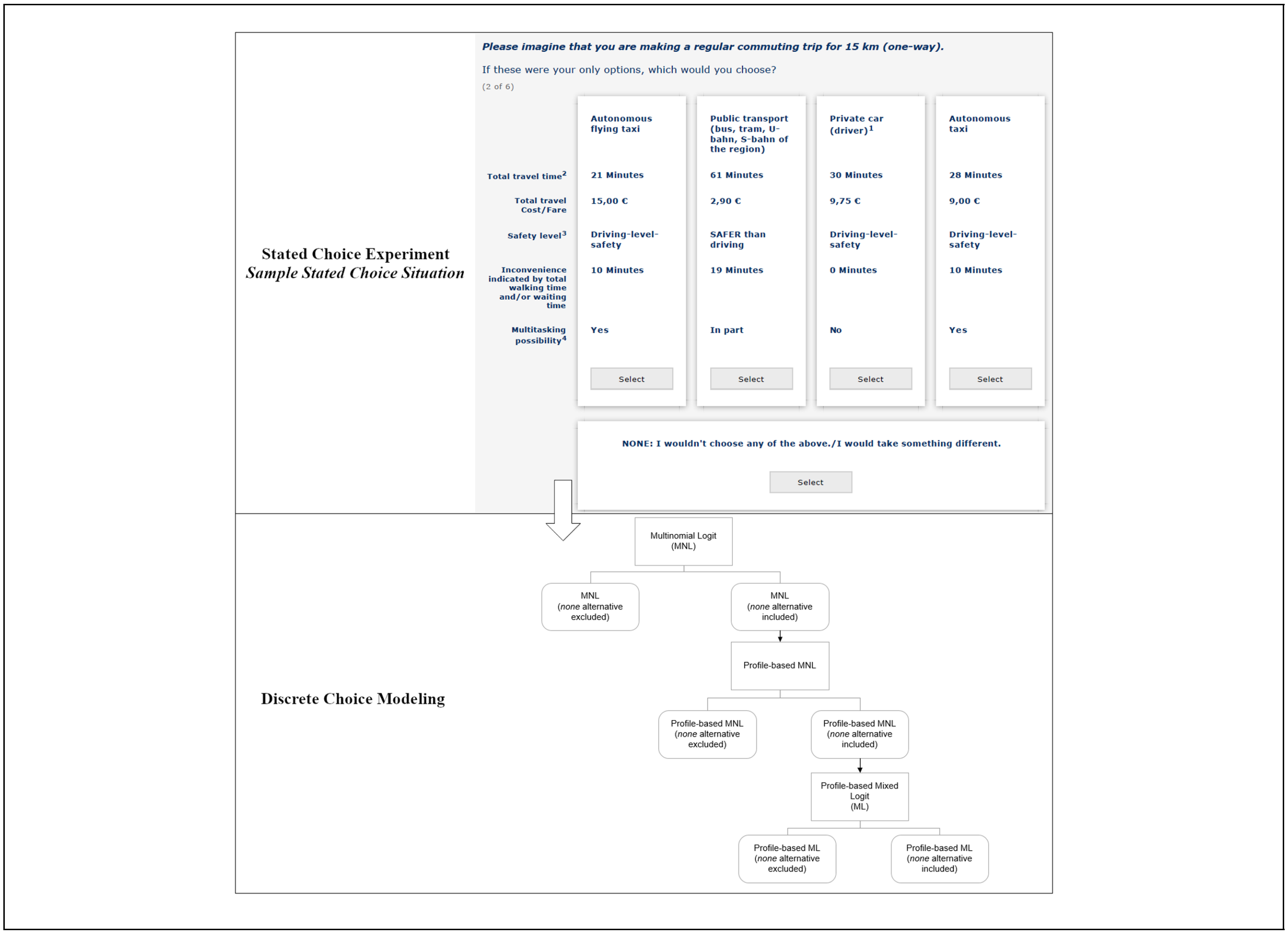

Figure 1. Methodological framework.

metropolitan region and who were aged younger than the legal age of driving (18 years old in Germany) were excluded from this study.

The survey was structured into four parts. The first part includes questions regarding the respondents' current travel patterns, such as most frequently used transportation modes, car availability, and satisfaction about current travel patterns. In the second part, five-point Likert scale attitudinal statements were included concerning attitudes toward the environment, new technology, and autonomous transportation modes. Four statements were provided regarding each aspect. The third part of the survey featured a series of 12 SC tasks, in which the respondents were asked to indicate their mode preferences based on two different trip purposes. In addition, to understand the conditions in which individuals would prefer AFT precisely, one independent question was given regarding the likelihood to choose AFT based on six trip purposes. To gain insights into the characteristics of the respondents, the survey ends with demographic questions, such as age, gender, family situation, employment, education, and income.

Stated Choice Experiment. The involved alternatives and attributes were defined based on the review of relevant past studies, expert consulting, and a focus group discussion implemented in a Munich-based interdisciplinary research institute.

Participants were firstly familiarized with the mobility service concepts by highlighting the vision of AT and AFT services (*4, 11*). To provide respondents concrete scenarios in which to make decisions, two trip purposes were anticipated to be feasible for AFT operations with a travel range of 15 km per direction, which represents the typical average travel distance for work- and business-related trips in Germany (*37*). One is *daily commuting trip* between the place of residence and workplace. The other one is *non-commuting private trip* between two locations with the intention of performing recreational or social activities.

This research aims to analyze the future transport demand focusing on autonomous ODM, possibly around the time that AVs are in use. Considering the characteristics of predefined trips that are mainly performed by private car and PT, four relatively comparable alternatives including private car (driver), PT, AT, and AFT, were involved in the choice tasks. An additional alternative *None of the above* was also included, allowing respondents to indicate that no offering is sufficiently attractive.

Five attributes were defined to specify each of the four transport mode alternatives. The attribute levels are described as follows:

- Total travel time (min)—defined as the door-to-door travel time, including the vehicle travel and the waiting, walking time, or both:
  Car (*18, 30, 42*); *PT* (*38, 49, 61*); *AT* (*28, 40, 52*); *AFT* (*12, 17, 21*)
- Total travel cost (€)—indicates the monetary cost would have to incur when using certain option for the trip:
  Car (*5.25, 7.50, 9.75*); *PT* (*1.00, 2.90, 5.80*); *AT* (*9, 11, 13*); *AFT* (*15, 25, 75*)
- Inconvenience indicated by total walking, waiting time, or both (min)—in a way indicates the inconvenience level of access and egress ("first mile" and "last mile," respectively), especially regarding shared modes:
  Car (*0, 2, 4*); *PT* (*15, 17, 19*); *AT* (*5, 10, 15*); *AFT* (*5, 7.5, 10*)
- Safety level—denotes the crash or fatality rates per 100 million passenger miles:
  Car (*Driving-level safety*); *PT* (*At least two times safer than driving*); *AT* (*At least two times safer than driving, Driving-level safety, Two times riskier than driving*); *AFT* (*At least two times safer than driving, Driving-level safety, Two times riskier than driving*)
- Multitasking possibility—distinguishes the vehicle automation levels between future and conventional transportation modes. It was set as a constant attribute which does not change across choice tasks but describes the mode property:
  Car (*No*); *PT* (*In-part*); *AT* (*Yes*); *AFT* (*Yes*)

A pilot test, including 28 participants, was implemented. Other than the increased clarity of the survey based on the participants' feedback, the hypothetical scenarios and attribute levels were adapted to increase the realism of the choice situations while maintaining the respondents' workload at a manageable level. Based on the pilot study results, six choice sets were created for each hypothetical trip purpose using random design following the minimal overlap principle (*38*); the content and order of the choice sets were identical across different scenarios. However, the order of the presented alternatives was randomized per block to reduce order bias (*38*). Each respondent received a unique version of the choice tasks. An example of the layout of the choice tasks is shown in the upper part of Figure 1. More detailed information regarding the experimental design can be found elsewhere (*26*).

Model Development

Several standard discrete choice model types were used in this research, including multinomial logit (MNL), nested logit, and mixed logit (ML). The specification of these models can be found in a suitable textbook (e.g., *39, 40*). The detailed model development process is described in the lower part of Figure 1. All models were estimated with Python Biogeme (*41*), using the optimization algorithms BIO and CFSQP (*42*).

Sample Composition and Analysis

This section presents the preliminary analysis of the sample data, providing inputs for further inferential statistical analysis.

Socio-Demographic Characteristics

The sample consists of 248 individuals. The main characteristics of the respondents in the dataset are reported in Table 1. Whereas the distribution of gender, employment status, and car availability situation correspond rather well with the German average (*43*), age, education level, and presence of children are less representative. The sample over-represents younger and highly educated respondents, which could be explained by the fact that these segments of the population may be more likely to respond to online-based surveys (*44, 45*). To further explore the characteristics of the potential subgroups, the mutual independence among several major socio-demographic variables is represented in Table 1, based on two profiles featured by the monthly household income level. The high-income (above 7000 €) profile comprises older-aged employed individuals with high education level, while the lower-income (500 € to 3000 €) group is mainly represented by well-educated individuals aged between 18 and 45 years old.

Current Modality Patterns and Satisfaction Rate

To understand the current modality patterns, the respondents were required to report their current most frequently used transportation mode and their corresponding satisfaction on a five-point Likert scale. The share of current most frequently used transportation

Table 1. Main Demographic Characteristics of Respondents

Variable	Sample characteristics	Population characteristics
Gender		
Male, Female	48.8%, 51.2%	48.6%, 51.4%
Age (years)		
18–25, 26–35, 36–45, 46–55, 56–65, >65	18.1%, 32.3%, 20.2%, 17.3%, 10.9%, 1.2%	9.2%, 21.7%, 22.4%, 22.2%, 16.8%, 7.7%
Employment status		
Employed, Student, Unemployed, Housemakers, Others	70.6%, 20.2%, 1.2%, 0.8%, 6.5%	87.1%, 2.9%, 2.2%, 4.6%, 3.2%
Education level completed		
High school, Apprenticeship, Bachelor's degree, Master's degree, PhD	8.9%, 3.6% 18.5%, 60.1%, 8.9%	34.1%, 40.7%, 22.7%[a], 2.5%
Presence of children (0–17 years old) in the household		
Yes, No	21.4%, 78.6%	41.4%, 58.6%[b]
Monthly household income (€)		
<1000, 1000–4000, 4000–7000, >7000, Prefer not to answer	10.5%, 41.2%, 22.2%, 8.5%, 17.7%	Average 4220 €[c]
Car availability		
Yes, No	59.7%, 40.3%	40.9%, 59.1%[d]

	Age (years)	Education level	Employment status		
			Employed	Student	Others
High-income profiles characterized by age, education and employment (>7000 €)	36–45	Equal to or above Master's degree	9.6%	None	None
	46–55	Equal to or above Master's degree	38.2%	None	None
	56–65	Lower than Bachelor's degree	4.8%	None	None
		Bachelor's degree	4.8%	None	None
		Master's degree	28.6%	None	None
	>65	Master's degree	14.3%	None	None
Lower-income profiles characterized by age, education and employment (500–3000 €)	18–35	Lower than Bachelor's degree	0.9%	4.6%	None
		Bachelor's degree	4.6%	10.6%	None
		Equal to or above Master's degree	22.7%	6.9%	2.3%
	36–45	Lower than Bachelor's degree	2.3%	None	None
		Bachelor's degree	0.9%	None	0.5%
		Equal to or above Master's degree	13.4%	None	0.9%
	46–55	Lower than Bachelor's degree	1.9%	None	None
		Bachelor's degree	1.4%	None	None
		Equal to or above Master's degree	12.5%	None	0.9%
	>55	Lower than Bachelor's degree	2.3%	None	None
		Bachelor's degree	0.9%	None	0.9%
		Equal to or above Master's degree	4.2%	None	4.2%

[a]Percentage of degree of university of applied sciences and university.
[b]Percentage of couples with children and one-person households and couples without children.
[c]Average monthly disposable income of Munich in 2016 (*46*).
[d]409 private cars per 1000 adult inhabitants (*43*).

means (indicated by the bar width) and the corresponding satisfaction rates are shown in Figure 2.

Stated Choice Analysis

Each of the 248 respondents completed 12 choice tasks, including six scenarios regarding each trip purpose. Consequently, 2,976 choices were observed based on the combined dataset regarding two trip scenarios. Car was chosen in 35%, PT in 37%, AT in 12%, and AFT in 13% of all observed choices. Also, the *None of the above* option was observed in 4% of choices. Figure 3 illustrates the impacts of age, income, and gender.

Attitudes of Different Demographics

Although the attitudinal variables were not directly incorporated into the models, the levels of agreement concerning several statements regarding new technologies (*33*), autonomous transportation modes and environmental concern (*33*), as well as the likelihood to take AFT regarding various trip purposes, are presented in

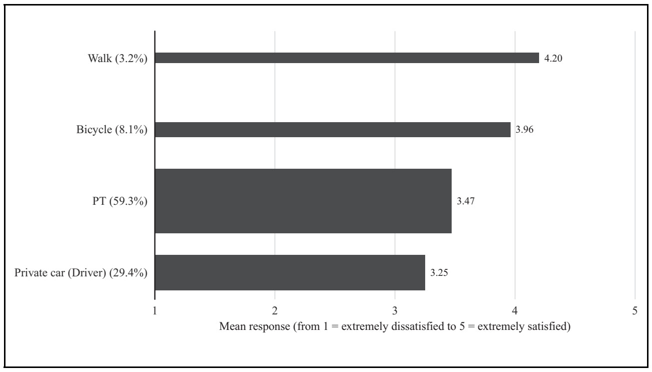

Figure 2. Average satisfaction rate stated by different modes users.

Figures 4 and 5 for better understanding respondents' choice behaviors.

Model Estimation Results

To test whether the involvement of the *None* alternative can improve the model performance, the main MNL models were estimated excluding and including the choice *None* respectively. The estimated results are summarized in Table 2. Although models with different sample size cannot be compared directly based on the statistical test, after examining the number of estimated parameters, the increase of the log-likelihoods (LLs), as well as the magnitudes and significance of the coefficients, the main MNL model including the *None* alternative seems to more fitting estimation. Only parameters which are significant at a 95% level are included in the *None*-including model, except for the safety level of AT and AFT, which have been proven to be significant for the model *None*-excluding alternative and were, thus, also included in the *None*-including model.

According to the main MNL estimation results, the *high-income* (above 7000 €) group, as well as the *lower-income* (500–3000 €) group, was found relatively more likely to have the propensity to use AFT. Therefore, considering the exploratory analysis regarding respondents' demographic characteristics, two sub-models based on two profiles were developed for further investigating the choice behavior of subgroups.

To describe the characteristics of the high-income individuals, only respondents with a monthly household income above 7000 € per month were examined, amounting to 8% of the sample. Similar to the procedure of estimating the MNL models, two profile-based MNL models, excluding and including the *None* choice, were estimated in parallel, followed by the development of an ML model with panel effects. The estimation results of high-income profile models are in Table 3, including only the parameters significant at a 95% level. The *high-income profile-based* MNL model excluding the *None* choice was found to be superior to the ML model including the *None* choice, based on the current result, when comparing the adjusted ρ^2 values, number of estimated parameters, and the increase of LLs.

In relation to the lower-income profile, the models were formed based on 46% of the sample with an income level between 500 € and 3000 €. Following the same modeling procedure as developing the main MNL models, a better model fit was attained by including the *None* option, considering the adjusted ρ^2, the number of

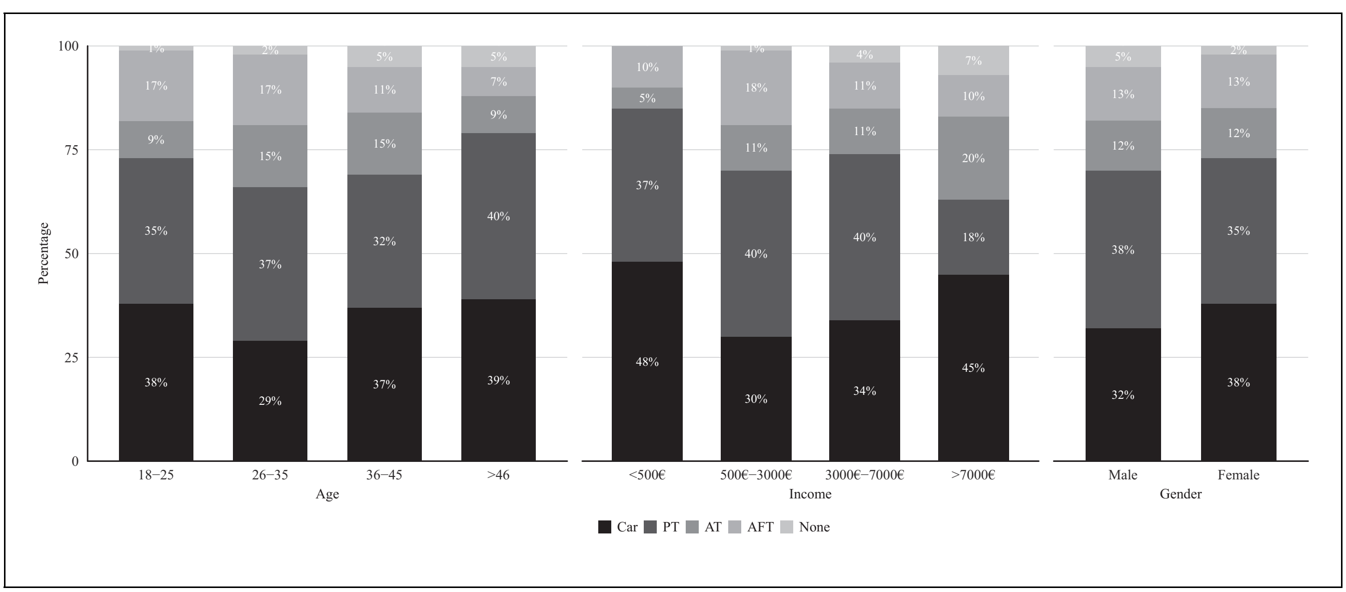

Figure 3. Example of mode choice decisions influenced by demographic characteristics.

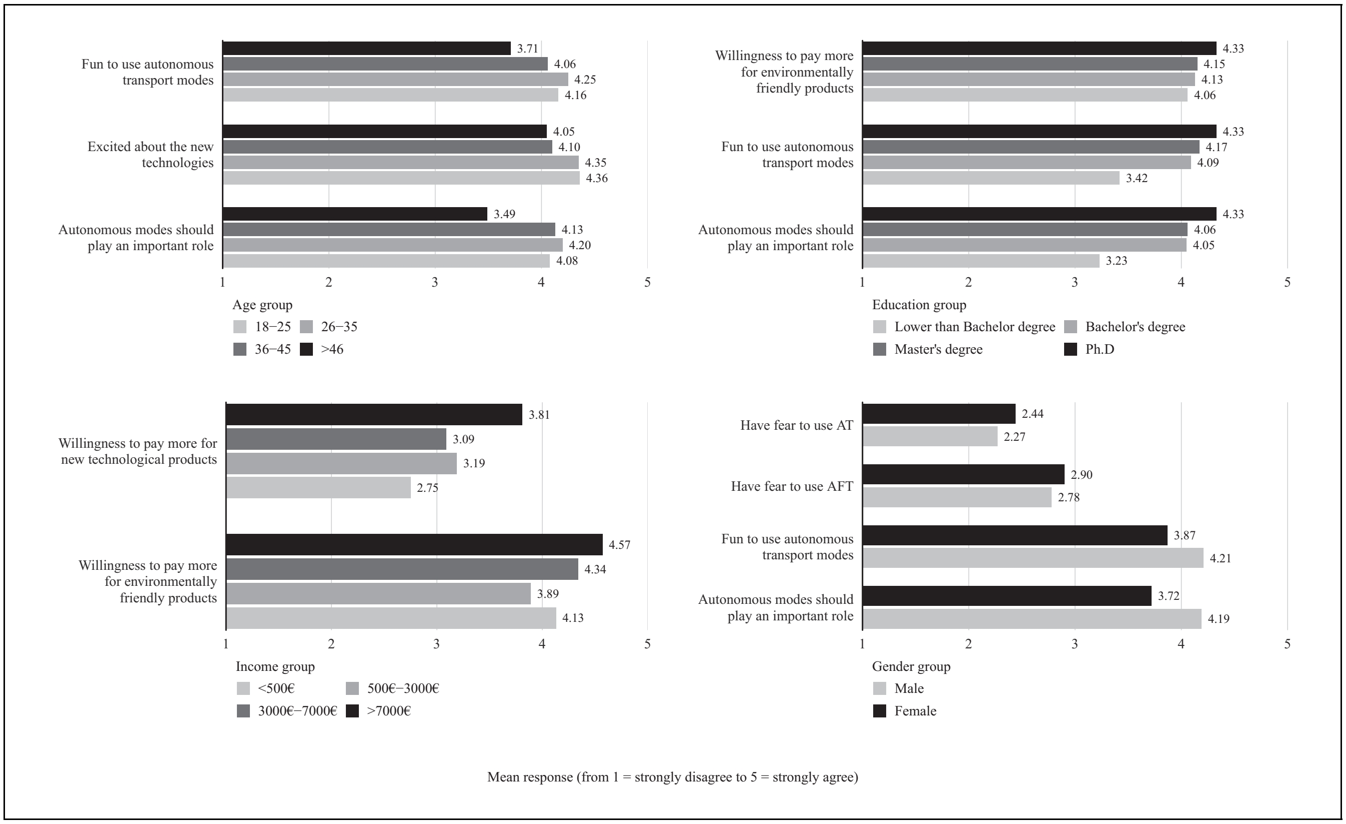

Figure 4. Attitudes associated with age, education, income, and gender.

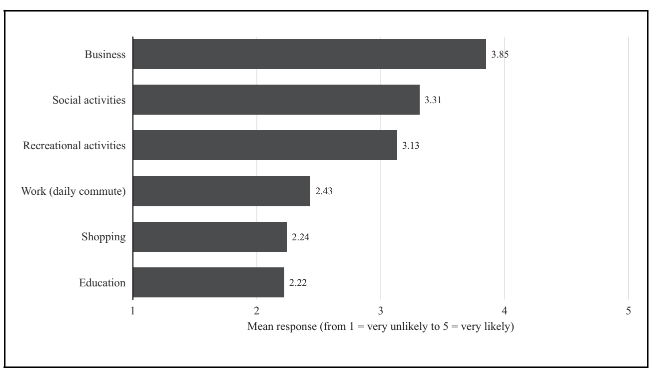

Figure 5. Likelihood of choosing AFT regarding different trip purposes.

estimated parameters, and the increase of LLs, as indicated in Table 4.

Discussion of Main Findings

Based on the model estimation results, this section discusses the impacts of relevant transportation service attributes and the transportation modes preferences across different demographics.

Transportation Service Attributes

Overall, according to Table 2, travel costs play a lesser role than travel times. Out of all travel time components, the **total travel time** proved to be the most influential (*26*). Walking, waiting time, or both, on the other hand, have no significant impact for AT and AFT (*26*). Such unexpected results may be caused by the difference in the perception of waiting time in case of ODM service as opposed to waiting and walking time of using scheduled PT services (*11*). Furthermore, to understand individuals' willingness to pay for travel time savings, the VOT measures without differentiating trip purposes were calculated concerning four transportation alternatives, based on the statistically significant coefficients of total travel time (T_{iq}) and travel cost (C_{iq}), following Equation 1. The VOT measures of car and PT are similar, showing estimated values of 27.55 €/hour and 27.47 €/hour, respectively. The considerably greater value is compared with the average VOT reported by German national studies (*47*), which may be explained by the significantly higher income level in Munich, the high quality of PT services, and the relatively higher VOT of a large percentage of involved business-oriented respondents. In fact, PT is not considered an inferior mode in much of Munich. Moreover, the VOT estimates of AT (32.57 €/hour)

Table 2. Estimated Results for the Main MNL Models

Coefficient	MNL (*None* alternative excluded) Car	PT	AT	AFT	MNL (*None* alternative included) Car	PT	AT	AFT	None
ASC	na	Base case	1.19* (2.02)	−2.76** (−6.51)	na	Base case	1.37* (2.34)	−2.92** (−7.11)	−6.91** (−24.25)
Travel cost	−1.91** (−8.14)	−1.61** (−6.59)	−2.03** (−5.08)	−0.48** (−9.42)	−1.96** (−8.47)	−1.66** (−6.91)	−2.10** (−5.25)	−0.47** (−9.50)	na
Travel time	−0.92** (−19.00)	−0.74** (−15.59)	−1.13** (−13.10)	−0.36* (−2.18)	−0.90** (−18.86)	−0.76** (−16.25)	−1.14** (−13.16)	−0.35* (−2.16)	na
Safety (reference = driving-level safety)									
Safer than driving	na	na	0.29* (2.01)	na	na	na	0.26 (1.90)	na	na
Riskier than driving	na	na	−0.35* (−2.16)	−0.30* (−2.21)	na	na	−0.36* (−2.21)	−0.26 (−1.94)	na
Waiting/walking time	na	−0.87** (−4.86)	na	na	na	−0.86** (−4.89)	na	na	na
Age (reference = 18–45)									
46–55	na	Base case	−1.10** (−8.71)	−1.10** (−8.71)	na	Base case	−1.12** (−8.93)	−1.12** (−8.93)	na
56–65	−0.61** (−3.81)	Base case	−1.10** (−8.71)	−1.10** (−8.71)	−0.70** (−4.39)	Base case	−1.12** (−8.93)	−1.12** (−8.93)	na
>65	−1.80** (−5.11)	Base case	na	−1.80** (−5.11)	−1.69** (−4.19)	Base case	na	−1.74** (−3.09)	−7.65** (−29.37)
Gender (reference = female)									
Male	na	na	na	na	−0.21* (−2.24)	Base case	na	na	na
Employment (reference = working people)									
Student	0.63** (4.29)	Base case	na	0.81** (4.34)	0.61** (4.24)	Base case	na	0.74** (4.63)	na
Others	0.47* (2.66)	Base case	na	na	0.45* (2.52)	Base case	na	na	na
Presence of children (0–17 years old) in the household (reference = no)									
Yes	Na	na	na	na	na	Base case	na	na	1.04** (5.25)
Car availability (reference = yes)									
No	−0.84** (−6.51)	Base case	−0.49** (−2.88)	−1.10** (−6.22)	−0.85** (−6.69)	Base case	−0.79** (−5.46)	−0.79** (−5.46)	na
Current means of transport (reference = car as driver)									
PT	−1.63** (−10.62)	Base case	−1.44** (−8.92)	−1.44** (−8.92)	−1.64** (−11.38)	Base case	−1.50** (−9.63)	−1.50** (−9.63)	−2.97** (−9.54)
Cycling and walking	−1.47** (−7.58)	Base case	−1.27** (−4.91)	−1.74** (−6.43)	−1.64** (−11.38)	Base case	−1.43** (−6.04)	−1.99** (−7.48)	na

(continued)

Table 2. (continued)

Coefficient	MNL (*None* alternative excluded) Car	PT	AT	AFT	MNL (*None* alternative included) Car	PT	AT	AFT	None
Trip purpose (reference = non-commuting private trip)									
Commuting	−0.35** (−3.34)	Base case	−0.40** (−2.91)	−0.71** (−5.14)	−0.39** (−3.79)	Base case	−0.45** (−3.23)	−0.72** (−5.34)	na
Monthly household income (reference = 3000–6000 €)									
<500 €	0.57* (2.06)	Base case	na	na	0.62* (2.25)	Base case	na	na	−6.98** (−23.44)
500–1000 €	na	Base case	0.60* (2.46)	0.84** (3.12)	na	Base case	0.75** (3.74)	0.75** (3.74)	na
1000–2000 €	na	Base case	na	0.64* (2.68)	na	Base case	na	0.50* (2.24)	na
2000–3000 €	na	Base case	na	0.58** (3.74)	na	Base case	na	0.52** (3.41)	−1.37** (−3.17)
6000–7000 €	na	Base case	na	−1.10* (−2.14)	na	Base case	na	−1.05* (−2.03)	1.58** (3.15)
>7000 €	0.81** (3.51)	Base case	1.32** (4.99)	0.69* (2.28)	0.86** (3.81)	Base case	1.30** (4.97)	0.79* (2.62)	0.67* (2.14)
Model information									
No. of parameters		40					47		
Initial LL		−3974.506					−4789.687		
Final LL		−2634.530					−2996.902		
Adjusted ρ^2		0.327					0.364		

Note: Coefficient: estimated values (robust *t*-test); na = not applicable (excluded insignificant values); significant values are marked by * (robust *p*-value <0.05) and ** (robust *p*-value <0.01); black-outlined values represent coefficients that are constrained to be the same; MNL = multinomial logit; ASC = alternative specific constant; PT = public transportation; AT = autonomous taxi; AFT = autonomous flying taxi; LL = log-likelihoods.

Table 3. Estimated Results for *High-Income Profile* Models

Coefficient	*High-income profile* MNL (*None* alternative excluded)				*High-income profile* ML (*None* alternative included)				
	Car	PT	AT	AFT	Car	PT	AT	AFT	None
ASC	3.20** (2.91)	Base case	4.76** (3.69)	na	6.16** (8.33)	Base case	6.16** (8.33)	6.16** (8.33)	6.16** (8.33)
Travel cost	−2.50* (−2.65)	na	na	−0.99** (−4.87)	−2.00* (−2.42)	na	na	−1.96** (−5.69)	na
Travel time	−1.17** (−7.05)	−0.92** (−6.02)	−2.25** (−5.87)	na	−0.97** (−6.97)	na	−1.64** (−7.97)	na	na
Safety (reference = driving-level safety)									
Safer than driving	na	na	na	na	na	na	1.04* (2.59)	na	na
Riskier than driving	na	na	na	na	na	na	na	na	na
Age (reference = 18–45)									
46–55	1.11* (2.80)	Base case	na	na	0.90* (2.72)	Base case	na	na	na
56–65	2.42* (2.62)	Base case	2.51** (3.08)	2.51** (3.08)	na	na	na	na	na
>65	na	na	na	na	na	na	na	na	na
Education level (reference = Bachelor)									
Lower than Bachelor	na	na	na	na	na	na	na	na	na
Master	na	na	na	na	na	Base case	na	na	−0.57* (−1.98)
PhD	na	na	na	na	na	Base case	na	−2.64** (−3.03)	−2.59* (−2.46)
Presence of children (0–17 years old) in the household (reference = no)									
Yes	na	Base case	na	−1.99** (−3.35)	−0.67* (−2.08)	Base case	na	−2.95** (−4.29)	na
Car availability (reference = yes)									
No	na	Base case	5.16** (4.24)	na	na	na	na	na	na
Current means of transport (reference = car as driver)									
PT	−2.56** (−4.77)	Base case	−2.18** (−4.16)	−2.18** (−4.16)	−1.73** (−4.26)	Base case	na	na	na
Cycling and walking	−2.28** (−2.91)	Base case	na	na	−2.47** (−3.26)	Base case	na	na	na
Interaction between monthly household income and trip purpose (reference = >7000 € * non-commuting)									
Commuting	−1.33** (−2.99)	Base case	−1.33** (−2.99)	−1.33** (−2.99)	na	Base case	−1.08** (−3.24)	−1.08** (−3.24)	na
Model information									
Number of draws	NA				1500				
Random coefficient	NA				0.003(1.38)				
No. of parameters	16				16				
Initial LL	−325.779				−405.578				
Final LL	−160.078				−239.588				
Adjusted ρ^2	0.460				0.370				

Note: Coefficient: estimated values (robust *t*-test); Significant values are marked by * (robust p-value < 0.05) and ** (robust p-value < 0.01); black-outlined values represent coefficients that are constrained to be the same; na = not applicable (excluded insignificant values); NA = not available; ASC = alternative specific constant; MNL = multinomial logit; ML = mixed logit; PT = public transportation; AT = autonomous taxi; AFT = autonomous flying taxi; LL = log-likelihoods.

and AFT (44.68 €/hour) conform to the tendency that consumers are willing to pay more for using autonomous mobility services (*10, 28, 48*), especially for using AFT.

$$(v_T)_{iq} \equiv -\left(\frac{dC_{iq}}{dT_{iq}}\right)_{V_{iq}} \equiv \frac{\partial V_{iq}/\partial T_{iq}}{\partial V_{iq}/\partial C_{iq}} \tag{1}$$

With regard to the perceived **safety** level, the coefficients of *riskier-than-driving* were proved significant regarding both AT and AFT. The negative sign indicates that using both autonomous transportation modes is expected to be at least as safe as driving a car. Meanwhile, the respondents seemed more sensitive to AT for being riskier than driving, according to the

Table 4. Estimated Results for *Lower-Income Profile* Models

Coefficient	*Lower-income profile* MNL (*None* alternative excluded)				*Lower-income profile* MNL (*None* alternative included)				
	Car	PT	AT	AFT	Car	PT	AT	AFT	None
ASC	3.30** (6.54)	Base case	na	na	2.33** (4.43)	Base case	2.73** (3.19)	na	−9.66** (−7.77)
Travel cost	−2.60** (−6.70)	na	na	−0.79** (−6.23)	−2.40** (−6.48)	−1.32** (−3.69)	−1.95** (−3.42)	−0.61** (−6.20)	na
Travel time	−1.07** (−13.93)	−0.64** (−11.75)	−0.91** (−13.08)	na	−0.98** (−13.33)	−0.68** (−10.46)	−1.17** (−9.66)	−0.95** (−4.77)	na
Safety (reference = driving-level safety)									
Safer than driving	na	na	0.52** (2.94)	na	na	na	0.38* (2.07)	na	na
Riskier than driving	na	na	na	na	na	na	na	na	na
Age (reference = 36–45)									
18–25	na	na	na	na	0.78** (3.53)	Base case	na	1.47** (4.71)	na
26–35	na	na	na	na	na	Base case	na	0.73** (3.06)	na
46–55	0.41* (2.17)	Base case	na	−0.81** (−3.11)	0.55** (3.12)	Base case	na	na	na
56–65	na	Base case	na	−0.73* (−1.99)	na	Base case	na	na	2.49** (4.80)
>65	na	na	na	na	na	na	na	na	na
Gender (reference = female)									
Male	−0.40* (−2.78)	Base case	na	na	−0.42** (−3.12)	Base case	na	na	na
Employment (reference = working people)									
Student	0.52* (2.29)	Base case	na	na	na	na	na	na	na
Others	na	na	na	na	na	na	na	na	na
Education level (reference = Bachelor)									
Lower than Bachelor	na	Base case	na	−1.12** (−2.99)	na	Base case	na	−1.04* (−2.47)	na
Master	na	na	na	na	na	Base case	na	na	3.27** (3.61)
PhD	na	na	na	na	na	na	na	na	na
Presence of children (0-17 years old) in the household (reference = no)									
Yes	na	na	na	na	na	Base case	na	na	2.17** (5.04)
Car availability (reference = yes)									
No	−1.20** (−6.43)	Base case	−0.73** (−2.97)	−0.76* (−2.74)	−1.11** (−6.05)	Base case	−0.79** (−3.21)	−0.68* (−2.34)	na
Current means of transport (reference = car as driver)									
PT	−1.13** (−5.40)	Base case	−0.99** (−4.17)	−1.98** (−7.93)	$\boxed{-1.23^{**}\ (-6.47)}$	Base case	$\boxed{-1.23^{**}\ (-6.47)}$	−2.24** (−7.80)	−2.35** (−5.26)

(continued)

Table 4. (continued)

Coefficient	Lower-income profile MNL (*None* alternative excluded)				Lower-income profile MNL (*None* alternative included)				
	Car	PT	AT	AFT	Car	PT	AT	AFT	None
Cycling and walking	−1.50**	Base case	−1.27**	−2.92**	−1.54**	Base case	−1.54**	−2.83**	1.79**
	(−4.98)		(−3.15)	(−5.51)	(−5.49)		(−5.49)	(−4.92)	(3.63)
Trip purpose (reference = non-commuting private trip)									
Commuting	−0.37*	Base case	na	−0.72**	−0.49**	Base case	−0.41*	−0.71**	na
	(−2.57)			(−3.70)	(−3.22)		(−2.09)	(−3.34)	
Model information									
No. of parameters			24				33		
Initial LL			−1838.226				−2221.024		
Final LL			−1196.134				−1314.529		
Adjusted ρ^2			0.336				0.393		

Note: Coefficient: estimated values (robust *t*-test); significant values are marked by * (robust *p*-value < 0.05) and ** (robust *p*-value < 0.01); black-outlined values represent coefficients that are constrained to be the same; na = not applicable (excluded insignificant values); ASC = alternative specific constant; MNL = multinomial logit; PT = public transportation; AT = autonomous taxi; AFT = autonomous flying taxi; LL = log-likelihoods.

significant estimations concerning all levels of AT. However, it should be acknowledged that the analysis regarding waiting, walking time, or both, and safety attributes may contain possibly distorted results, as a consequence of respondents' possible misinterpretations or uncertainty of travel time components, and probable presumptions toward autonomous flying vehicles, which may be caused by the artificial nature of the SP choice experiment (*49*).

Policy Implications

The main MNL estimation results indicate **age** has an impact, and that individuals aged between 46 and 65 years old may be relatively less likely to favor any of the autonomous modes, perhaps because they are less open to trying new technology (*33*). In contrast, a possible connection between lower-**income** individuals aged 18 to 35 years old and their propensity to accept AFT is revealed for the *lower-income* group. Within this subgroup, the younger the respondents, the more likely they are to favor AFT. Nonetheless, within the *high-income* group, a strong relationship between the employed individuals aged 56 to 65 years old and their preference of autonomous transportation services is suggested by the result, which may be explained by the stronger willingness to pay for new technological and environmentally friendly products. However, no difference between **genders**, male and female, was observed regarding the adoption of AFT in this study. The results in Table 2 only indicate that males tend to favor private car less than females and find "car" the least attractive among the four provided transportation alternatives. Moreover, individuals with lower income and lower **education** levels are less likely to accept AFT, as seen in Table 4. This may be caused by having fewer environmental concerns and, potentially, the more negative attitudes toward the autonomous transportation modes stated by the respondents with a degree lower than a bachelor's degree. Considering the impact of income, individuals with **children** and belonging to the *high-income* group tend to favor AFT less than those without children, according to the result in Table 3.

Current modality patterns also play a role in mode preferences. The results suggest that respondents who are currently using PT or soft modes (walking or cycling) most frequently are less likely to favor any autonomous modes (main MNL). Current PT users having lower income find the PT most attractive, followed by similar attitudes toward the car and AT; however, switching to AFT seems relatively unlikely, perhaps because PT users are somewhat satisfied with their **current travel pattern**. Similarly, for the soft modes users with lower income, AFT is likely to be the least favorable alternative. They may find none of the available choices is desirable, or expect other modes to be provided. This result can possibly be explained by the fact that most cyclists in Munich are satisfied with the existing bicycle traffic system (*50*). Regarding the impact of **car availability**, individuals without a car available in the household may find the PT as the most appealing mode, but they tend to prefer autonomous modes to car (main MNL). In particular, those who belong to the *high-income* group are believed to have a higher propensity to adopt AT. However, compared with individuals with a car available, those who do not have a car are likely to have a lower propensity to choose both autonomous modes. Mode choice decisions also vary across **trip purposes**. For daily commutes, PT may be considered as the most desirable choice, followed by car and AT, whereas AFT seems least likely to be selected (main MNL). Individuals may be less open to using novel mobility options (*10*), compared with the choice regarding non-commuting private trips.

Conclusion

The convergence of technologies and new business models enabled by the digitalization and electrification of propulsion is making it possible to explore UAM as a new way for people to move within urban areas. Taking Munich, Germany, as an example, this case study investigates the transport modes preferences, and notably, the adoption of AFT and UAM, by estimating the potential influence of service attributes which may affect people's choices among given transport alternatives and identifying the characteristics of the potential user groups with higher propensity to accept AFT and UAM services.

A SP survey including a SC experiment was conducted through en-route and online flyer distribution. The results of the survey ($N = 248$) were quantitatively analyzed based on a main MNL model together with two profile-based MNL models. The model estimation results indicate an expected trend that the respondents with a higher VOT may be more willing to accept autonomous transportation modes. Regardless of respondents' possible presumption concerning vehicles' safety features, safety may be a critical determinant of adoption of AVs and AFT. Some policy implications were also derived. The overall results suggest that market penetration rates for AFT and UAM may be greater among younger respondents (18–35 years old) and older travelers (56–65 years old) with high income who also have a relatively high propensity to use AT. However, switching to any of the autonomous transportation alternatives is less likely if the individuals currently use PT or soft modes most frequently. Regarding different trip purposes, AFT and UAM seem more desirable for performing trip purposes, such as business trips, rather than using them for daily commutes. This result is also complementary to the findings of multiple eVTOL market research studies (*18, 51*).

Some main limitations regarding this study have been identified and should be considered when assessing the presented results. First, this research may be susceptible to potential hypothetical biases, which are caused by the hypothetical nature of the SC experiment (*10, 33*) and SP data. Regarding the design of SC tasks, further research could integrate revealed preference from the subjects to form individual specific reference settings in the choice tasks. The scope of the choice experiment could be expanded by including more transportation modes, various first- and last-mile scenarios, and differing trip distances. It should be noted that a pertinent design is required to ensure that choice scenarios can reflect the realistic operation range of AFT. In addition, as existing literature points out, the preferences explicated by the respondents in the survey may not accurately reflect the preferences by the time the hypothetical alternatives are available in the market; longitudinal studies to investigate the choice decisions at different time points may be helpful (*10, 33*). Second, the combined results based on the main MNL and two sub-models suggested that the motives of using AFT and UAM might differ substantially across subgroups. The existing taste heterogeneity among subgroups could be further examined, using more advanced modeling methodologies based on data that are more extensive.

It is worth noting that other research regarding UAM adoption is currently ongoing (e.g., *19*). Transport mode choice research with relevance to UAM is particularly expected to be further developed. Despite the potential methodological biases, the results provide a preliminary understanding of the transportation modes preferences in a hypothetical UAM environment, and the relative importance of the attribute of interest has been revealed. The survey results, as well as the statistical analysis output, could be useful for further integrating UAM into simulation models which enable evaluations of novel urban transportation concepts and their operational setup.

Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: MF, RR, CA; data collection: MF, RR; analysis and interpretation of results: MF, CA; draft manuscript preparation: MF, RR, CA. All authors reviewed the results and approved the final version of the manuscript.

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The Standing Committee on Emerging and Innovative Public Transport and Technologies (AP020) peer-reviewed this paper (19-02164).