Towards understanding user adoption of urban air mobility

Christelle Al Haddad[a], Emmanouil Chaniotakis[a], Anna Straubinger[b], Kay Plötner[b], Constantinos Antoniou[a]

[a] *Technical University of Munich*
[b] *Bauhaus Luftfahrt e.V*
contact information: email:christelle.haddad@tum.de/mobile phone:+4915224251582

Abstract

Recent advances in areas of autonomous vehicles and shared mobility services have been accompanied with a research interest in urban air mobility (UAM). This service however remains subject to many limitations, notably community acceptance. In this paper, a study on the perception of UAM is presented, in which a stated preference survey was completed to assess its time adoption. Obtained results were evaluated using exploratory factor analysis, followed by discrete choice models including multinomial logit models and ordered logit models, with time adoption as a dependent variable. Results highlighted the importance of safety and trust, affinity to automation, data concerns, social attitude, and socio-demographics for adoption. Factors such as time savings, costs of automation, and service reliability were strongly influential as well. There was also an indication that skeptical respondents, i.e. choosing unsure, had a behavior similar to late adopters. The summarized results helped to extend the Technology Acceptance Model to be applied for urban air mobility, providing meaningful recommendations and policy implications.

Keywords: urban air mobility, user adoption, technology acceptance model, discrete choice modeling

1. Introduction

The deployment of shared mobility services are providing users with more efficient travel, characterized by a lower demand for parking spaces, lower vehicle ownership, but also reduced environmental impacts resulting from lower emissions (Baptista et al., 2014). At the same time, autonomous vehicles promise safe and comfortable transportation, leading to an increasing research interest in ground shared autonomous mobility (Fagnant & Kockelman, 2014), and possibly the exploration of the third dimension: the skyscape. The latter has notably been observed in the so-called "urban air mobility (UAM)" research community, with different models for the new service. Airbus (2018) introduces urban air mobility as the on-demand sharing mobility operated by vertical take-off and landing aircraft (VTOL) for intra-city passenger trips. Airbus' long-term vision for UAM entails electrical self-piloted VTOLs, such as Vahana and CityAirbus demonstrators, for one or more passengers respectively. The development of different concepts for short-haul passenger air trips is facilitated by technological advances in terms of battery storage, electrical power transmission and distributed propulsion systems (Shamiyeh et al., 2017). Uber elevate introduce their economic model for air taxis assuming a four-seat capacity (including the pilot if the vehicle is not self-piloted), for which passengers have the possibility to share the flight and save thereby on the ride cost (Uber Elevate, 2016). Still, urban air mobility is constrained to many aspects related to regulations, infrastructure availability, air traffic control, environmental impacts, but also community acceptance (Vascik, 2017). This paper helps to fill this gap on acceptance by focusing on a better understanding of UAM's time adoption outside a mode choice context. The investigation is based on the development of a novel stated preference survey design, with an aim to reveal significant factors in the adoption of this service. The methodology of this work is first presented, followed by the results, after which a discussion of the main findings is given along with the main work's recommendations and conclusions.

2. Methodology

A preliminary step before designing the survey is to review technology acceptance models, as well as the acceptance of autonomous vehicles, to highlight the most prominent factors in these studies that could also be applied to urban air mobility. These include the perceived reliability of automation, the perceived vehicle's safety, the perceived locus of control, data concerns, the perceived usefulness, service-related attributes (cost, time, etc.), and other socio-demographic parameters. The stated preference survey was first conducted, then analyzed descriptively to get a first insight on the collected data. After that, models were developed using first exploratory factor analysis, then discrete choice modeling including multinomial logit models (MNL) and ordered logit models (OLM); ordered models were built using findings from MNLs and observed patterns in time adoption.

2.1. Survey Design

The survey was structured in four parts, with a total of 31 questions (or question groups[1]) and required around 10 to 15 minutes to be completed. The first and last parts of the survey targeted respondents' travel behavior and socio-demographics, respectively. In the second part, UAM was introduced by presenting some of its properties found in the pertinent literature. To illustrate the system operation from origin to destination, a scheme was drawn and benchmarked against taxi operation, as shown in Figure 1 below.

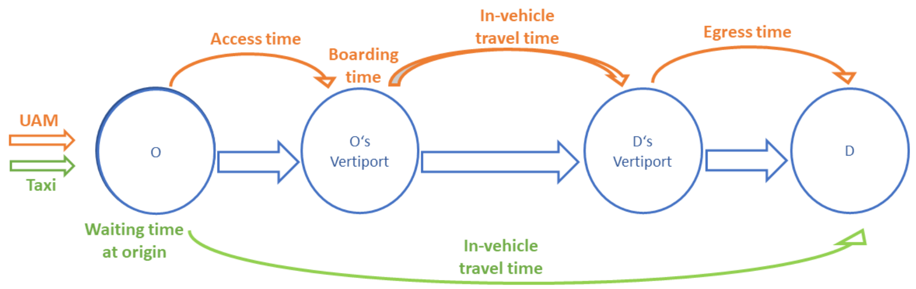

Figure 1: UAM process (*own illustration*)

As the main objective of this study is to understand the perception of respondents in terms of their acceptance and stated time adoption, two scenarios were given to present realistic attributes of the service (trip duration and fare). After defining the service and its properties, respondents were first asked to rank (from 1 to 9) the factors they considered most important for the adoption of this service. In this part, several questions were asked in the form of five-point Likert scale agreement statements in an attempt to reveal some latent variables affecting automation. For instance, data and ethical concerns was one aspect to be investigated; an example of such statements is: "my fear of cyber-security could prevent me from using UAM". Other constructs that were examined were trust and the value given for safety (or even the locus of control), cost perception, and travel time savings. At the end of this part, respondents were asked to state when they were most likely going to use UAM. Alternatives included options ranging from the first year of operation (Y1), the second or third years of operation (Y2-Y3), the fourth or fifth year of opertaion (Y4-Y5), starting the sixth year of its operation (Y6+), to never (non-adopters), and unsure (uncertain adopters). Respondents

[1]A question consisted sometimes of a matrix including several agreement statements, focusing on one attribute for instance.

were also asked to state their trip purpose for UAM use. The third part of the survey aimed at revealing respondents' social attitudes, including their familiarity with various on-demand services, the use of social media platforms, the comfort with online services, with flying, the willingness to share a ride with strangers, and the enjoyment of driving a car. Respondents' environmental awareness was also investigated through several agreement statements.

2.2. Descriptive analysis and model development

After collecting the data (survey responses), a preliminary descriptive analysis was performed to understand the sample distribution, but also the attitudes (through agreement statements) of different demographics. Exploratory factor analysis (EFA) was then applied to the second and third parts of the survey pertaining to the respondents' perceptions and social behaviors respectively. This method was used to reduce the data's dimensionality, but also to identify latent constructs behind the variables. In this study, EFA was applied using R statistical software (R Core Team, 2019) and the function *factanal* to apply the maximum likelihood estimation (MLE) as a factor extraction method. The suggested number of factors was obtained from the Kaiser-Guttman method. Also, since the factors were assumed to be uncorrelated, varimax orthogonal rotation was used. Loadings less than 0.3 were removed to reduce the noise in the data and the factor analysis was run again. Factors were expected to explain at least 10% of the variables' variance (Costello & Osborne, 2005). Factor scores were computed using *factor.scores* and the "component" method, a weighted sum of the factor loads. Discrete choice modeling was applied to analyze and identify the significant factors (independent variables) for the given choices, since the answer options of the survey are discrete categories of stated time adoption. Using Python Biogeme (Bierlaire, 2003), both multinomial and ordered logit models were built. Starting from multinomial logit models and based on the inputs from the factor analysis, models were developed in stepwise regression, first forward (from saturated models) where only variables of high significance (about 95% or 90 % according to importance) were kept, then backward (from empty models) where significant variables were added one after the other. The first models were generic, then alternative specific models were developed, where independent variables were specific to the different outcomes.

3. Results

3.1. Survey descriptive analysis

The survey generated 221 responses, with a subsample of 97 respondents from the Munich region. Among the 221 respondents, 36.65% -i.e. the majority- stated that they would adopt UAM in the second or third year of its implementation, followed by 22.17% claiming an adoption during its first year, 14.03 % during its fourth and fifth year, 2.71 % starting its sixth year, and 3.17 % stating that they would never adopt the service. Moreover, 21.27% of the respondents expressed uncertainty ("unsure") on their time adoption of UAM. The analysis of the results highlighted the importance of safety for UAM adoption as the majority of respondents (more than 50 %) ranked it as the most important factor in their intention to adopt UAM. Also, a strong indication towards the importance of UAM costs, trip duration, on-time reliability, and operation characteristics was given. Less important factors included trip purpose, vehicle characteristics, boarding process and booking experience.

Similarly, the analysis of the attitudes of different demographics showed the importance of these factors and their influence on the adoption intention. For instance, females were found to have a lower tendency of being early adopters, and a higher of being "unsure" about their adoption time. This was also confirmed by an overall higher affinity to automation by male respondents due to a higher enjoyment and trust of automated systems, more experience in advanced driver assistance systems, and a higher perception of usefulness of such systems and of UAM, but also the higher comfort with flying of male respondents compared to their female counterparts. On the other hand, females seemed to accord a higher level of importance to service reliability and cyber-security in the context of UAM. In terms of safety requirements, females showed higher expectations in terms of the presence of in-vehicle cameras and more stringent requirements for an operator on the ground and to override the vehicle in case of emergency.

3.2. Model estimations

3.2.1. Exploratory Factor Analysis

For respondents' perceptions, or the survey's second part, four factors were extracted explaining a cumulative variance of 52% of the total variance, and presented in Table 1. By looking at the latent meaning that these variables could explain, four factors are extracted and interpreted as the value of time savings, the affinity to automation, data concerns, and safety concerns. For social attitudes, or the survey's third part, four factors were also extracted explaining a cumulative variance of 55% of the total variance, and were grouped into: affinity to online services, environmental awareness, affinity to social media, and affinity to sharing.

Table 1: Factor analysis on respondents' perceptions

Loadings	Factor 1	Factor 2	Factor 3	Factor 4
Travel time savings 5min	0.78			
Travel time savings 10min	0.98			
Travel time savings 20min	0.59			
Enjoy automation		0.80		
Trust automation		0.75		
UAM is useful		0.51		
Fear of cyber–security			0.70	
Fear that data goes to a third party			0.53	
Loss of job concerns			0.49	
Operator on the ground				0.67
In–vehicle safety cameras				0.50
Sum of square of loadings	2.01	1.66	1.14	0.96
Proportion variance	0.18	0.15	0.10	0.09
Cumulative variance	0.18	0.33	0.44	0.52
Factor interpretation	Value of time savings	Affinity to automation	Data and ethical concerns	Safety concerns

3.3. Discrete Choice Modeling

3.3.1. Multinomial logit model

The coefficient estimates for the multinomial logit model were in general reasonable in sign and magnitude and consistent with prior expectations [2]. For instance, estimates for the affinity to automation were highly significant and positive mostly for early adoption, but also (to a lesser extent) for later years and uncertain respondents; the same impact was observed for the affinity to social media (notably WhatsApp affinity; for most respondents: Y1-Y5 and unsure) and full-time employment. Cost factors also had a significant positive impact on adoption. Scaling UAM prices to taxis' highly contributed to early adoption, whereas a high importance accorded to cost parameters contributed to later adoption levels. On the other hand, previous crash experiences (with injuries) and higher data concerns (including fear of cyber-security and concerns of data being passed to third parties) had influential negative impacts on early adoption and adoption in general (for crash experiences, with lesser impacts on later adoption). Safety concerns also negatively contributed to adoption with a high influence on immediate adoption and later adoption. Female respondents were in general less likely than their male counterparts to adopt UAM (for all years) and highly educated respondents (doctorate level or higher) less likely to adopt it in its early years. Moreover, German as a survey language (compared to English) was highly correlated with uncertainty. Service provider reputation showed a significant and positive role in adoption, notably for immediate and uncertain adoption. Furthermore, higher income level respondents were less likely to be late adopters of UAM. The perception

[2] Most factors in this table are significant at least to the 95% confidence level with a t-value higher than 1.96, or in some cases to the 90% with a t-value higher than 1.65

of travel time importance was also decisive in UAM adoption for the second and third years and the value of time savings for later adoption. Finally, public transport commuters were more likely to adopt UAM during its later years and the alternative-specific constant for respondents stating a very late or non-adoption was positive and highly significant.

3.3.2. Ordered logit models

Ordered logit models were built with time adoption as a dependent variable. Although time frame can be ordered from the first to the sixth or more years (even never), the category “unsure” can’t be ranked in that scale. Therefore, based on previously observed patterns in the MNL model (such as observed patterns in automation affinity or gender attributes), two cases were proposed. In the first case, the ordered categories were as follows: Y1; Y2-Y3; Y4-Y5; Unsure; Y6+/Never. The second case was built from the first by merging the “unsure” category with the last one, of late to non-adopters. The corresponding categories were therefore: Y1; Y2-Y3; Y4-Y5; Unsure, Y6+ and Never. Table 2 represents the final OLM model for case 1. The highly significant cut values indicate that adoption is indeed ordered and people who are unsure display a behavior that is ranked between late (Y4-Y5) and extremely late or non-adopters (Y6+ or Never). This was rather expected from the patterns observed in MNL models. The significant parameters in this model are the highly significant ones from the MNL model. Affinity to automation, full-time employment, and cost as taxi are associated with an early adoption. Similarly, data concerns and starting language German (with a lesser degree of significance) are strongly correlated with a later adoption.

Table 2: Ordered logit model for UAM adoption: Case 1 (N=221)

	estimate	std. error	t–stat
Parameters			
Affinity to automation	-0.26	0.07	-3.54
Cost as taxi	-0.37	0.13	-2.82
Starting language German	0.61	0.30	2.05
Data and ethical concerns	0.27	0.08	3.32
Full–time employment	-0.96	0.26	-3.68
Intercepts			
Y1—Y2–Y3	-4.22	0.85	-4.97
Y2–Y3—Y4–Y5	-2.16	0.21	9.96
Y4–Y5—Unsure	-1.36	0.14	5.93
Unsure—Y6+/Never	0.87	0.31	7.10
Summary statistics			
$\bar{\rho}^2$	0.25		
AIC	585.10		
BIC	615.69		

The results of the second case model showed that uncertain respondents are more likely to adopt UAM at a later stage, or not to use it at all. In both cases, uncertain adopters are associated with rather late adoption; the only difference is that one case considers uncertainty as part of non-adoption and the other regards it as one degree less. Therefore as both models have more or less the same meaning, deciding on the number of ordered categories depends on personal judgment and preference: parsimony vs. richness.

4. Discussion and conclusions

4.1. Summary of findings

The model findings pertaining to acceptance were incorporated to extend the Technology Acceptance Model for the application of UAM. In this model (Figure 2), trust played a significant factor and was in turn positively impacted by the perceived reliability of automation, the perceived vehicle’s safety, the perceived locus of control and the previous experience with automation; data concerns in contrast negatively influenced trust. Moreover, socio-demographics and affinity to automation were overarching parameters; perceived usefulness, social behavior, value of time, perceived costs and data and ethical concerns were all contributing factors in the behavioral intention. Perceived ease of use (in this case service booking or boarding) was not observed as influential and was therefore removed from the model. The findings of this work provide meaningful insights on UAM acceptance and use with strong recommendations and policy implications

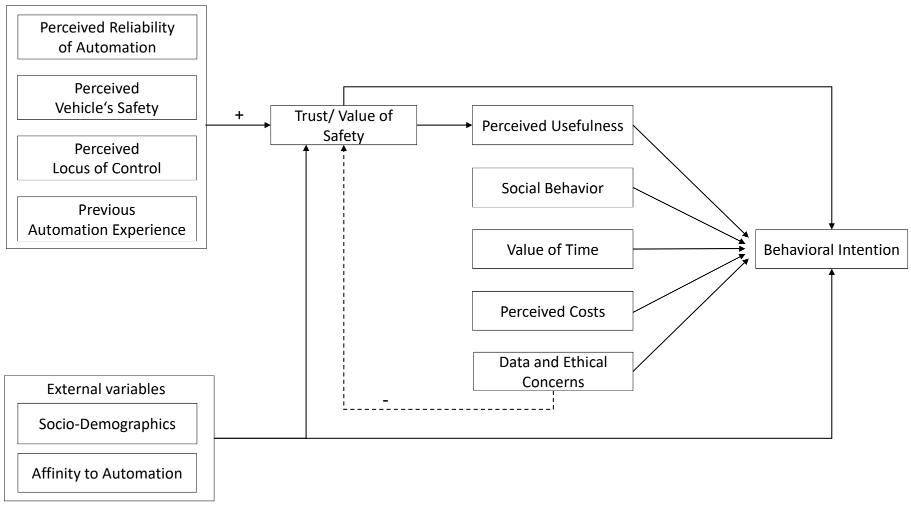

Figure 2: Extended Technology Acceptance Model for urban air mobility

4.2. Policy implications

The findings of this work indicate the need for responsible policymaking by relevant stakeholders, to ensure a smooth system integration and an examination of the relevant aspects in UAM implementation. Accordingly, skepticism regarding missing or erroneous information is likely to be reduced with a higher transparency and more stringent rules acting upon the most relevant factors like safety, privacy, information sharing, etc. The implications can be summarized in the following. Awareness on automation in general is necessary to ensure more transparency on service attributes such as trip duration and costs. Policymaking should focus on areas of safety, including automation reliability (service's performance and on-time reliability). Surveillance cameras could for instance contribute to the safety feeling that is necessary for trust. Furthermore, the importance of the human factor should not be disregarded, with an emphasis on operator availability on the ground, for the locus of control perception of users. Finally, service attributes including cost considerations should be taken into account; for instance price ranges similar to taxis' could receive higher acceptance among the public. Environmental implications of UAM such as noise and visual impacts are also areas in need of further examination. Data and ethical concerns have to be addressed on a policy level with transparent regulations on data sharing. Finally, for a service aiming to be inclusive, UAM would need to be integrated with existing transportation systems, and not compete with them, in order to ensure seamless transportation. Future research motivation could focus on the modeling methodology and build a nested ordered logit model with one or more ordered nests, or develop a hybrid latent class model for which both analysis methods (factor analysis and choice models) would be combined. Another motivation could be to test the extended technology acceptance model, by applying a confirmatory factor analysis (CFA).

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