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An exploratory empirical analysis of willingness to hire and pay for flying taxis and shared flying car services

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ABSTRACT

A new transportation mode that can simultaneously operate on land and in the air, namely the flying cars, is anticipated to penetrate the automobile fleet between 2020 and 2025. Due to their flexible mobility patterns and automated operational characteristics, flying taxi and shared flying car services are expected to expand the existing shared mobility services (such as Uber, Lyft, and similar services) of the urban transportation network. Despite their forthcoming introduction in the shared mobility market, public perceptions and expectations about these services have not been investigated in travel demand literature. This study aims to provide an exploratory analysis of public willingness to hire and pay for flying taxis and shared flying car services, and to identify the determinants of the willingness to hire and pay for such services. Using data collected from an online survey, individuals' willingness to hire and to pay for flying taxi and shared flying car services are statistically modeled within a correlated grouped random parameters bivariate probit framework. The analysis shows that various socio-demographic characteristics and individuals' opinions towards the perceived benefits and challenges of flying cars affect public willingness to hire and pay for flying taxi and shared flying car services. Even though the awareness about the operation of flying taxis and shared flying car services is possibly limited in the public sphere, the findings of this study can provide insights into the challenges that policymakers, manufacturing companies, and shared mobility providers will face with the introduction of such flying car services in the transportation networks.

1. Introduction

Over the last decades, the worldwide demand for automobiles has risen steadily, either for passenger or goods transportation. Despite their growing capacities, the transportation infrastructure systems remain in constant need for expansion in order to accommodate increasing traffic volumes as well as to address passengers' demand for low and reliable travel times, enhanced safety and security and straightforward access to different transportation modes. To that end, recent technological advancements have paved the way for the introduction of innovative transportation technologies and systems such as electric vehicles, carpooling systems and autonomous or intelligent transportation systems. Earlier research has attempted to identify the consumers' perception patterns towards the acceptance of electric vehicles and possible benefits and infrastructure requirements (Egbue and Long, 2012; Tamor et al., 2013; Dong et al., 2014; Shin et al., 2015; Rezvani et al., 2018). Carsharing schemes provide flexible and accessible mobility patterns and have significant potential in alleviating urban traffic congestion (Shaheen et al., 2006; Habib et al., 2012; Budd, 2016). In the last decade, automotive industry has been leaning towards the introduction of autonomous vehicles, which, in turn, led to an abundance of studies exploring public perceptions, opinions and possible transformations of travel behavior (Rödel et al., 2014; Choi and Ji, 2015; Kyriakidis et al., 2015; Bansal et al., 2016; Ellis et al., 2016; Nordhoff et al., 2016; Fu and

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Table 1
Distribution of respondents' willingness to hire and willingness to pay for an Uber/Lyft ride in a flying car.

Dependent Variables	Somewhat likely	Very likely	**Overall Likely**	Somewhat unlikely	Very unlikely	**Overall Unlikely**
Willingness to hire a Flying Taxi (as Uber/Lyft) if						
Operated by a human driver	38.64%	23.66%	**62.30%**	17.51%	20.19%	**37.70%**
Operated as autonomous	30.02%	21.48%	**51.50%**	22.91%	25.59%	**48.50%**
Willingness to pay for an Uber/Lyft ride in a flying car compared to current average rate of $1.5/mile:						
Do not wish to pay more	20.32%	36.32%	**56.64%**	16.16%	27.20%	**43.36%**
Would pay up to $1 more	36.51%	31.75%	**68.25%**	8.89%	22.86%	**31.75%**
Would pay between $1 and $2 per mile more	33.01%	22.12%	**55.13%**	17.47%	27.40%	**44.87%**
Would pay between $2 and $3 per mile more	25.64%	13.54%	**39.17%**	20.86%	39.97%	**60.83%**
Would pay between $3 and $5 per mile more	15.97%	8.79%	**24.76%**	24.28%	50.96%	**75.24%**
Would pay between $5 and $10 per mile more	7.18%	6.06%	**13.24%**	19.78%	66.99%	**86.76%**
Would pay between $10 and $20 per mile more	5.29%	2.40%	**7.69%**	12.98%	79.33%	**92.31%**
Would pay over $20 per mile more	3.37%	1.77%	**5.14%**	9.47%	85.39%	**94.86%**

Kim, 2016; Becker and Axhausen, 2017; Xu et al., 2018). Special consideration has been also given to the joint implementation of car-sharing schemes and autonomous technologies through the operation of shared autonomous vehicles (SAVs). Previous studies (Zhang et al., 2015; Krueger et al., 2016) have investigated individuals' expectations regarding the travel time, waiting time, travel cost characteristics of the shared autonomous vehicles.

As a result of the recent technological advancements, a newly emerging transportation mode, namely the flying cars, are expected to join the traffic fleet. Based on recent developments and announcements, availability of flying cars in the automotive market is expected to take place between 2020 and 2025 (Becker, 2017; Oppitz and Tomsu, 2018). Several start-up companies, which have developed flying car prototypes, currently focus on accelerating the introduction of flying cars into the traffic fleet (to name a few, Terrafugia, AeroMobil, Kitty Hawk and Opener). Opener, one of the latest contenders in flying car development, has recently demonstrated their prototype, which combines near-vertical take-off and landing capabilities. In a collaborative effort, Audi and Airbus have developed and presented a modular flying taxi concept named "Pop.Up Next", which consists of a flight module, a passenger capsule and an autonomous ground module (Audi and Italdesign, 2018). NASA is collaborating with Uber to establish a new ridership framework (referred to as "urban air mobility") for densely populated metropolitan areas, assess possible impacts of small aircrafts on such areas as well as identify challenges and appropriate countermeasures related to air traffic control system (NASA, 2018a; NASA, 2018b). Several other companies have announced their willingness to invest in designing and manufacturing flying cars, such as, Airbus, Volocopter and EHang (Shamiyeh et al., 2017). Despite the growing interest in this emerging technology, the adoption of flying cars by the commuting population, in terms of the anticipated level of ownership or use, remains uncertain. Even though the expected acquaintance cost of flying cars may constitute a possible adoption barrier, their flexible operation as well as their multiple-passenger capacity (they can accommodate two to four passengers) pave the way for flying taxis or new shared mobility services based on flying cars.

The aim of this study is to identify the key factors that may affect individuals' willingness to hire and willingness to pay for flying taxis and shared flying car services. In line with previous studies focusing on travelers' perceptions (Greghi et al., 2013; Molin et al., 2017; Zimmermann et al., 2018) a survey is designed and distributed in order to extract opinions and preferences pertaining to flying cars and flying taxis along with the socio-demographic and behavioral background of the respondents. Survey data are used for the joint statistical analysis of individuals' willingness to hire and willingness to pay for flying taxi and shared services. To account for significant modeling issues arising from possible systematic unobserved variations among the survey responses (specifically, unobserved heterogeneity, unbalanced panel effects, cross-equation error term correlation and correlation among the unobserved effects), the correlated grouped random parameters bivariate probit modeling framework is employed. The results of the analysis show that individuals' willingness to hire and willingness to pay for flying taxi services are affected by various socio-demographic and behavioral characteristics as well as individuals' perceptions regarding the perceived concerns and benefits of flying cars.

2. Data description

An online survey was designed to collect socio-demographic and behavioral information as well as opinions regarding flying cars and taxis with the aid of SurveyMonkey (an online based survey conducting platform). The survey was distributed by 35 students and employees from the University at Buffalo during March 2017. The collected data included responses from 692 individuals. The country of residence of the survey respondents was identified through tracing the Internet Protocol (IP) addresses from the online survey. Out of 692 respondents, 584 were found to be from the United States, 50 from India, and the remaining 58 were from seventeen other countries around the world.[1]

The survey consisted of three sections. The first section was aimed at introducing the respondents to the concept of flying car as a transportation mode. Specifically, it included a detailed written description of the generalized operational characteristics and features of a typical flying car model (i.e., take-off and landing requirements, range, cruising speed, safety features, and useful load). In addition, multiple high resolution images, and a video illustrating the operation of a flying car were included. Followed by the introductory session, the first set of questions were asked, which involved the respondents' level of familiarity with advanced vehicle safety features (e.g., emergency automatic braking, lane keeping assist, adaptive cruise control, left turn assist, adaptive headlights and blind spot monitoring). The respondents were also asked whether they have ever owned a vehicle with any of these safety features. The purpose of including these questions in the survey was to identify a measure of the respondents' level of exposure to modern vehicle technologies, as such exposure may affect their perceptions towards flying cars and flying taxi services. The responses to the questions involving level of familiarity with advanced vehicle safety features were recorded in a four point Likert scale, with the option to choose from one of the following available choices: "very unfamiliar", "somewhat unfamiliar", "somewhat familiar", and "very familiar".

The second section focused on capturing the respondents' perceptions towards flying cars in general. In this section, the first set of questions aimed at determining whether the respondents were willing to

[1] These seventeen countries were Australia, Canada, Dominican Republic, Greece, Iran, Nepal, New Zealand, Nigeria, Oman, Qatar, Saudi Arabia, Sri Lanka, Switzerland, Thailand, Turkey, United Arab Emirates, and United Kingdom.

hire a flying taxi (as an Uber/Lyft ride) if it is human operated, and if it is autonomous. The subsequent set of questions were intended to evaluate the respondents' willingness to pay for an Uber/Lyft ride in flying car on a "per mile" basis, compared to the current average cost of a conventional ground Uber/Lyft ride (approximately $1.5 per mile). The comparative scale was developed to determine the amount per mile, up to which the respondents were willing to pay for a flying taxi ride opposed to the base rate of $1.5/mile. The amounts were subdivided into eight categories in an ascending order: do not wish to pay more, would pay $1 more, between $1 to $2 more, between $2 to $3 more, between $3 to $5 more, between $5 to $10 more, between $10 to $20 more, and over $20 more. The responses to the aforementioned survey questions were also recorded in a similar four point Likert scale, with the available options being "very unlikely", "somewhat unlikely", "somewhat likely", and "very likely". The distribution of the responses is presented in Table 1.

The next set of questions was intended to evaluate the respondents' perceptions towards a number of trip-, safety-, environment-, and cost-specific benefits that may occur from the use of flying cars. Another set of questions was aimed to assess if the respondents were concerned about a number of safety-, operational-, and security-specific issues that may arise from the operation of flying cars. The last set of questions in the second section was aimed at evaluating the respondents' opinion towards a number of potential security measures, which would contribute to ensure safe and secure operation of flying cars. The measures that were included in the questions are as follows: use of existing FAA regulations for air traffic control, air-road police enforcement, profiling and background checking of flying car owners/operators, and establishing no-fly zones near sensitive locations. The responses to the questions involving potential benefits, and potential security measures were recorded in a similar four point Likert scale as in the willingness to use and pay questions. In addition, the choices available to respond to the concern related questions were "not at all concerned", "slightly concerned", "moderately concerned", and "very concerned".

The last section of the survey was intended to collect the respondents' socio-economic characteristics (e.g., age, gender, marital status, educational attainment, income, household characteristics), and driving history (e.g. average annual miles driven, number of non-severe and severe accident involvements, history of car maintenance expense). The responses from the third section were obtained through open-ended or multiple-choice questions.

Focusing on the key sociodemographic attributes of the survey data, 59.6% of the sample consists of male respondents. The average age of the respondents is 30.4 years. In terms of educational attainment, 72% of the respondents have a college degree or higher. With regards to the household income level, 22.3% of the respondents have an annual household income of $30,000 or below, 13% of the respondents have an annual household income between $30,000 and $50,000, 64.7% of the respondents have an annual household income of $50,000 or above. Turning to the driving experience of the respondents, 29 out of the 692 respondents reported that they do not have a driver's license. Respondents who have driver's license were found to have 12 years of driving experience on average.

Descriptive statistics of the key variables that were found to affect the willingness to hire and willingness to pay for Uber/Lyft ride in a flying car are summarized in Table 2. For additional studies conducted based on the same survey data, see also Ahmed et al. (2019, 2020), and Eker et al. (2019, 2020a, 2020b).

3. Methodology

To understand the decision-making mechanism of potential users of flying taxis and shared flying cars, individuals' willingness to hire and willingness to pay are statistically modeled using the data collected from the aforementioned survey.

The dependent variables for the statistical models were derived from the survey questions related to the respondents' willingness to hire and pay for flying taxis and shared flying car services. For each variable, the distribution of the received responses is presented in Table 1. Since the responses were recorded in a 4-point scale, it is likely that adjacent Likert-style responses reflecting similar viewpoints against the question (e.g., somewhat likely and very likely) are affected by systematic, respondent-specific unobserved characteristics. To account for such unobserved characteristics, the responses were aggregated. Specifically, the "somewhat likely" and "very likely" responses were aggregated to "overall likely"; and the "somewhat unlikely" and "very unlikely" responses were aggregated to "overall unlikely". Such aggregation led to the formation of binary dependent variables, thus allowing the application of binary outcome modeling techniques for the statistical analysis.

The probable presence of similar unobserved characteristics among the willingness to hire and willingness to pay responses may lead to error terms that are correlated across individually estimated models, thus, resulting in biased parameter estimates (Washington et al., 2011; Russo et al., 2014; Anastasopoulos, 2016; Anastasopoulos and Mannering, 2016; Sarwar et al., 2017a, 2017b; Fountas et al., 2018a, 2018c, 2020; Fountas and Anastasopoulos, 2018). To account for the correlation of error terms, the bivariate probit modeling approach is employed, which allows to simultaneously model two dependent variables interrelated to each other. The bivariate probit modeling framework is defined as (Milioti et al., 2015; Greene, 2017; Sarwar et al., 2017a; Kuljanin et al., 2018),

$$\begin{aligned} Y_{i,1} &= \boldsymbol{\beta}_{i,1}\mathbf{X}_{i,1} + \varepsilon_{i,1}, \quad y_{i,1} = 1 \; if \; Y_{i,1} > 0, \; and \; y_{i,1} = 0 \; otherwise \\ Y_{i,2} &= \boldsymbol{\beta}_{i,2}\mathbf{X}_{i,2} + \varepsilon_{i,2}, \quad y_{i,2} = 1 \; if \; Y_{i,2} > 0, \; and \; y_{i,2} = 0 \; otherwise \end{aligned} \tag{1}$$

where the correlated cross-equation error terms are expressed as,

$$\begin{pmatrix} \varepsilon_{i,1} \\ \varepsilon_{i,2} \end{pmatrix} \sim N\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix}\right] \tag{2}$$

where, $\mathbf{X}$ is a vector of explanatory variables that affect the willingness to hire and willingness to pay for flying taxi and shared flying car services for observation i, $\boldsymbol{\beta}$ is a vector of estimable parameters corresponding to X, y corresponds to integer binary outcome (zero or one for both dependent variables), ε represents a normally distributed error term (having mean equal to zero and variance equal to one) and ρ is the cross-equation correlation coefficient of the error terms. The cumulative density function and log-likelihood function for the bivariate probit model are then respectively defined as (Greene, 2017),

$$\Phi(Y_1, Y_2, \rho) = \frac{\exp\left[-0.5\left(Y_1^2 + Y_2^2 - 2\rho Y_1 Y_2\right)/\left(1-\rho^2\right)\right]}{\left[2\pi\sqrt{(1-\rho^2)}\right]} \tag{3}$$

and

As the survey was distributed by 35 individuals from different socio-demographic backgrounds, common unobserved characteristics may be

Table 2
Descriptive statistics of key variables.

Variable Description	Mean or Percentage	Std. Dev.	Min.	Max.
Socio-demographic Characteristics				
Gender indicator (1 if the respondent is female, 0 otherwise)	39.7%	–	0	1
Age of the respondent	30.432	12.729	16	94
Ethnicity indicator (1 if the respondent is Asian, 0 otherwise)	22.5%	–	0	1
Ethnicity indicator (1 if the respondent is Caucasian, 0 otherwise)	57.1%	–	0	1
Ethnicity indicator (1 if the respondent is not Asian or Caucasian, 0 otherwise)	20.4%	–	0	1
Current living area indicator (1 if the respondent is currently living in city center, 0 otherwise)	13.2%	–	0	1
Current living area indicator (1 if the respondent is currently living in rural area, 0 otherwise)	9.8%	–	0	1
Education level indicator (1 if the respondent has a post graduate degree, 0 otherwise)	23.2%	–	0	1
Education and income level indicator (1 if the respondent has a college degree and household income between 40,000 and 100,000 dollars, 0 otherwise)	19.4%	–	0	1
Education and income level indicator (1 if the respondent has a college degree and household income above 100,000 dollars, 0 otherwise)	16.7%	–	0	1
Income level indicator (1 if the respondent's annual household income is between 40,000 and 100,000 dollars, 0 otherwise)	37.1%	–	0	1
Income level indicator (1 if the respondent's annual household income is $100,000 or above, 0 otherwise)	33.1%	–	0	1
Income level indicator (1 if the respondent's annual household income is between $20,000 and $40,000, 0 otherwise)	11.8%	–	0	1
Income level indicator (1 if the respondent's annual household income is between $50,000 and $150,000, 0 otherwise)	48.2%	–	0	1
Household population indicator (1 if the respondent is from single person household, 0 otherwise)	13.4%	–	0	1
Household worker indicator (1 if there are more than two working individuals in the household, 0 otherwise)	31.8%	–	0	1
Household worker indicator (1 if there is no working individual in the household, 0 otherwise)	10.4%	–	0	1
Household motor vehicle ownership indicator (1 if the household has one or no registered and operable motor vehicles, 0 otherwise)	26.7%	–	0	1
Driving experience indicator (1 if the respondent's number of years having driving license is between 4 and 6 years, 0 otherwise)	31.0%	–	0	1
Driving experience indicator (1 if the respondent's number of years having driving license is between 20 and 40 years, 0 otherwise)	14.9%	–	0	1
Opinions and Preferences				
Familiarity with vehicle safety features indicator (1 if the respondent has ever owned a vehicle with lane keeping assist/lane centering feature, 0 otherwise)	16.6%	–	0	1
Familiarity with vehicle safety features indicator (1 if the respondent has ever owned a vehicle with left turn assist and adaptive headlights, 0 otherwise)	11.6%	–	0	1
Safety concern indicator (1 if the respondent is moderately to very concerned about the safety consequences of equipment/system failure, 0 otherwise)	82.8%	–	0	1
Safety concern indicator (1 if the respondent is very concerned about the safety consequences of equipment/system failure, 0 otherwise)	59.1%	–	0	1
Accident concern indicator (1 if the respondent is very concerned about accidents on the airway, 0 otherwise)	56.0%	–	0	1
Purchase cost concern indicator (1 if the respondent is very concerned about the purchase cost of flying cars, compared to a conventional vehicle; 0 otherwise)	51.7%	–	0	1
Interaction concern indicator (1 if the respondent is moderately concerned about interaction with other flying cars on the airway, 0 otherwise)	26.2%	–	0	1
Interaction concern indicator (1 if the respondent is very concerned about interaction with other flying cars on the airway, 0 otherwise)	54.0%	–	0	1
Take-off/landing facility concern indicator (1 if the respondent is moderately concerned about the ease of access to take-off/landing facility, 0 otherwise)	28.6%	–	0	1
Privacy and legal concern indicator (1 if the respondent is moderately to very concerned about personal information privacy and legal liability for flying car owners/operators, 0 otherwise)	59.9%	–	0	1
General concern indicator (1 if the respondent is very concerned about ease of access to take-off/landing facilities, performance in poor weather, noise from operation and take-off/landing, security against hackers/terrorists, legal liability for flying car ownership; 0 otherwise)	20.5%	–	0	1
Safety benefit indicator (1 if the respondent thinks fewer crashes on the roadway are likely, 0 otherwise)	65.7%	–	0	1
Less severe crash benefit indicator (1 if the respondent thinks less severe crashes on the roadway are very likely, 0 otherwise)	20.2%	–	0	1
Travel time benefit indicator (1 if the respondent thinks lower travel time to destination is very likely, 0 otherwise)	54.8%	–	0	1
Travel time reliability indicator (1 if the respondent thinks reliable travel time to destination is unlikely, 0 otherwise)	21.4%	–	0	1
Less traffic congestion benefit indicator (1 if the respondent thinks that less traffic congestion on the roadway is somewhat likely, 0 otherwise)	36.9%	–	0	1
Lower vehicle maintenance benefit indicator (1 if the respondent thinks lower vehicle maintenance cost is unlikely, 0 otherwise)	74.8%	–	0	1
Environmental benefit indicator (1 if the respondent thinks lower CO_2 emission is very likely, 0 otherwise)	12.4%	–	0	1
In-vehicle activity indicator (1 if the respondent thinks in-vehicle non-driving activities are very likely, 0 otherwise)	37.1%	–	0	1
Safety benefit and in-vehicle activity indicator (1 if the respondent thinks fewer crashes and more in-vehicle non-driving activities are likely, 0 otherwise)	49.3%	–	0	1
Less severe crash and lower travel time benefit indicator (1 if the respondent thinks less severe crashes and lower travel time to destination are likely, 0 otherwise)	53.3%	–	0	1
Travel time and environmental benefit indicator (1 if the respondent thinks lower travel time to destination and lower CO_2 emission are likely to occur, 0 otherwise)	32.6%	–	0	1
Travel time and less congestion benefit indicator (1 if the respondent thinks more reliable travel time to destination and less traffic congestion are likely, 0 otherwise)	71.5%	–	0	1
Travel time reliability and in-vehicle activity indicator (1 if the respondent thinks reliable travel time and more in-vehicle non-driving activities are likely, 0 otherwise)	58.8%	–	0	1
Potential security measure indicator (1 if the respondent thinks that establishing no-fly zones near sensitive locations would likely improve security against hackers/terrorists, 0 otherwise)	78.8%	–	0	1
Potential security measure indicator (1 if the respondent thinks that establishing air-road police enforcement and no-fly zones near sensitive locations would unlikely improve security against hackers/terrorists, 0 otherwise)	17.2%	–	0	1
Non-severe accident indicator (1 if the respondent has experienced more than one non-severe accident in last five years, 0 otherwise)	9.8%	–	0	1
Average annual miles driven indicator (1 if the respondent drives between 5000 and 7500 miles per year, 0 otherwise)	10.9%	–	0	1
Vehicle maintenance expense indicator (1 if the respondent has spent $2500 or less in the last five years, 0 otherwise)	73.3%	–	0	1

$$\sum_{i=1}^{N}\left[y_{i,1}y_{i,2}\ \ln\Phi\left(\boldsymbol{\beta}_{i,1}\mathbf{X}_{i,1},\boldsymbol{\beta}_{i,2}\mathbf{X}_{i,2},\rho\right)+\left(1-y_{i,1}\right)y_{i,2}\ \ln\Phi\left(-\boldsymbol{\beta}_{i,1}\mathbf{X}_{i,1},\boldsymbol{\beta}_{i,2}\mathbf{X}_{i,2},-\rho\right)+\left(1-y_{i,2}\right)y_{i,1}\ \ln\Phi\left(\boldsymbol{\beta}_{i,1}\mathbf{X}_{i,1},-\boldsymbol{\beta}_{i,2}\mathbf{X}_{i,2},-\rho\right)\right.$$
$$\left.+\left(1-y_{i,1}\right)\left(1-y_{i,2}\right)\ln\Phi\left(-\boldsymbol{\beta}_{i,1}\mathbf{X}_{i,1},-\boldsymbol{\beta}_{i,2}\mathbf{X}_{i,2},\rho\right)\right] \tag{4}$$

present within the distributor-specific survey responses.[2] It should be noted that the number of responses collected by the survey distributors varies between 7 and 41. Due to this variation in number of responses collected by each survey distributor, unbalanced panel effects may be present across the survey responses (Choo and Oum, 2013; Chow, 2014; Yokomi et al., 2017; Sarwar et al., 2017a, 2017b; Asahi and Murakami, 2017; Fountas et al., 2018b, 2018c, 2019; Fountas and Anastasopoulos, 2018; Ahmed et al., 2020). Besides, the effect of the explanatory variables may vary across observations due to the presence of unobserved heterogeneity, i.e., the effect of unobserved characteristics on the respondents' opinions (Hainen et al., 2013; Chu, 2014; Anastasopoulos, 2016; Anastasopoulos et al., 2017; Fountas and Anastasopoulos, 2017; Mathew et al., 2017; Brueckner and Abreu, 2017; Song et al., 2018). To account for these two misspecification issues, grouped random parameters are introduced in the bivariate probit modeling framework, which allows the parameter estimates to vary across the groups of observations. Introduction of grouped random parameters allows for possibility of correlation among the unobserved effects captured by the random parameters (Greene, 2017; Pantangi et al., 2020). To identify the effect of such possible correlations, grouped random parameters are introduced as (Greene, 2017; Fountas et al., 2018c; Pantangi et al., 2019),

$$\boldsymbol{\beta}_i=\boldsymbol{\beta}+\boldsymbol{\Gamma}\delta_i \tag{5}$$

where, $\boldsymbol{\beta}$ denotes the mean value of the random parameters vector, $\boldsymbol{\Gamma}$ is a symmetric matrix (also defined as Cholesky matrix) used to compute the standard deviations of the random parameters, δ represents a randomly distributed term having mean equal to zero and variance equal to one. To account for the possible correlation among the effects captured by the random parameters, the $\boldsymbol{\Gamma}$ matrix is unrestrictive in nature and allows the off-diagonal elements to be non-zero. The computation of the standard deviations of the correlated grouped random parameters is based on the diagonal and non-zero off-diagonal elements of the $\boldsymbol{\Gamma}$ matrix. The standard deviation of each correlated random parameter is computed as:

$$\sigma_j=\sqrt{\sigma_{k,k}{}^2+\sigma_{k,k-1}{}^2+\sigma_{k,k-2}{}^2+\ldots+\sigma_{k,1}{}^2} \tag{6}$$

where, σ_j denotes the standard deviation of the random parameter, $\sigma_{k,k}$ is the respective diagonal element of the $\boldsymbol{\Gamma}$ matrix and $\sigma_{k,k-1}, \sigma_{k,k-2}\ldots\sigma_{k,1}$ denotes the below diagonal non-zero elements of the estimated $\boldsymbol{\Gamma}$ matrix. The standard error and t-statistic computation for the standard deviation of each random parameter are conducted by utilizing the following procedure (Fountas et al., 2018c):

$$SE_{\sigma_j}=\frac{S_{\sigma_{jn}}}{\sqrt{N}} \tag{7}$$

where, SE_{σ_j} is the standard error of the standard deviation (averaged across the observations), $S_{\sigma_{jn}}$ is the standard deviation of the observation specific σ_{jn} and N is the number of observation, which is the number of panels in this specific case. Then, the t-statistic is computed as,

$$t_{\sigma j}=\frac{\sigma_j}{SE_{\sigma_j}} \tag{8}$$

To estimate the bivariate probit models, a simulated maximum likelihood approach was undertaken. Halton draws were used for the optimization of numerical simulations. In contrary to earlier research that has suggested 200 Halton draws for robust model estimation (Halton, 1960), 1200 Halton draws were used in this study to obtain stable parameter estimates.

Finally, to interpret the effect of each independent variable on the dependent variables, pseudo-elasticities (averaged over all observations) are computed as (Washington et al., 2011),

$$E=\Phi\left(\frac{\beta_jX_{j,1}}{\sigma}|X_i=1\right)-\Phi\left(\frac{\beta_jX_{j,1}}{\sigma}\middle|X_i=0\right) \tag{9}$$

where, $\Phi(.)$ is the cumulative distribution function of the standard normal distribution.

4. Results and discussion

The estimation results and pseudo-elasticities of the correlated grouped random parameter bivariate probit models for willingness to hire flying taxi and shared flying car services are presented in Table 3 and Table 4, respectively. Model estimation results and pseudo-elasticities of willingness to pay for flying taxis and shared flying car services are presented in Table 5, Table 6, Table 7, Table 8, Table 9, Table 10, Table 11; and Table 12; respectively.

All possible variables and variable combinations were examined to estimate the models, and the variables, which were found to be statistically significant at 0.90 level of confidence or greater, were utilized in the model specifications. For the random parameters, many distributions were examined (normal, triangular, Weibull, lognormal, etc.), and the normal distribution was found to provide the best statistical fit in all cases. The cross-equation error term correlations of all models are statistically significant at a level of confidence greater than 0.90. In case of the first willingness to pay model, the two dependent variables are "do not wish to pay more" and "would pay up to $1 per mile more", as compared to the current average rate of $1.5/mile. Since the first variable involves the respondents' unwillingness to pay more, and the second variable involves respondents' willingness to pay up to 1$ per mile more, there is visible contrast in the information represented by the variables. However, it should be noted that both variables express respondents' opinion towards flying taxis/shared flying car services. It is, therefore, likely that the responses to these questions are affected by common unobserved characteristics. This assumption is validated by the statistically significant cross-equation error correlation term for the bivariate probit model, which verifies the existence of commonly shared unobserved characteristics affecting both dependent variables.

4.1. Factors related to socio-demographic characteristics

The model estimation results show that a number of socio-demographic characteristics affect individuals' willingness to hire and

[2] The survey distributors collected responses from their social network (including family members, friends and acquaintances). Such a sample naturally poses several challenges, in terms of model estimation, robustness and unbiasedness of the estimated parameters, and explanatory model capacity. However, these challenges are accounted for with the bivariate probit framework and in combination with the correlated grouped random parameters approach. The methodological advantages of implementing random parameters in an econometric modeling framework to account for unobserved heterogeneity, sample size bias, convenience sampling, and several other issues have been demonstrated by previous research (Anastasopoulos and Mannering, 2009; Washington et al., 2011; Mannering and Bhat, 2014; Mannering et al., 2016; Greene, 2017; Fountas et al., 2018c, 2019).

Table 3
Estimation results of the correlated grouped random parameters bivariate probit model of public willingness to hire human operated or autonomous flying taxi/Uber/Lyft (t-statistic in parentheses).

Variables	Willingness to Hire Flying taxi/Uber/Lyft	
	Human operated	Autonomous
Socio-demographic characteristics		
Gender indicator (1 if the respondent is female, 0 otherwise)	0.394 (3.39)	–
Standard deviation of parameter distribution	*0.421 (4.25)*	–
Ethnicity indicator (1 if the respondent is Asian, 0 otherwise)	–	0.339 (2.27)
Current living area indicator (1 if the respondent is currently living in rural area, 0 otherwise)	–	−0.568 (−2.30)
Education and income level indicator (1 if the respondent has a college degree and household income between 40,000 and 100,000 dollars, 0 otherwise)	−0.339 (−2.61)	–
Income level indicator (1 if the respondent's annual household income is between 40,000 and 100,000 dollars, 0 otherwise)	–	−0.307 (−2.35)
Household population indicator (1 if the respondent is from single person household, 0 otherwise)	–	0.524 (3.09)
Opinions and preferences		
Familiarity with vehicle safety features indicator (1 if the respondent has ownership of a vehicle with left turn assist and adaptive headlights, 0 otherwise)	0.381 (2.32)	–
Safety concern indicator (1 if the respondent is very concerned about the safety consequences of equipment/system failure, 0 otherwise)	–	−0.239 (−1.90)
Take-off/landing facility concern indicator (1 if the respondent is moderately concerned about the ease of access to take-off/landing facility, 0 otherwise)	0.331 (2.46)	–
Safety benefit indicator (1 if the respondent thinks fewer crashes on the roadway are likely, 0 otherwise)	–	0.302 (2.55)
Travel time benefit indicator (1 if the respondent thinks lower travel time to destination is very likely, 0 otherwise)	0.282 (2.53)	–
Travel time reliability indicator (1 if the respondent thinks reliable travel time to destination is unlikely, 0 otherwise)	–	−0.342 (−2.43)
Standard deviation of parameter distribution	–	*0.631 (20.85)*
Environmental benefit indicator (1 if the respondent thinks lower CO2 emission is very likely, 0 otherwise)	–	0.588 (3.05)
In-vehicle activity indicator (1 if the respondent thinks in-vehicle non-driving activities are very likely, 0 otherwise)	0.164 (1.65)	–
Potential security measure indicator (1 if the respondent thinks that establishing air-road police enforcement and no-fly zones near sensitive locations would unlikely improve security against hackers/terrorists, 0 otherwise)	−0.320 (−2.44)	–
Cross equation correlation	0.823 (17.45)	
Number of survey collectors	35	
Number of respondents	553	
Log-likelihood at convergence	−590.797	
Log-likelihood at zero	−748.046	
Akaike information criterion (AIC)	1219.6	
Aggregate distributional effect of random parameters across the respondents		
	Above zero	**Below zero**
Gender indicator (1 if the respondent is female, 0 otherwise)	82.53%	17.47%
Travel time reliability indicator (1 if the respondent thinks reliable travel time to destination is unlikely, 0 otherwise)	29.39%	70.61%

Elements of the Cholesky Matrix [t-statistics in brackets], and correlation coefficients (in parentheses) for the random parameters		
	Gender indicator	Travel time reliability indicator
Gender indicator	0.422 [4.22] (1.000)	0.459 [-3.17] (−0.728)
Travel time reliability indicator	−0.459 [-3.17] (−0.728)	0.433 [2.91] (1.000)

willingness to pay for flying taxi and shared flying car services. Female respondents are found to be more likely (as compared to male respondents) to hire human operated flying taxis (the pseudo-elasticity is 0.138, as indicated in Table 4). It was also found that older respondents are not willing to pay more than the currently prevailing rate for Uber/Lyft services (as indicated by the negative coefficients in the willingness to pay models presented in Tables 5, 7, 9 and 11).

Respondents from different ethnic groups were found to show different attitudes towards willingness to hire and pay for flying taxi services. For instance, Asians are more likely (as compared to non-Asians) to hire autonomously operated flying taxi services (the pseudo-elasticity is 0.107, as indicated in Table 4). Caucasians are not willing to pay more than the currently prevailing rate (the pseudo-elasticity is 0.091, as indicated in Table 6). The unwillingness of Caucasians to pay for flying taxi services is further demonstrated by the findings from subsequent willingness to pay models (as indicated by the negative coefficients in the willingness to pay models presented in Tables 9 and 10). Individuals from ethnic background other than Asian and Caucasian exhibit mixed willingness to pay patterns, since the corresponding indicator variable resulted in a random parameter, with 74.30% of these respondents being willing to pay between $2 and $3 per mile more than the current rate. The opposite is observed for the remaining 25.70% of the respondents.

The area where the respondents are currently living was found to play a role in their willingness to hire and pay for flying taxi services.[3] Respondents currently living in rural areas are not willing to hire autonomous flying taxi services (the pseudo-elasticity is −0.244, as indicated in Table 4). Since rural areas are less prone to traffic congestion and parking restrictions, the benefits of flying taxis may not be so appealing for residents of rural areas. However, respondents currently living in city centers are more likely (by 0.031, as indicated by the pseudo-elasticity in Table 12) to pay over $20 per mile more than the currently prevailing rate, as compared to respondents not living in city centers. This finding may be reflecting the respondents' expectations for lower and reliable travel times in congestion-prone urban areas, from the use of shared flying car services.

The respondents' educational attainment and household income level were also found to affect their willingness to hire and pay for flying taxi services. Post graduate degree holders are not willing to pay

[3] Note that to capture cross-cultural characteristics, country and region indicator variables were introduced in the models. However, none of them turned out to be statistically significant. This might be due to specific characteristics of the dataset used in this study. In this context, further analysis would be an interesting area for future research.

between $10 and $20 per mile more than the current rate (the pseudo-elasticity is −0.047, as indicated in Table 12). Respondents from households with annual income between $40,000 and $100,000 are not willing to hire autonomous flying taxis (the pseudo-elasticity is −0.102, as indicated in Table 4). However, respondents from households with annual income above $100,000 are willing to pay between $3 and $5 per mile more than the current Uber/Lyft rate (the pseudo-elasticity is 0.077, as indicated in Table 10). These findings indicate that individuals from mid-income households are not generally willing to hire flying taxis. On the other hand, individuals from high-income households are more welcoming towards the idea of hiring flying taxis, and are likely willing to spend more than the current ridesharing services to avail the potential travel benefits likely to be offered by flying cars. However, if the cost of a ride in a flying taxi exceeds by a large margin (greater than $10 per mile) the current rate, respondents from low, and medium-high income households (the annual income in these households is between $20,000 and $40,000, and between $50,000 and $150,000, respectively) show unwillingness to pay for such service (as indicated by the negative coefficients in Table 11). Interestingly, respondents with college degree and from medium-income households (the annual income is between $40,000 and $100,000), are not willing to hire human operated flying taxis (the pseudo-elasticity is −0.144, as indicated in Table 4). Similarly, respondents with college degree and from high-income households (where the annual income is greater than $100,000) are not willing to pay more than the current Uber/Lyft rate (the pseudo-elasticity is 0.139, as indicated in Table 6).

Table 4
Elasticities and pseudo-elasticities of the explanatory variables included in the model of public willingness to hire human operated or autonomous flying taxi/Uber/Lyft.

Variables	Willingness to Hire Flying taxi/Uber/Lyft	
	Human operated	Autonomous
Socio-demographic characteristics		
Gender indicator (1 if the respondent is female, 0 otherwise)	0.138	–
Ethnicity indicator (1 if the respondent is Asian, 0 otherwise)	–	0.107
Current living area indicator (1 if the respondent is currently living in rural area, 0 otherwise)	–	−0.244
Education and income level indicator (1 if the respondent has a college degree and household income between 40,000 and 100,000 dollars, 0 otherwise)	−0.144	–
Income level indicator (1 if the respondent's annual household income is between 40,000 and 100,000 dollars, 0 otherwise)	–	−0.102
Household population indicator (1 if the respondent is from single person household, 0 otherwise)	–	0.178
Opinions and preferences		
Familiarity with vehicle safety features indicator (1 if the respondent has ownership of a vehicle with left turn assist and adaptive headlights, 0 otherwise)	0.183	–
Safety concern indicator (1 if the respondent is very concerned about the safety consequences of equipment/system failure, 0 otherwise)	–	−0.117
Take-off/landing facility concern indicator (1 if the respondent is moderately concerned about the ease of access to take-off/landing facility, 0 otherwise)	0.119	–
Safety benefit indicator (1 if the respondent thinks fewer crashes on the roadway are likely, 0 otherwise)	–	0.149
Travel time benefit indicator (1 if the respondent thinks lower travel time to destination is very likely, 0 otherwise)	0.102	–
Travel time reliability indicator (1 if the respondent thinks reliable travel time to destination is unlikely, 0 otherwise)	–	−0.158
Environmental benefit indicator (1 if the respondent thinks lower CO2 emission is very likely, 0 otherwise)	–	0.244
In-vehicle activity indicator (1 if the respondent thinks in-vehicle non-driving activities are very likely, 0 otherwise)	0.080	–
Potential security measure indicator (1 if the respondent thinks that establishing air-road police enforcement and no-fly zones near sensitive locations would unlikely improve security against hackers/terrorists, 0 otherwise)	−0.160	–

The model estimation results also revealed that the respondents' willingness to hire and pay for flying taxi service is influenced by their household's population, number of working individuals, and status of car ownership. Respondents from single-person household are willing to hire autonomous flying taxis (the pseudo-elasticity is 0.178, as indicated in Table 4). On the other hand, respondents from households with more than two working individuals are not willing to pay more than the current Uber/Lyft rate (the pseudo-elasticity is 0.096, as indicated in Table 6). In addition, respondents from households with no working members are not willing to pay up to $1 per mile more than the current rate (the pseudo-elasticity is −0.164, as indicated in Table 6). Turning to the household vehicle ownership status, it was found that 77.84% of the respondents from households with one or no licensed and operable motor vehicles are willing to pay between $3 and $5 per mile more than the current rate (as indicated by the distributional split of the corresponding random parameter in Table 9). The opposite is observed for the remaining 22.16% of the respondents.

Driving experience of the respondents was also found to affect their willingness to pay for flying taxis and shared flying car services. Respondents having between 20 and 40 years of driving experience (as compared to respondents having less than 20 or greater than 40 years of driving experience) are not willing to pay more than the current Uber/Lyft rate for flying taxi services. On the other hand, respondents having between 4 and 6 years of driving experience are willing to pay over $20 per mile more than the current rate (as compared to respondents having less than 4 or greater than 6 years of driving experience).

4.2. Factors related to opinions and preferences

A number of behavioral and perceptional attributes of the respondents are found to affect their willingness to hire and willingness to pay for flying taxis and shared flying car services. Respondents who are familiar with advanced vehicle safety features are willing to hire human operated flying taxis (the pseudo-elasticity is 0.183, as indicated in Table 4). Similarly, 83.26% of the respondents who are familiar with another vehicle safety feature, i.e., lane keeping assist, are also willing to pay between $1 and $2 per mile more than the current rate for Uber/Lyft rides (as indicated by the distributional split of the corresponding random parameter in Table 7). The same group of respondents are also willing to pay between $2 and $3 per mile more than the current rate (the pseudo-elasticity is 0.185, as indicated in Table 8).

A number of potential concerns arising from the future operation of flying cars are also found the affect the respondents' willingness to hire and willingness to pay for flying taxi and shared flying car services. Respondents who are very concerned about safety consequences of equipment/system failure of flying cars are not willing to hire autonomous flying cars (the pseudo-elasticity is −0.117, as indicated in Table 4). Similarly, respondents who are moderately to very concerned about the same issue are not willing to pay more than the current Uber/Lyft rate (the pseudo-elasticity is 0.162, as indicated in Table 6). However, the same group of respondents also expressed their willingness to pay up to $1 per mile more than the current rate (as indicated by the distributional split of the corresponding random parameter in Table 5). The same group of respondents are also willing to pay between $1 and

Table 5
Estimation results of the correlated grouped random parameters bivariate probit model of public willingness to pay for a flying taxi ride (do not wish to pay more, and up to $1 more) compared to current Uber/Lyft rate of $1.5/mile (t-statistic in parentheses).

Variables	Do not wish to pay more	Up to $1 per mile more
Constant	−0.722 (−2.96)	–
Standard deviation of parameter distribution	*0.134 (2.20)*	–
Socio-demographic characteristics		
Age of the respondent	–	−0.016 (−3.89)
Ethnicity indicator (1 if the respondent is Caucasian, 0 otherwise)	0.257 (1.79)	–
Education and income level indicator (1 if the respondent has a college degree and household income above 100,000 dollars, 0 otherwise)	0.353 (1.90)	–
Household worker indicator (1 if there are more than two working individuals in the household, 0 otherwise)	0.268 (1.86)	–
Household worker indicator (1 if there is no working individual in the household, 0 otherwise)	–	−0.525 (−1.93)
Opinions and preferences		
Safety concern indicator (1 if the respondent is moderately to very concerned about the safety consequences of equipment/system failure, 0 otherwise)	0.411 (1.65)	0.807 (3.15)
Standard deviation of parameter distribution	–	*0.253 (35.73)*
Accident concern indicator (1 if the respondent is very concerned about accidents on the airway, 0 otherwise)	–	−0.757 (−4.09)
Interaction concern indicator (1 if the respondent is moderately concerned about interaction with other flying cars on the airway, 0 otherwise)	–	0.343 (1.76)
Privacy and legal concern indicator (1 if the respondent is moderately to very concerned about personal information privacy and legal liability for flying car owners/operators, 0 otherwise)	0.345 (2.01)	–
Less severe crash benefit indicator (1 if the respondent thinks less severe crashes on the roadway are very likely, 0 otherwise)	0.409 (2.02)	–
Travel time benefit indicator (1 if the respondent thinks lower travel time to destination is very likely, 0 otherwise)	–	0.359 (2.04)
Travel time reliability and in-vehicle activity indicator (1 if the respondent thinks reliable travel time and more in-vehicle non-driving activities are likely, 0 otherwise)	–	0.531 (2.91)
Potential security measure indicator (1 if the respondent thinks that establishing no-fly zones near sensitive locations would likely improve security against hackers/terrorists, 0 otherwise)	–	0.407 (2.41)
Non-severe accident indicator (1 if the respondent has experienced more than one non-severe accident in last five years, 0 otherwise)	−0.396 (−1.97)	–
Cross equation correlation	0.235 (2.25)	
Number of survey collectors	35	
Number of respondents	534	
Log-likelihood at convergence	−609.339	
Log-likelihood at zero	−690.717	
Akaike information criterion (AIC)	1258.7	
Aggregate distributional effect of random parameters across the respondents		
	Above zero	**Below zero**
Constant	0%	100%
Safety concern indicator (1 if the respondent is moderately to very concerned about the safety consequences of equipment/system failure, 0 otherwise)	99.93%	0.07%
Elements of the Cholesky Matrix [t-statistics in brackets], and correlation coefficients (in parentheses) for the random parameters		
	Constant	Safety concern indicator
Constant	0.134 [2.20] (1.000)	−0.170 [-2.34] (−0.669)
Safety concern indicator	−0.170 [-2.34] (−0.669)	0.188 [2.50] (1.000)

$2 per mile more than the current rate (the pseudo-elasticity is 0.201, as indicated in Table 8). These findings illustrate the mixed effect that safety concerns have on the willingness to hire and willingness to pay for shared flying services. It is likely that they may be capturing individuals' skepticism regarding not only the hybrid on-ground and in-air operation of flying cars, but also any emerging technologies that are not exclusive to flying cars.

Respondents who are concerned about ease of access to the take-off/landing facilities for flying cars are willing to hire human operated flying taxis (the pseudo-elasticity is 0.119, as indicated in Table 4). Similarly, respondents who are concerned about possible interactions among flying cars on the airway are willing to pay up to $1 per mile more than current Uber/Lyft rate (the pseudo-elasticity is 0.119, as indicated in Table 6). These findings indicate that despite being concerned, the respondents are still willing to hire and pay for flying taxi services. It is likely that the anticipated mobility benefits of flying cars are encouraging the respondents to use this new technology. However, respondents who are very concerned about the interactions among flying cars on the airway are not willing to pay over $20 per mile more than the current rate (the pseudo-elasticity is −0.034, as indicated in Table 12). This finding shows that the interaction concern, coupled with associated high expenses, can cause a decline in interest towards willingness to hire and pay for flying taxi services.

Respondents who are very concerned about accidents on the airway are not willing to pay up to $1 per mile more than current Uber/Lyft rate for flying taxi services (the pseudo-elasticity is −0.237, as indicated in Table 6). Similarly, respondents who are concerned about personal information privacy and legal issues stemming from the future use of flying cars are not willing to pay more than the current rate for flying taxi services (the pseudo-elasticity is 0.136, as indicated in Table 6). It was also found that the respondents who are very concerned about multiple issues arising from the use of flying cars (ease of access to the take-off/landing facilities, performance in poor weather, noise from operation and take-off/landing, security against hackers/terrorists, and legal issues) are not willing to pay between $1 and $2 per mile, or between $2 and $3 per mile more than the current rate (the pseudo-elasticities are −0.204 and −0.196, respectively, as indicated in Table 8).

With regard to the perceived benefits of flying cars, respondents who expect lower travel times and more in-vehicle non-driving activities with the introduction of flying cars, are willing to hire human operated flying taxis (the pseudo-elasticities are 0.102 and 0.080, respectively, as indicated in Table 4). Respondents who expect fewer crashes on the roadway and less CO_2 emissions after the introduction of flying cars, are

Table 6
Elasticities and pseudo-elasticities of the explanatory variables included in the model of public willingness to pay for a flying taxi ride (do not wish to pay more, and up to $1 per mile more) compared to current Uber/Lyft rate of $1.5/mile.

Variables	Do not wish to pay more	Up to $1 per mile more
Socio-demographic characteristics		
Age of the respondent	–	−0.005
Ethnicity indicator (1 if the respondent is Caucasian, 0 otherwise)	0.091	–
Education and income level indicator (1 if the respondent has a college degree and household income above 100,000 dollars, 0 otherwise)	0.139	–
Household worker indicator (1 if there are more than two working individuals in the household, 0 otherwise)	0.096	–
Household worker indicator (1 if there is no working individual in the household, 0 otherwise)	–	−0.164
Opinions and preferences		
Safety concern indicator (1 if the respondent is moderately to very concerned about the safety consequences of equipment/system failure, 0 otherwise)	0.162	0.254
Accident concern indicator (1 if the respondent is very concerned about accidents on the airway, 0 otherwise)	–	−0.237
Interaction concern indicator (1 if the respondent is moderately concerned about interaction with other flying cars on the airway, 0 otherwise)	–	0.119
Privacy and legal concern indicator (1 if the respondent is moderately to very concerned about personal information privacy and legal liability for flying car owners/operators, 0 otherwise)	0.136	–
Less severe crash benefit indicator (1 if the respondent thinks less severe crashes on the roadway are very likely, 0 otherwise)	0.169	–
Travel time benefit indicator (1 if the respondent thinks lower travel time to destination is very likely, 0 otherwise)	–	0.101
Travel time reliability and in-vehicle activity indicator (1 if the respondent thinks reliable travel time and more in-vehicle non-driving activities are likely, 0 otherwise)	–	0.185
Potential security measure indicator (1 if the respondent thinks that establishing no-fly zones near sensitive locations would likely improve security against hackers/terrorists, 0 otherwise)	–	0.120
Non-severe accident indicator (1 if the respondent has experienced more than one non-severe accident in last five years, 0 otherwise)	−0.130	–

similarly willing to hire autonomous flying taxis (the pseudo-elasticities are 0.149 and 0.244, respectively, as indicated in Table 4). Mixed patterns are observed for respondents who do not expect more reliable travel times with the introduction of flying cars. Specifically, 70.61% of these respondents are not willing to hire autonomous flying taxis (as indicated by the distributional split of the corresponding random parameter in Table 3). This result possibly reflects experienced drivers who appreciate the mobility benefits of the passenger car use. As for the effect of perceived benefits of flying cars on the respondents' willingness to pay, the findings are intuitive. Respondents who expect lower travel time are willing to pay up to $1 per mile more than the current Uber/Lyft rate (the pseudo-elasticity is 0.101, as indicated in Table 6). Similarly, respondents who expect more reliable travel time and more in-vehicle non-driving activities (as compared to current and traditional ground transportation options) are also willing to pay up to $1 per mile more than the current rate (the pseudo-elasticity is 0.185, as indicated in Table 6). In line with these findings, respondents who expect fewer crashes and more in-vehicle non-driving activities (as compared to current and traditional ground transportation options) are willing to pay between $1 and $2 per mile more than the current rate (the pseudo-elasticity is 0.148, as indicated in Table 8). In addition, respondents who expect more reliable travel time and less traffic congestion (as compared to current and traditional ground transportation options) are willing to pay between $1 and $2 per mile more than the current rate (the pseudo-elasticity is 0.140, as indicated in Table 8). Moreover, respondents who are expecting lower travel time and less CO_2 emissions (as compared to current and traditional ground transportation options) are willing to pay between $2 and $3 per mile more than the current rate (the pseudo-elasticity is 0.153, as indicated in Table 8). A similar trend is observed for the next pricing scenario as well. Respondents who expect less severe crashes and lower travel times (as compared to current and traditional ground transportation options) are willing to pay between $3 and $5 per mile more, or between $5 and $10 per mile more than the current Uber/Lyft rate. The corresponding pseudo-elasticities are 0.126 and 0.074, respectively (as shown in Table 10). However, in cases where the respondents think that less traffic congestion is somewhat likely (as compared to current and traditional ground transportation options), they are found to be less willing to pay between $10 and $20 per mile more, or over $20 per mile more than the current rate for flying taxi services (the pseudo-elasticities are −0.070 and −0.042, respectively, as indicated in Table 12). The increased cost may outweigh the perceived benefits, which possibly reflects the primary role of travel cost in individuals' decision-making mechanism.

Perceptions regarding security issues of flying cars' operation also affect the respondents' willingness to hire and willingness to pay for flying taxis and shared flying car services. Respondents who are skeptical about the effectiveness of establishing air-road police and establishing no-fly zones near sensitive areas are not willing to hire human-operated flying taxis (the pseudo-elasticity is −0.160, as indicated in Table 4). In contrast, respondents with positive opinion towards establishing no-fly zones near sensitive locations are willing to pay up to $1 per mile more than the currently prevailing rate (the pseudo-elasticity is 0.120, as indicated in Table 6). These findings show that perceptions towards the efficiency of security measures may play an influential role in the decision-making mechanism of individuals. The latter is specifically important for the legislative and policy making authorities, who may address the security concerns of potential passengers of flying taxis, by implementing a meticulous policy framework that could include measures of similar nature.

Turning to the accident history of the respondents, it is found that respondents who experienced at least two or more non-severe accidents in the last five years (as compared to respondents that experienced less than two non-severe accidents in the last five years, including respondents that did not experience non-severe accidents) are willing to pay between $1 and $2 more per mile, or between $2 and $3 per mile more than the current Uber/Lyft rate for flying taxi services (the pseudo-elasticities are 0.220 and 0.228, respectively, as indicated in Table 8). It is likely that the accidents experienced while utilizing ground transportation modes have elevated the respondents' expectations regarding safety benefits from flying cars, leading to greater willingness to pay. Exposure to driving as well as vehicle maintenance expenses are found to negatively affect the willingness to pay for flying taxi services. Respondents who drive between 5000 and 7500 miles annually are not willing to pay between $5 and $10 per mile more than the current Uber/Lyft rate (the pseudo-elasticity is −0.069, as indicated in Table 10). In addition, respondents who spent $2500 or less for vehicle maintenance in the last five years are not willing to pay between $1 and $2 per mile more, or between $2 and $3 per mile more than the current Uber/Lyft rate for flying taxi services (the pseudo-elasticities are −0.146 and −0.084, respectively, as indicated in Table 8).

Table 7
Estimation results of the correlated grouped random parameters bivariate probit model of public willingness to pay for a flying taxi ride (between $1 and $2 per mile more, between $2 and $3 per mile more) compared to current Uber/Lyft rate of $1.5/mile (t-statistic in parentheses).

Variables	Between $1 and $2 per mile more	Between $2 and $3 per mile more
Socio-demographic characteristics		
Age of the respondent	−0.010 (−2.32)	−0.012 (−3.05)
Ethnicity indicator (1 if the respondent is not Asian or Caucasian, 0 otherwise)	–	0.308 (2.10)
Standard deviation of parameter distribution	–	*0.472 (26.71)*
Opinions and preferences		
Familiarity with vehicle safety features indicator (1 if the respondent has ownership of a vehicle with lane keeping assist/lane centering feature, 0 otherwise)	0.514 (2.82)	0.490 (2.34)
Standard deviation of parameter distribution	*0.533 (3.39)*	–
Safety concern indicator (1 if the respondent is moderately to very concerned about the safety consequences of equipment/system failure, 0 otherwise)	0.441 (2.47)	–
General concern indicator (1 if the respondent is very concerned about ease of access to take-off/landing facilities, performance in poor weather, noise from operation and take-off/landing, security against hackers/terrorists, legal liability for flying car ownership; 0 otherwise)	−0.568 (−3.01)	−0.458 (−2.69)
Safety benefit and in-vehicle activity indicator (1 if the respondent thinks fewer crashes and more in-vehicle non-driving activities are likely, 0 otherwise)	0.268 (1.66)	–
Travel time and environmental benefit indicator (1 if the respondent thinks lower travel time to destination and lower CO2 emission are likely to occur, 0 otherwise)	–	0.359 (3.37)
Travel time and less congestion benefit indicator (1 if the respondent thinks more reliable travel time to destination and less traffic congestion are likely, 0 otherwise)	0.277 (2.11)	–
Non-severe accident indicator (1 if the respondent has experienced more than one non-severe accident in last five years, 0 otherwise)	0.561 (2.13)	0.588 (2.14)
Vehicle maintenance expense indicator (1 if the respondent has spent $2500 or less in the last five years, 0 otherwise)	−0.323 (−2.67)	−0.220 (−2.03)
Cross equation correlation	0.918 (31.21)	
Number of survey collectors	35	
Number of respondents	526	
Log-likelihood at convergence	−522.041	
Log-likelihood at zero	−711.072	
Akaike information criterion (AIC)	1082.1	
Aggregate distributional effect of random parameters across the respondents		
	Above zero	**Below zero**
Ethnicity indicator (1 if the respondent is not Asian or Caucasian, 0 otherwise)	74.30%	25.70%
Familiarity with vehicle safety features indicator (1 if the respondent has ownership of a vehicle with lane keeping assist/lane centering feature, 0 otherwise)	83.26%	16.74%

Elements of the Cholesky Matrix [t-statistics in brackets], and correlation coefficients (in parentheses) for the random parameters

	Familiarity with vehicle safety features indicator	Ethnicity indicator
Familiarity with vehicle safety features indicator	0.533 [3.39] (1.000)	0.381 [2.47] (0.808)
Ethnicity indicator	0.381 [2.47] (0.808)	0.278 [2.19] (1.000)

4.3. Interpretation of random parameters correlation

The correlation coefficients of the random parameters refer to the correlation among the unobserved characteristics captured by the random parameters, which may include a wide range of possible influential factors, from socio-demographic characteristics to perceptual factors affecting the decision-making mechanism of individuals.

The correlation between the two random parameters (gender indicator and travel time reliability indicator) in the willingness to hire model is negative (the coefficient is −0.728, as presented in Table 3), which essentially indicates that the interaction of the unobserved factors captured by these random parameters has mixed effect on willingness to hire flying taxis. In this context, the respondent-specific variations (captured by the gender indicator) and the systematic perceptual variations (captured by the travel time reliability indicator) have counterbalancing effect on individuals' willingness to hire.

In the willingness-to-pay models, the correlation coefficient is negative only in the first model, and positive in the other three models. The positive correlation coefficient implies the uniform effect of the interactions of unobserved characteristics (captured by the random parameters) on individuals' willingness to pay. Interestingly, one of the two random parameters in the first willingness-to-pay model is the constant term. The identified variations in the effect of constant term reflect the heterogeneous nature of the perceptual data, but also the significant presence of collector-specific variations. The latter is important, because the grouped random parameters models inherently account for panel effects. However, the significant effect of the collector-specific variations also resulted in constant-specific variations across the groups of survey responses. Furthermore, as the survey data reflect opinions of individuals regarding an emerging technology that is not physically witnessed and tested by the respondents, the heterogeneous nature of the responses is highly expected.

5. Summary and conclusion

Considering the rapid technological developments in the transportation sector, the commercial introduction of flying cars is anticipated over the next few years. This study provides a preliminary, exploratory investigation of the perceptions, expectations and opinions of travelers regarding the use of flying taxis and shared flying car services. To that end, two principal components, which would possibly determine the demand of flying taxis in near future, were explored: willingness to hire and willingness to pay under different pricing scenarios. An online survey was conducted and responses about flying taxis

Table 8
Elasticities and pseudo-elasticities of the explanatory variables included in the model of public willingness to pay for a flying taxi ride (between $1 and $2 per mile more, between $2 and $3 per mile more) compared to current Uber/Lyft rate of $1.5/mile.

Variables	Between $1 and $2 per mile more	Between $2 and $3 per mile more
Socio-demographic characteristics		
Age of the respondent	−0.005	−0.005
Ethnicity indicator (1 if the respondent is not Asian or Caucasian, 0 otherwise)	–	0.113
Opinions and preferences		
Familiarity with vehicle safety features indicator (1 if the respondent has ownership of a vehicle with lane keeping assist/ lane centering feature, 0 otherwise)	0.152	0.185
Safety concern indicator (1 if the respondent is moderately to very concerned about the safety consequences of equipment/system failure, 0 otherwise)	0.201	–
General concern indicator (1 if the respondent is very concerned about ease of access to take-off/landing facilities, performance in poor weather, noise from operation and take-off/landing, security against hackers/terrorists, legal liability for flying car ownership; 0 otherwise)	−0.204	−0.196
Safety benefit and in-vehicle activity indicator (1 if the respondent thinks fewer crashes and more in-vehicle non-driving activities are likely, 0 otherwise)	0.148	–
Travel time and environmental benefit indicator (1 if the respondent thinks lower travel time to destination and lower CO2 emission are likely to occur, 0 otherwise)	–	0.153
Travel time and less congestion benefit indicator (1 if the respondent thinks more reliable travel time to destination and less traffic congestion are likely, 0 otherwise)	0.140	–
Non-severe accident indicator (1 if the respondent has experienced more than one non-severe accident in last five years, 0 otherwise)	0.220	0.228
Vehicle maintenance expense indicator (1 if the respondent has spent $2500 or less in the last five years, 0 otherwise)	−0.146	−0.084

Table 9
Estimation results of the correlated grouped random parameters bivariate probit model of public willingness to pay for a flying taxi ride (between $3 and $5 per mile more, between $5 and $10 per mile more) compared to current Uber/Lyft rate of $1.5/mile (t-statistic in parentheses).

Variables	Between $3 and $5 per mile more	Between $5 and $10 per mile more
Constant	−0.769 (−5.14)	−1.159 (−4.18)
Socio-demographic characteristics		
Age of the respondent	–	0.017 (3.19)
Ethnicity indicator (1 if the respondent is Caucasian, 0 otherwise)	−0.264 (−1.98)	–
Income level indicator (1 if the respondent's annual household income is $100,000 or above, 0 otherwise)	0.354 (2.21)	–
Household motor vehicle ownership indicator (1 if the household has one or no registered and operable motor vehicles, 0 otherwise)	0.398 (2.67)	–
Standard deviation of parameter distribution	*0.519 (3.73)*	–
Driving experience indicator (1 if the respondent's number of years having driving license is between 20 and 40 years, 0 otherwise)	−0.505 (−1.77)	−1.465 (−3.17)
Opinions and preferences		
Purchase cost concern indicator (1 if the respondent is very concerned about the purchase cost of flying cars, compared to a conventional vehicle; 0 otherwise)	−0.439 (−2.52)	−0.769 (−2.75)
Lower vehicle maintenance benefit indicator (1 if the respondent thinks lower vehicle maintenance cost is unlikely, 0 otherwise)	–	−0.461 (−3.61)
Less severe crash and lower travel time benefit indicator (1 if the respondent thinks less severe crashes and lower travel time to destination are likely, 0 otherwise)	0.437 (2.91)	0.559 (2.97)
Standard deviation of parameter distribution	*0.260 (34.28)*	–
Average annual miles driven indicator (1 if the respondent drives between 5000 and 7500 miles per year, 0 otherwise)	–	−0.741 (−2.77)
Cross equation correlation	0.964 (40.46)	
Number of survey collectors	35	
Number of respondents	496	
Log-likelihood at convergence	−331.861	
Log-likelihood at zero	−464.022	
Akaike information criterion (AIC)	699.7	
Aggregate distributional effect of random parameters across the respondents		
	Above zero	**Below zero**
Household motor vehicle ownership indicator (1 if the household has one or no registered and operable motor vehicles, 0 otherwise)	77.84%	22.16%
Less severe crash and lower travel time benefit indicator (1 if the respondent thinks less severe crashes and lower travel time to destination are likely, 0 otherwise)	95.36%	4.64%
Elements of the Cholesky Matrix [t-statistics in brackets], and correlation coefficients (in parentheses) for the random parameters		
	Household motor vehicle ownership indicator	Less severe crash and lower travel time benefit indicator
Household motor vehicle ownership indicator	0.519 [3.73] (1.000)	0.175 [2.34] (0.674)
Less severe crash and lower travel time benefit indicator	0.175 [2.34] (0.674)	0.192 [2.56] (1.000)

Table 10
Elasticities and pseudo-elasticities of the explanatory variables included in the model of public willingness to pay for a flying taxi ride (between $3 and $5 per mile more, between $5 and $10 per mile more) compared to current Uber/Lyft rate of $1.5/mile.

Variables	Between $3 and $5 per mile more	Between $5 and $10 per mile more
Socio-demographic characteristics		
Age of the respondent	–	0.001
Ethnicity indicator (1 if the respondent is Caucasian, 0 otherwise)	−0.097	–
Income level indicator (1 if the respondent's annual household income is $100,000 or above, 0 otherwise)	0.077	–
Household motor vehicle ownership indicator (1 if the household has one or no registered and operable motor vehicles, 0 otherwise)	0.082	–
Driving experience indicator (1 if the respondent's number of years having driving license is between 20 and 40 years, 0 otherwise)	−0.097	−0.137
Opinions and preferences		
Purchase cost concern indicator (1 if the respondent is very concerned about the purchase cost of flying cars, compared to a conventional vehicle; 0 otherwise)	−0.107	−0.118
Lower vehicle maintenance benefit indicator (1 if the respondent thinks lower vehicle maintenance cost is unlikely, 0 otherwise)	–	−0.094
Less severe crash and lower travel time benefit indicator (1 if the respondent thinks less severe crashes and lower travel time to destination are likely, 0 otherwise)	0.126	0.074
Average annual miles driven indicator (1 if the respondent drives between 5000 and 7500 miles per year, 0 otherwise)	–	−0.069

were collected from 692 individuals from different socio-demographic backgrounds. The correlated grouped random parameters bivariate probit modeling framework was employed for the joint modeling of willingness to hire and willingness to pay scenarios.

The statistical analysis revealed that a number of socio-demographic characteristics (gender, age, ethnicity, education level, income level, household population), individual-specific factors (driving experience, accident history, vehicle maintenance expenses) as well as perceived concerns and benefits of flying cars affect individuals' willingness to hire and willingness to pay for flying taxis. A few factors, namely the age of respondents and cost-related concerns, have overall homogeneous negative effects on various willingness to pay scenarios. In contrast, perceived benefits of flying cars (e.g. lower and more reliable travel time, fewer and less severe crashes, more in-vehicle non-driving

Table 11
Estimation results of the correlated grouped random parameters bivariate probit model of public willingness to pay for a flying taxi ride (between $10 and $20 per mile more, over $20 per mile more) compared to current Uber/Lyft rate of $1.5/mile (t-statistic in parentheses).

Variables	Between $10 and $20 per mile more	Over $20 per mile more
Socio-demographic characteristics		
Age of the respondent	−0.020 (−4.42)	−0.048 (−6.95)
Ethnicity indicator (1 if the respondent is Caucasian, 0 otherwise)	−0.443 (−2.73)	–
Current living area indicator (1 if the respondent is currently living in city center, 0 otherwise)	–	0.442 (2.19)
Education level indicator (1 if the respondent has a post graduate degree, 0 otherwise)	−0.948 (−3.36)	–
Income level indicator (1 if the respondent's annual household income is between $20,000 and $40,000, 0 otherwise)	−1.135 (−2.17)	–
Income level indicator (1 if the respondent's annual household income is between $50,000 and $150,000, 0 otherwise)	–	−0.413 (−1.94)
Driving experience indicator (1 if the respondent's number of years having driving license is between 4 and 6 years, 0 otherwise)	–	0.352 (1.75)
Opinions and preferences		
Purchase cost concern indicator (1 if the respondent is very concerned about the purchase cost of flying cars, compared to a conventional vehicle; 0 otherwise)	−0.600 (−2.40)	–
Standard deviation of parameter distribution	*0.380 (2.17)*	–
Interaction concern indicator (1 if the respondent is very concerned about interaction with other flying cars on the airway, 0 otherwise)	–	−0.840 (−2.46)
Standard deviation of parameter distribution	–	*0.635 (36.17)*
Less traffic congestion benefit indicator (1 if the respondent thinks that less traffic congestion on the roadway is somewhat likely, 0 otherwise)	−0.701 (−2.54)	−1.092 (−2.89)
Cross equation correlation	0.971 (14.34)	
Number of survey collectors	35	
Number of respondents	543	
Log-likelihood at convergence	−172.68	
Log-likelihood at zero	−246.147	
Akaike information criterion (AIC)	377.4	
Aggregate distributional effect of random parameters across the respondents		
	Above zero	**Below zero**
Purchase cost concern indicator (1 if the respondent is very concerned about the purchase cost of flying cars, compared to a conventional vehicle; 0 otherwise)	5.72%	94.28%
Interaction concern indicator (1 if the respondent is very concerned about interaction with other flying cars on the airway, 0 otherwise)	9.29%	90.71%
Elements of the Cholesky Matrix [t-statistics in brackets], and correlation coefficients (in parentheses) for the random parameters		
	Purchase cost concern indicator	Interaction concern indicator
Purchase cost concern indicator	0.380 [2.17] (1.000)	0.486 [2.26] (0.765)
Interaction concern indicator	0.486 [2.26] (0.765)	0.409 [1.90] (1.000)

Table 12
Elasticities and pseudo-elasticities of the explanatory variables included in the model of public willingness to pay for a flying taxi ride (between $10 and $20 per mile more, over $20 per mile more) compared to current Uber/Lyft rate of $1.5/mile.

Variables	Between $10 and $20 per mile more	Over $20 per mile more
Socio-demographic characteristics		
Age of the respondent	−0.002	−0.002
Ethnicity indicator (1 if the respondent is Caucasian, 0 otherwise)	−0.050	–
Current living area indicator (1 if the respondent is currently living in city center, 0 otherwise)	–	0.031
Education level indicator (1 if the respondent has a post graduate degree, 0 otherwise)	−0.047	–
Income level indicator (1 if the respondent's annual household income is between $20,000 and $40,000, 0 otherwise)	−0.111	–
Income level indicator (1 if the respondent's annual household income is between $50,000 and $150,000, 0 otherwise)	–	−0.024
Driving experience indicator (1 if the respondent's number of years having driving license is between 4 and 6 years, 0 otherwise)	–	0.012
Opinions and preferences		
Purchase cost concern indicator (1 if the respondent is very concerned about the purchase cost of flying cars, compared to a conventional vehicle; 0 otherwise)	−0.080	–
Interaction concern indicator (1 if the respondent is very concerned about interaction with other flying cars on the airway, 0 otherwise)	–	−0.034
Less traffic congestion benefit indicator (1 if the respondent thinks that less traffic congestion on the roadway is somewhat likely, 0 otherwise)	−0.070	−0.042

activities, less CO_2 emission) have overall positive effect on willingness to hire and willingness to pay for shared flying car services. Furthermore, the heterogeneous nature of the responses is captured through the identification of random parameters related to various socio-demographic characteristics as well as perceived concerns and benefits of flying cars.

The findings from this study, albeit preliminary in nature, indicate that the potential flying taxis and shared flying car service providers may focus on developing a pricing policy acceptable to various groups of potential travelers as well as on enhancing the safety elements of shared mobility services. On the other hand, policy makers and legislative authorities may concentrate on developing a policy framework that can ensure maximum accessibility to the travelers as well as taking care of all possible security issues. All in all, it is evident that the implementation of an attractive pricing and regulatory framework for flying taxis and shared flying car services has the potential to significantly alter the currently dominant conventional ground transportation system as well as the mobility and daily travel patterns.

Authors' Contributions

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Declaration of competing interest

None.

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