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An exploratory investigation of public perceptions towards key benefits and concerns from the future use of flying cars

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A B S T R A C T

The imminent introduction of flying cars in the traffic fleet is anticipated to modify the mobility patterns of urban commuters. Flying cars' hybrid operation on the ground and in the air, in conjunction with their (semi-) automated capabilities, may lead to more appealing trip considerations, such as travel time, fuel consumption, or environmental emissions, as well as to the emergence of new sources of concerns for the potential users. In this context, the future adoption of flying cars is directly associated with individuals' perceptions of the benefits and concerns arising from the use of flying cars. This paper aims to identify the perceptual patterns of individuals towards travel time, cost and environmental benefits, as well as towards challenges arising from key flying cars operational characteristics. To that end, grouped random parameters bivariate probit models of individuals' perceptions are estimated using data collected from an online survey of 692 individuals. The statistical analysis shows that a number of socio-demographic, behavioral, and attitudinal characteristics affect respondents' expectations and concerns towards the adoption and implementation of flying cars. Even though individuals' perceptions are anticipated to undergo substantial changes until the introduction of flying cars in the traffic fleet, the findings of this work may shed more light on perceptual nuances with critical effect on public interest about the adoption of flying cars.

1. Introduction

Recent advances in automobile technology have led to emerging transportation systems with significant potential to modify two fundamental components of the driving task. The first component is associated with the subject of the driving task. Although the latter has been recognized as an exclusive outcome of a human-involved process, the introduction of various automation capabilities in vehicle operation seeks to establish semi-automated or fully driverless mobility patterns (Fagnant and Kockelman, 2015; Bansal et al., 2016; Bagloee et al., 2016; Litman, 2017; Milakis et al., 2017). Specifically, the forthcoming emergence of the fully connected and autonomous vehicles (also referred to as self-driving vehicles) aims to provide safer mobility, lower travel times, increased transportation accessibility to various population groups, as well as more sustainable system-wide traffic operations (Kyriakidis et al., 2015; Bansal and Kockelman, 2017; Fagnant and Kockelman, 2018).

With respect to the second component, the driving task is inherently associated with the use of ground transportation networks. However, recent developments pave the way for a new transportation technology that simultaneously provides mobility in two spatial dimensions, on the ground and in the air (Eker et al., 2019). Flying cars constitute novel vehicular elements of such technology being designed to operate as conventional vehicles in the ground transportation networks and as personal aircrafts in the air. The recent interest of the manufacturing companies in developing flying car prototypes, as well their intention to rapidly commercialize them, demonstrate that flying cars will be available in the automobile market soon, possibly between 2020 and 2025 (Marks, 2014; Becker, 2017; Oppitz and Tomsu, 2018).[1] To that end, major car and aircraft manufacturers have already developed and successfully tested flying car prototypes. These manufacturers include Terrafugia (a member of the Volvo group), Airbus, Boeing, Cora, Ehang184, Lilium, Workhorse and Volocopter, and other companies.

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[1] For a detailed description of the technical specifications of flying cars, see also Eker et al. (2019).

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The anticipated penetration of flying cars in the transportation network is expected to amend various aspects of urban mobility. The capability of flying cars to take off and land vertically without the use of extensive runways (as they only need clearance zones with a diameter of 100 feet or longer) substantiates their potential for daily, short-, or medium-distance trips. Their range of travel distance in the air can reach up to 500 miles, whereas their maximum cruising speed can vary between 100 and 200 mph depending on the prototypes' technical characteristics. As far as their navigation is concerned, the latest flying car prototypes are equipped with fully autonomous navigation features (as, for example, in the Terrafugia's TF-X model or the Boeing's passenger air vehicle). However, during the first stages of their deployment, the operation of flying cars is anticipated to be undertaken by appropriately trained and licensed pilots, as the transition to fully autonomous navigation will require a mature regulatory framework (Templeton, 2019). With regard to their engine characteristics, the operation of flying cars will be based on hybrid engine systems combining electric motors with gasoline engines. Such an engine configuration is primarily driven by the use of electric propulsion, which constitutes one of the latest advances in the vertical take-off and landing (VTOL) technologies. In this context, recent design concepts are devoted to the development of fully electric flying cars. For example, Uber is closely collaborating with various aircraft manufacturers to create a fleet of electric, vertical take-off and landing aircrafts.

The fully- or semi-automated navigation capabilities of flying cars in combination with the unrestricted selection of trip origin and destination (given that airport facilities are not necessary for their operation) allow the identification of the shortest route, either solely in the air or both in the air and on the ground. With these features determining the duration of the flying car trips, their establishment in the traffic fleet may significantly decrease travel times, especially for trips across urban or suburban areas. In a similar manner, the user-controlled level of interaction with other components of the ground transportation networks as well as the user-controlled involvement to the traffic congestion patterns may increase travel time reliability, since major sources of travel time uncertainty can be avoided.

As the travel time implications grow their appeal to daily commuters, the implementation of flying cars may also mitigate traffic congestion in urban and downtown districts, with subsequent effect on the total fuel consumption produced by the ground transportation networks. Specifically, non-drivers or commuters' groups with inflexibility in travel time variations, may gradually substitute conventional vehicles with flying cars, removing, thus, considerable traffic volumes from congested transportation networks. In addition, the automated features of flying cars, as well as their cost characteristics, may result in the establishment of on-demand shared flying car services. This is an operationally feasible possibility as most of the flying car prototypes can accommodate two to four passengers. Interestingly, Uber currently investigates the development of aerial ridesharing services based on vehicles with vertical take-off and landing capabilities. This service – called "Uber Air" – aims at providing on-demand aerial transportation either within densely populated cities, or between cities and suburban areas, and is expected to be commercially launched by 2023 in Dallas and Los Angeles in the USA, and in Melbourne, Australia (Uber, 2019). Such shared transportation services could optimize not only the capacity of the flying car fleet that will be deployed, but also the efficiency of the existing highway network. Even when they operate as conventional ground vehicles, their automation and connectivity features may allow traffic flow improvements, involvement in centralized traffic operations, and minimization of fuel-consuming maneuvers.[2] The deployment of aerial ridesharing services constitutes a key component of the "Urban Air Mobility" (UAM) concept envisioned by NASA, towards the creation of an integrated air transportation framework for passengers and goods in urban environments (NASA, 2018).

Apart from the travel time considerations, the user's cost constitutes another major trip characteristic that may be affected by the introduction of flying cars. The – currently estimated – acquisition cost of a flying car varies from $200,000 to $600,000[3], which is higher compared to the cost of conventional or fully autonomous vehicles (Wadud, 2017). Another important cost consideration stems from the expenses required for the operation of flying cars, and especially the expenses associated with their maintenance and their fuel consumption. Given that various flying car prototypes include either electric or gasoline-based engines, the fuel expense patterns of flying cars have not been yet unfolded to their full extent. The fuel consumption relating to their on-ground operation may not considerably differ from the autonomous vehicles' consumption; whereas, their in-air operation may require greater engine power, thus resulting in greater fuel consumption. The latter has also environmental implications, since higher CO_2 and other pollutant emissions may be generated due to the energy-consuming in-air operation of flying cars. However, the aforementioned macroscopic or microscopic cost implications may be counterbalanced by the emergence of shared flying cars, which may have the potential to not only reduce average transportation costs, but also to transform the current mobility status from the *a priori* use of an ownership-based vehicle fleet, to trip-based use of a shared flying car fleet.

In this context, the level of penetration of flying cars in the traffic fleet is highly associated with the public expectations and attitudinal perspectives towards two fundamental dimensions of public acceptance: (i) the anticipated benefits and concerns arising from the future use of flying cars; and (ii) the public adoption of flying cars, as expressed through their acquisition or use by the commuting population. While these two components reflect two separate layers of individuals' decision-making mechanism, they can be also considered as interrelated, since the assessment of public perception can result in the identification of public awareness gaps that can retard or disrupt the massive adoption of flying cars. Therefore, the investigation of public perceptions about travel time, cost, environmental, and operational considerations of flying cars has the potential to shed more light on the specific benefits and concerns that may serve as motives or barriers, respectively, for the successful implementation of this emerging technology.

On the basis of the aforementioned public acceptance components, Eker et al. (2019) provide a preliminary assessment of public adoption of flying cars through the investigation of the factors affecting individuals' willingness to buy and use flying cars. The statistical analysis showed that the perceived benefits and concerns arising from the operation of flying cars constitute major determinants of individuals' willingness to adopt flying cars for various trip and pricing scenarios. In this context, a deeper understanding of the individual-specific characteristics (such as, sociodemographic attributes, behavioral characteristics, trip preferences) that, in fact, determine public perception, can assist policymakers, transportation consultants, legislative agencies, and manufacturers in preparing a strategic roadmap with policy actions that can enhance the adoption of flying cars by targeted groups of individuals.

In line with earlier research devoted to the public perception of other emerging transportation technologies (Egbue and Long, 2012; Carley et al., 2013; Schoettle and Sivak, 2014; Kyriakidis et al., 2015; Shin et al., 2015; Bansal et al., 2016; Harper et al., 2016; Nayum et al., 2016; Daziano et al., 2017; Dias et al., 2017; Dong et al., 2017; Vinayak

[2] Similar benefits are also anticipated from the introduction of shared connected vehicles in the traffic fleet. For further details on the traffic implications of shared autonomous vehicles, see Fagnant and Kockelman (2014), Krueger et al. (2016), Fagnant and Kockelman (2018), and Loeb et al. (2018).

[3] The range of the acquisition cost of a flying car is based on the currently announced prices of various flying car models. For example, Terrafugia's basic model is approximately priced at $280,000, whereas the model "Liberty" of PAL-V is approximately priced at $600,000.

et al., 2018; Van Brummelen et al., 2018; Alemi et al., 2018; Langbroek et al., 2018; Westin et al., 2018), the current paper aims at providing an empirical assessment of public perception towards benefits and concerns arising from the use of flying cars. To that end, an online survey was developed and disseminated to 692 individuals, who provided their attitudinal perspectives towards the implications of flying cars use, along with extensive information about their sociodemographic and behavioral background. This paper thus seeks to go beyond providing merely an overview of public perceptions, by identifying key socio-demographic, behavioral, and attitudinal factors that, in turn, affect and shape individuals' perceptual patterns towards travel time, cost, environmental, and operational considerations associated with the future use of flying cars. To that end, using the collected information from the surveys, the individuals' perceptions of benefits and concerns arising from the use of flying cars are statistically modeled. Given the current uncertainty associated with the infrastructural, technical, training, and licensing requirements of flying cars, as well as the subjective nature of the survey responses, the individuals' perceptions constitute significant sources of unobserved variations that can affect – to some extent – statistical inferences (Rasouli and Timmermans, 2014). To account for such variations, which may arise either from perceptual similarities relating to the benefits and concerns of flying cars, or from unobserved individual-specific characteristics, discrete outcome statistical and econometric approaches are used. The findings of the statistical analysis can be leveraged for the identification of policy interventions targeted either on critical perceptions of flying cars, or on socio-demographic aspects with influential role in the decision-making mechanism of potential flying car users.

2. Data

In order to capture individuals' expectations towards key implications of flying cars, a web-based survey was conducted in March 2017, using the online platform "SurveyMonkey". Specifically, the survey was distributed through 35 students and employees of the University at Buffalo, who served as survey-collectors. The latter collectors were provided with unique web links and extensively disseminated the online questionnaire to 692 individuals. The vast majority of the respondents (84.3%) were located in the United States, whereas the remaining respondents were located in various countries worldwide; the country of each respondent was identified through the Internet Protocol (IP) of each survey response[4]. With regard to the socio-demographic composition of the respondents, approximately 60% of the sample represents male respondents (and 40% female respondents). Focusing on the educational attainment, approximately 72% of the respondents hold a bachelor's or a post-graduate degree. The average respondent age is approximately 30 years old, while the median annual household income of the respondents falls within the range of \$50,000–\$75,000. As far as the ethnicity/race characteristics are concerned, 57% of the respondents are classified as Caucasian/White, 23% of the respondents as Asian, while the remaining 20% of the respondents self-identified as members of other ethnic groups (e.g., African American, American Indian, or Hispanic).

To account for the limited awareness of respondents with regard to the operations of flying cars, an information session consisting of a detailed description, various images, and video recordings relating to the capabilities of flying cars preceded the survey questions. The survey questionnaire was designed on the basis of three conceptual dimensions corresponding to distinct classes of information. The first conceptual dimension is associated with the individuals' expectations towards the adoption of flying cars (Eker et al., 2019). Specifically, the respondents were asked about their willingness to buy a flying car under various pricing scenarios, as well as their willingness to use a flying car for various trip scenarios. For the aforementioned trip scenarios, various trip purposes, trip distances, and time-of-the-day combinations were considered. For a detailed description of the data elements and data collection process, see Eker et al. (2019).

Another conceptual dimension of the survey questions was devoted to the perceptions of individuals with regard to the benefits and concerns stemming from the use of flying cars. As far as the benefits are concerned, respondents were asked about their expectations regarding the emergence of various trip-, traffic-, cost-, and environment-related benefits after the introduction of flying cars. The key potential benefits include the reduction of travel times, the increase of travel time reliability, the expected cost implications of the flying cars in terms of fuel or vehicle maintenance expenses, as well as the decrease of transportation-related CO_2 emissions. It should be noted that the individuals expressed their expectations on the basis of a four-point Likert scale, by rating the likelihood of occurrence for each possible benefit as "very unlikely", "somewhat unlikely", "somewhat likely", or "very likely".

Turning to the questions about the possible concerns arising from the use of flying cars, respondents were asked about their level of concern about several operational implications, such as the interactions with other vehicles on the roadway or other vessels on the airway, the flying car performance in inclement weather conditions, or the learning process that may be required for the operation of a flying car. In line with the 'benefits' set of questions, the level of concern of respondents in relation to the aforementioned considerations was expressed through four-point Likert style questions, with the possible outcomes being "Not at all concerned", "Slightly concerned", "Moderately concerned", and "Very concerned". Similarly, respondents were asked about possible relocation preferences after the introduction of flying cars, as well as about their opinions on possible policy interventions (e.g., background check of flying car operators, air traffic control, and establishment of air-road police) that could potentially tackle security issues arising from the operation of flying cars.

The third conceptual dimension of the collected information focuses on individuals' familiarity with advanced driver assistance systems (e.g., emergency automatic braking, adaptive cruise control, blind spot monitoring, etc.) as well as on their socio-economic and behavioral background. The latter includes socio-demographic characteristics (e.g., marital status, education level, income level, gender, age, race/ethnicity, household composition, and household location), information about their driving history (in terms of driving experience, driving exposure, and accident history), as well as habitual and behavioral characteristics (e.g., alcohol consumption, driving behavior in the vicinity of a traffic signal, driving preferences, and speed limit perceptions).

Table 1 provides an overview of individuals' perceptions regarding travel time, cost, environmental, and operational benefits and concerns arising from the use of flying cars, while Table 2 provides descriptive statistics of key variables – the variables that were identified as statistically significant determinants of individuals' perceptions in the statistical analysis. Table 1 shows that the vast majority of respondents expect that the introduction of flying cars will result in lower and more reliable travel times (85.85% and 79.10% of respondents, respectively). In contrast, the majority of respondents do not expect lower operational cost or lower environmental burden with the introduction of flying cars (70.58% and 64.63% of respondents, respectively), since they consider the reduction of fuel expenses or CO_2 emissions unlikely to occur. Table 2 shows that individuals are overall concerned for all the aforementioned operational implications of flying cars, with the flying car performance in poor weather conditions, the interaction with other vehicles on the roadway, and the interactions with other vessels on the airway, constituting the major factors of concern (for 86.82%, 80.55%, and 73.95% of the respondents, respectively).

[4] Apart from United States, survey responses from eighteen other countries were also included in the sample: 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.

Table 1
Distribution of respondents' perceptions of travel time, cost, environmental and operational benefits and concerns of flying cars.

Benefits	Overall unlikely	Overall likely
Lower travel time to destination	14.15%	85.85%
More reliable travel time to destination	20.90%	79.10%
Lower fuel expenses	70.58%	29.42%
Lower CO_2 emissions	64.63%	35.37%
	Overall unconcerned	**Overall concerned**
Concerns		
Interaction with other vehicles on the roadway	26.05%	73.95%
Interaction with other flying cars or vessels on the airway	19.45%	80.55%
Flying car performance in poor weather (storm, high wind, rain, snow, etc.)	13.18%	86.82%
Learning to operate/use a flying car	33.92%	66.08%

[a]The percentage corresponding to the "overall unlikely" outcome includes the individuals who selected the "very unlikely" or "somewhat unlikely" outcome. Similar aggregation was adopted for the "overall likely" outcome. Furthermore, the percentage corresponding to the "overall concerned" outcome includes the individuals who selected the "moderately concerned" or "very concerned" outcome, whereas the "overall unconcerned" outcome is derived from the aggregation of the "not at all concerned" and "slightly concerned" outcomes.

3. Methodological approach

Table 1 provides a preliminary screening of public perception about the anticipated benefits and concerns arising from the use of flying cars. The determinants of public perception, though, cannot be obtained through the descriptive statistics of survey responses. To identify the factors that affect individuals' expectations and constitute potential indicators of future policy interventions, the benefit- and concern-specific responses are statistically modeled.

From a theoretical perspective, the public perceptions towards the benefits and concerns about flying cars are investigated in reference to three major conceptual pillars captured by the survey-based data collection: socio-demographic characteristics; attitudinal preferences; and perceived behavioral patterns. Such three pillars are generally in line with various facets of the theory of planned behavior (TPB – see also Ajzen, 1991). The latter theory has been frequently employed for the investigation of decision-making mechanism in transportation-related choices (e.g., Thorhauge et al., 2016; Buckley et al., 2018; Jing et al., 2019). Socio-demographic characteristics have the potential to unmask aggregate trends in the perceptions of general population, especially when such perceptions are associated with emerging transportation technologies (Becker and Axhausen, 2017). They can also capture – to some extent – beliefs about behavioral outcomes or social norm-specific patterns that cannot be extensively identified through a survey-based data collection (Darnton, 2008). The attitudinal preferences and behavioral traits can capture aspects of individuals' decision-making mechanism that are inherent in the TPB theory, such as behavioral intention, subjective norms, and perceived behavioral control. In this theoretical context, to account for the subjective evaluation of benefits and concerns, we employ a statistical and econometric framework with significant potential in addressing subjectivity-related heterogeneity (Mannering et al., 2016).

From a statistical viewpoint, the key travel time, cost, environmental, and operational benefits and concerns arising from the use of flying cars may constitute major sources of systematic unobserved variations. Such variations stem from systematic perceptual patterns across considerations of the same conceptual nature, such as the travel time-related benefits, or the interaction-related concerns. For example, individuals may perceive the benefits associated either with lower travel times, or more reliable travel times in a similar manner. Such similarities may result in commonly shared unobserved variations across the dependent variables that represent perceptions about benefits or concerns of the same conceptual nature. In statistical terms, such unobserved systematic variations are captured by the error terms relating to the specific dependent variables, which – in this case – may be significantly correlated (Becker et al., 2017; Fountas and Anastasopoulos, 2018; Fountas and Rye, 2019; Pantangi et al., 2019; Sarwar et al., 2017a, 2017b). To account for the possible error term correlation of – conceptually similar – dependent variables, the bivariate modeling framework is employed.

For model estimation, the four ordinal responses of the benefit- and concern-specific questions were aggregated into two discrete outcomes; with such aggregation, conceptually similar perceptions of individuals are represented by a homogeneous outcome. Thus, for the benefit-specific questions, the dependent variables have two discrete outcomes: "overall unlikely" and "overall likely". Similarly, the concern-specific dependent variables have also two outcomes: "overall concerned" and "overall unconcerned". To that end, the binary discrete outcome framework is coupled with the bivariate approach for the statistical modeling of individuals' perceptions. Such integrated modeling setting enables simultaneous modeling of two dependent variables that share similar or same unobserved characteristics, while accounting concurrently for the correlation of the relevant error terms (this type of correlation is referred to as contemporaneous or cross-equation error term correlation). The bivariate probit model is as follows (Khoo and Asitha, 2016; Pantangi et al., 2019; Sarwar et al., 2017a; Greene, 2016):

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

with the error terms being expressed as:

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

where, $\mathbf{X}$ is a vector of independent variables that determine individuals' perceptions with regard to the benefits and concerns arising from the use of flying cars, $\boldsymbol{\beta}$ denotes a vector of coefficients corresponding to $\mathbf{X}$, $w_{i,1}$ and $w_{i,2}$ correspond to the observed binary outcomes of the dependent variables, ε is a random error term assumed to follow the standard normal distribution, and λ is the cross-equation correlation coefficient of the error terms. In this context, the cumulative function of the bivariate normal distribution as well as the log-likelihood function of the bivariate probit model are respectively defined as (Greene, 2016),

$$\Phi(W_1, W_2, \lambda) = \frac{\exp[-0.5(W_1^2 + W_2^2 - 2\rho W_1 W_2)/(1-\lambda^2)]}{[2\pi\sqrt{(1-\lambda^2)}]} \tag{3}$$

and

$$\begin{aligned} &\textstyle\sum_{i=1}^{N} [w_{i,1}w_{i,2}\ln\Phi(\boldsymbol{\beta}_{i,1}\mathbf{X}_{i,1}, \boldsymbol{\beta}_{i,2}\mathbf{X}_{i,2}, \lambda) + (1-w_{i,1})w_{i,2}\ln\Phi(-\boldsymbol{\beta}_{i,1}\mathbf{X}_{i,1}, \boldsymbol{\beta}_{i,2}\mathbf{X}_{i,2}, -\lambda) \\ &+ (1-w_{i,2})w_{i,1}\ln\Phi(\boldsymbol{\beta}_{i,1}\mathbf{X}_{i,1}, -\boldsymbol{\beta}_{i,2}\mathbf{X}_{i,2}, -\lambda) \\ &\quad + (1-w_{i,1})(1-w_{i,2})\ln\Phi(-\boldsymbol{\beta}_{i,1}\mathbf{X}_{i,1}, -\boldsymbol{\beta}_{i,2}\mathbf{X}_{i,2}, \lambda)] \end{aligned} \tag{4}$$

Apart from perceptual patterns relating to benefits and concerns of similar conceptual nature, other sources of unobserved variations may also affect the individuals' perception mechanism (Kang et al., 2013). Such sources may be associated with personal preferences, experience and priorities, limited awareness about advanced transportation technologies, or attitudinal patterns of individuals that cannot be captured through the survey-based data collection process (Belgiawan et al., 2017). To account for the effect of unobserved characteristics on individuals' perceptions (i.e., unobserved heterogeneity – for further details on unobserved heterogeneity and its features see: Mannering and Bhat, 2014; Anastasopoulos, 2016; Mannering et al., 2016; Fatmi and Habib, 2017; Fountas et al., 2018b; Guo et al., 2018), random

Table 2
Descriptive statistics of key variables.

Variable Description	Mean	Std. Dev.	Min.	Max.
Socio-demographics				
Gender indicator (1 if the respondent is female, 0 otherwise)	0.398	–	0	1
Square of the age of the respondent	1087.866	1031.774	256	8836
Inverse of square of the age of the respondent	0.002	0.001	0.0001	0.004
Age indicator (1 if the respondent is younger than 25, 0 otherwise)	0.460	–	0	1
Age indicator (1 if the respondent is older than 45, 0 otherwise)	0.182	–	0	1
Current living area indicator (1 if the respondent lives in city center, 0 otherwise)	0.136	–	0	1
Current living area indicator (1 if the respondent lives in rural area, 0 otherwise)	0.095	–	0	1
Ethnicity indicator (1 if the respondent is Asian, 0 otherwise)	0.226	–	0	1
Education indicator (1 if the respondent has a technical college degree or college degree, 0 otherwise)	0.546	–	0	1
Income indicator (1 if the respondent's annual household income is less than $30,000, 0 otherwise)	0.182	–	0	1
Income indicator (1 if the respondent's annual household income is between $20,000 and $40,000, 0 otherwise)	0.123	–	0	1
Income indicator (1 if the respondent's annual household income is between $30,000 and $50,000, 0 otherwise)	0.130	–	0	1
Income indicator (1 if the respondent's annual household income is between $30,000 and $75,000, 0 otherwise)	0.290	–	0	1
Income indicator (1 if the respondent's annual household income is between $50,000 and $150,000, 0 otherwise)	0.492	–	0	1
Income indicator (1 if the respondent's annual household income is greater than $75,000, 0 otherwise)	0.487	–	0	1
Opinions and Preferences				
Vehicle safety features indicator (1 if the respondent never owned a car with an advanced safety feature, 0 otherwise)	0.459	–	0	1
Vehicle safety features indicator (1 if the respondent is not familiar with advanced safety features, 0 otherwise)	0.139	–	0	1
Aggressive driving indicator (1 if the respondent thinks that s/he normally drives not aggressively, 0 otherwise)	0.449	–	0	1
Aggressive driving indicator (1 if the respondent thinks that s/he normally drives very aggressively, 0 otherwise)	0.092	–	0	1
Driving speed indicator (1 if the respondent normally drives faster than 65 mph on an interstate with a 65 mph speed limit and little traffic, 0 otherwise)	0.762	–	0	1
Driving speed indicator (1 if the respondent normally drives faster than 75 mph on an interstate with a 65 mph speed limit and little traffic, 0 otherwise)	0.137	–	0	1
Speed limit opinion indicator (1 if the respondent completely disagrees with the statement: "Speed limits on high speed freeways should only be suggestive", 0 otherwise)	0.094	–	0	1
Speed limit opinion indicator (1 if the respondent disagrees or completely disagrees with the statement: "Speed limits on high speed freeways should only be suggestive", 0 otherwise)	0.298	–	0	1
Speed limit opinion indicator (1 if the respondent agrees or completely agrees with the statement: "Speed limits on high speed freeways should only be suggestive", 0 otherwise)	0.311	–	0	1
Red light reaction indicator (1 if the respondent accelerates and crosses the signal when approaching a traffic signal which is green initially but turns yellow, 0 otherwise)	0.158	–	0	1
Driver preference indicator (1 if the respondent generally prefers to drive herself/himself when there are more than two licensed drivers in a vehicle on a trip, 0 otherwise)	0.454	–	0	1
Driver preference indicator (1 if the respondent is not sure (varies) about driving herself/himself when there are more than two licensed drivers in a vehicle on a trip, 0 otherwise)	0.299	–	0	1
Accident history indicator (1 if the respondent has had at least one non-severe or severe accident in the last 5 years, 0 otherwise)	0.327	–	0	1
Accident history indicator (1 if the respondent has had more than one non-severe accidents in the last 5 years, 0 otherwise)	0.099	–	0	1
Annual mileage driven (in 1000 miles)	10.523	9.882	0	50
Mileage indicator (1 if the respondent annually drives less than 5,000 miles, 0 otherwise)	0.305	–	0	1
Mileage indicator (1 if the respondent annually drives greater than 15,000 miles, 0 otherwise)	0.185	–	0	1
Mileage indicator (1 if the respondent annually drives greater than 20,000 miles, 0 otherwise)	0.092	–	0	1

parameters are incorporated in model estimation. The random parameters modeling allows for the effect of explanatory variables – as expressed through the parameter estimates – to vary across the observational units of the dependent variable (Chen and Mahmassani, 2015; Satishkumar et al., 2018). In this paper, we allow for the parameter estimates to vary not across the separate survey responses, but across groups of survey responses corresponding to different survey collectors. In this manner, unbalanced panel effects stemming from possible systematic variations across the collector-specific survey responses are effectively captured. The grouped random parameters are formulated as (Washington et al., 2011; Fountas and Anastasopoulos, 2017; Sarwar et al., 2017a; Anastasopoulos et al. 2017; Fountas et al., 2018a, 2018c; Menon et al., 2019; Hyland et al., 2018):

$$\boldsymbol{\beta}_k = \boldsymbol{\beta} + v_k \tag{5}$$

where, $\boldsymbol{\beta}$ is the vector of parameter estimates and v_k denotes a random, collector-specific term with zero mean and variance σ^2. With regard to the distributional specification of the grouped random parameters, various parametric density functions (e.g., normal, log-normal, triangular, uniform, and Weibull) were investigated, and the normal distribution provided the best statistical fit.

The estimation of the grouped random parameters within a bivariate context is a computationally cumbersome process, especially due to the excessive number of the required numerical integrations. For this reason, a simulated likelihood estimation approach is employed, with the numerical integrations being generated on the basis of a Halton sequence technique (Halton, 1960). To obtain stable and consistent parameter estimates, the statistical models were estimated with 500 Halton draws (Anastasopoulos, 2016; Fountas et al., 2018a).

To gain further insights into the magnitude of the effect of explanatory variables, (pseudo-) elasticities are computed. Specifically, in order to identify the effect on individuals' perceptions, due to 1% change in the value of any continuous explanatory variable, the elasticity of the specific variable is computed as (Washington et al., 2011):

$$E = \left[1 - \Phi\left(\frac{\beta_k X_{k,i}}{\sigma}\right)\right]\beta_k X_{k,i} \tag{6}$$

In case of indicator variables, and in order to identify the effect on individuals' perceptions due to a change from "0″ to "1", the pseudo-elasticity is computed as follows (Washington et al., 2011):

$$E = \Phi\left(\frac{\beta_j X_{j,1}}{\sigma}\ |X_i = 1\right) - \Phi\left(\frac{\beta_j X_{j,1}}{\sigma}\ |X_i = 0\right) \tag{7}$$

4. Analysis results

To identify the determinants of individuals' perceptions towards the future use of flying cars, grouped random parameters bivariate probit models are estimated for pairs of benefit-specific or concern-specific survey responses. The selection of pairs of dependent variables that are simultaneously modeled is based on two criteria: (i) commonly shared unobserved characteristics between benefits or concerns, which may imply possible interrelationship between the corresponding dependent variables; and (ii) the identification of statistically significant error term correlation between the dependent variables.[5] In total, two grouped random parameters bivariate probit models are estimated for the benefit-related individuals' expectations; while two grouped random parameters bivariate probit models are estimated for the concern-related individuals' expectations. For model estimation, all possible variables and variable interactions were examined, and the variables that were identified as statistically significant at 0.90 level of confidence or higher, are included in the model specifications. The magnitude of the estimated cross-equation correlation coefficients supports the use of the bivariate modeling framework in all model specifications.

4.1. Benefit-specific perceptions

Tables 3 and 4 present the estimation results and (pseudo-)elasticities of the bivariate model of individuals' expectations about the potential of flying cars to result in lower and more reliable travel times, respectively. The estimation results and (pseudo-)elasticities of the bivariate model of individuals' expectations regarding lower fuel expenses and lower CO_2 emissions from the future use of flying cars are presented in Tables 5 and 6, respectively.

A number of socio-demographic characteristics are found to affect individuals' perceptions on the future use of flying cars. For example, older individuals are less likely to expect a decrease of CO_2 emissions with the use of flying cars. The majority (69.42%, as shown in Table 3) of respondents older than 45 years old acknowledge the potential of flying cars to provide more reliable travel times; whereas, about one third (30.58%) of respondents older than 45 years old are less likely to expect benefits in terms of travel time reliability. This finding may be capturing the perceptions of elderly travelers, who may not be well-aware of the capabilities of emerging transportation technologies, or may be exaggerating current technical uncertainties relating to the future operation of flying cars. The income level of individuals' households is another significant determinant. For example, Table 5 shows that individuals from lower income households are less likely (by −0.087, as shown by its pseudo-elasticity in Table 4) to anticipate more reliable travel times from the use of flying cars. In contrast, individuals from medium and high income households (annual income greater than $75,000) are more likely (by 0.073, as shown by the pseudo-elasticities in Table 4) to anticipate lower travel times from the future use of flying cars. With respect to the cost and environmental benefits of flying cars, individuals from medium or high income households are found to have heterogeneous perceptions; their majority (65.57% and 55.30%, respectively) are less likely to anticipate lower fuel expenses and lower CO_2 emissions, respectively, from the use of flying cars. This result may stem either from the common perception that the in-air operation will require stronger engine power, or from the existence of various technical specifications regarding the engine characteristics of flying cars (e.g., various flying car models include electric engine, gasoline-based engine, or hybrid engine). Moreover, individuals who permanently live in densely populated areas (such as the city center and vicinity) are more likely (by 0.157, as indicated by the pseudo-elasticities in Table 6) to anticipate lower fuel expenses from the use of flying cars. This finding may be reflecting environmental and energy benefits of flying cars from their anticipated congestion-free traffic operation, as compared to highly congested surface transportation of traditional vehicles.

As far as the familiarity with advanced transportation technologies is concerned, individuals who never owned a car with advanced safety features have mixed perceptions with respect to the expected environmental benefits of flying cars. The reduction of CO_2 emissions due to the use of flying cars is viewed as a less likely outcome by the majority (63.93%, as shown in Table 5) of these respondents; whereas for the rest of the respondents (36.07%, as shown in Table 5), this outcome is more likely to occur.

Moving to the behavioral and attitudinal determinants, individuals who perceive themselves as very aggressive drivers are less likely to anticipate reduction of travel times from the future use of flying cars. On the contrary, expectations for lower travel times vary across drivers with self-reported speeding behavior (e.g., drivers who normally drive faster than 75 mph on an interstate with speed limit of 65 mph and little traffic). Notably, for the majority (70.59%, as shown in Table 3) of these respondents, the self-reported speeding behavior increases the likelihood of expectations for lower travel times. Such mixed expectations of individuals with aggressive driving behavior may possibly be attributed to their perceptions of the required time for the take-off and landing operations of flying cars. For example, some individuals may have perceived the time requirements of flying cars' take-off and landing similar to those related to airport operations and conclude that trip durations will include such operational delays.

Another source of perceptual variations arises from individuals with varying willingness to drive in shared trips (e.g., drivers who are not sure about driving themselves when other licensed drivers are also present in a vehicle). The majority (76.53%, as shown in Table 3) of these individuals are more likely to associate the use of flying cars with more reliable travel times to destination, while the opposite is observed for the remaining 25.83% of individuals. This subgroup of drivers may be more susceptible to undesirable driving circumstances (such as, off-peak-hour congestion, traffic disruptions due to accidents, or workzone presence) that can result in unexpected travel delays. The potential non-involvement of flying cars in such traffic situations may be serving as a contributing factor towards the enhancement of the perceived travel time reliability.

Furthermore, individuals who endorse the suggestive role of speed limits are more likely (by 0.09, as shown by the (pseudo-)elasticities in Table 6) to expect lower fuel-related expenses. Driving exposure has also influential effect in shaping individuals' expectations about the benefits of flying cars. Specifically, individuals with greater annual mileage are less likely (by −0.0003, as shown by the elasticities in Table 4) to expect lower travel times. Similarly, individuals with low annual mileage (less than 5000 miles per year) are more likely to expect a decrease in fuel expenses and CO_2 emissions from the future use of flying cars. Both findings possibly capture the effect of habitual driving patterns on the individuals' perceptions, since keen car-users may be more skeptical to the benefits of emerging transportation technologies, as opposed to car-users with little experience.

Focusing on the cross-equation error term correlation, the specific coefficient was found to be positive in both benefit-specific models. That means the unobserved characteristics captured by the error terms of the bivariate probit specification have a homogeneous and unidirectional effect on both model components. In other words, such characteristics either both increase, or both decrease the likelihood of the benefit-specific perceptions (Fountas et al., 2019; Pantangi et al.,

[5] Note that multivariate probit models were initially estimated in order to gain further insights regarding the cross-equation correlation of the error terms corresponding to the potential dependent variables of the bivariate models. The results of the multivariate probit models showed that pairs of variables with significant conceptual similarity (e.g., variables reflecting travel time- or interaction-specific perceptions) are indeed associated with strong cross-equation error term correlation. Thus, these pairs of variables were used as dependent variables in the grouped random parameters bivariate probit models.

Table 3
Estimation results of the grouped random parameters bivariate probit model of travel time-related perceptions.

Variable	Lower travel time to destination		More reliable travel time to destination	
	Coeff.	*t*-stat	Coeff.	*t*-stat
Constant	1.117	8.97	0.834	9.97
Socio-demographics				
Age indicator (1 if the respondent is older than 45, 0 otherwise)	–	–	0.370	1.90
Standard deviation of parameter distribution	–	–	0.729	2.98
Income indicator (1 if the respondent's annual household income is between $30,000 and $50,000, 0 otherwise)	–	–	−0.303	−1.67
Income indicator (1 if the respondent's annual household income is greater than $75,000, 0 otherwise)	0.354	2.33	–	–
Opinions and Preferences				
Aggressive driving indicator (1 if the respondent thinks that s/he normally drives very aggressively, 0 otherwise)	−0.541	−2.04	–	–
Driving speed indicator (1 if the respondent normally drives faster than 75 mph on an interstate with a 65 mph speed limit and little traffic, 0 otherwise)	0.272	1.07	–	–
Standard deviation of parameter distribution	0.503	2.62	–	–
Driver preference indicator (1 if the respondent is not sure (varies) about driving herself/himself when there are more than two licensed drivers in a vehicle on a trip, 0 otherwise)	–	–	0.282	1.75
Standard deviation of parameter distribution	–	–	0.434	2.90
Annual mileage driven (in 1000 miles)	−0.013	−2.08	–	–
Cross equation correlation	0.747	9.53		
Number of survey collectors	35			
Number of respondents	531			
Log-likelihood at convergence	−417.28			
Log-likelihood at zero	−499.66			
Akaike information criterion (AIC)	860.60			
Aggregate distributional effect of random parameters across the respondents				
	Above zero		**Below zero**	
Age indicator (1 if the respondent is older than 45, 0 otherwise)	69.42%		30.58%	
Driver preference indicator (1 if the respondent is not sure (varies) about driving herself/himself when there are more than two licensed drivers in a vehicle on a trip, 0 otherwise)	76.53%		23.47%	
Driving speed indicator (1 if the respondent normally drives faster than 75 mph on an interstate with a 65 mph speed limit and little traffic, 0 otherwise)	70.59%		29.41%	

Table 4
(Pseudo-)elasticities of the explanatory variables included in the model of travel time-related perceptions.

Variable	Lower travel time to destination	More reliable travel time to destination
Socio-demographics		
Age indicator (1 if the respondent is older than 45, 0 otherwise)	–	0.084
Income indicator (1 if the respondent's annual household income is between $30,000 and $50,000, 0 otherwise)	–	−0.087
Income indicator (1 if the respondent's annual household income is greater than $75,000, 0 otherwise)	0.073	–
Opinions and Preferences		
Aggressive driving indicator (1 if the respondent thinks that s/he normally drives very aggressively, 0 otherwise)	−0.139	–
Driving speed indicator (1 if the respondent normally drives faster than 75 mph on an interstate with a 65 mph speed limit and little traffic, 0 otherwise)	0.051	–
Driver preference indicator (1 if the respondent is not sure (varies) about driving herself/himself when there are more than two licensed drivers in a vehicle on a trip, 0 otherwise)	–	0.068
Annual mileage driven (in 1000 miles)	−0.0003	–

2019). This finding underscores the conceptual interrelationship between the extent and reliability of travel times, as well as between fuel expenses and CO_2 emissions in the perceptual mechanism of individuals. For the travel time model, the controlled involvement of flying cars in the ground transportation traffic may constitute a driving force for the identified interrelationship; whereas, established perceptions towards the energy demand features of the current commercial aircrafts may underpin the identified interrelationship between fuel expenses and CO_2 emissions.

4.2. Concern-specific perceptions

Tables 7 and 8 present the estimation results and (pseudo-)elasticities of the bivariate model of individuals' concerns about the interactions of flying cars with other vehicles on the roadway and interactions with other flying cars or vessels on the airway, respectively. The estimation results and (pseudo-) elasticities of the bivariate model of individuals' concerns regarding the performance of flying cars in poor weather (storm, high wind, rain, snow, tec.) and the learning process

Table 5
Estimation results of the grouped random parameters bivariate probit model of cost and environmental perceptions.

Variable	Lower fuel expense		Lower CO_2 emissions	
	Coeff.	t-stat	Coeff.	t-stat
Constant	−0.741	−5.70	–	–
Socio-demographics				
Inverse of square of the age of the respondent	–	–	−222.70	−4.27
Current living area indicator (1 if the respondent lives in city center, 0 otherwise)	0.454	3.27	–	–
Income indicator (1 if the respondent's annual household income is between $50,000 and $150,000, 0 otherwise)	−0.214	−1.52	−0.075	−0.65
Standard deviation of parameter distribution	0.535	6.72	0.565	6.63
Opinions and Preferences				
Vehicle safety features indicator (1 if the respondent never owned a car with an advanced safety feature, 0 otherwise)	–	–	−0.197	−1.75
Standard deviation of parameter distribution	–	–	0.553	5.63
Speed limit opinion indicator (1 if the respondent agrees or completely agrees with the statement: "Speed limits on high speed freeways should only be suggestive", 0 otherwise)	0.277	2.35	–	–
Mileage indicator (1 if the respondent annually drives less than 5,000 miles, 0 otherwise)	0.217	1.74	0.305	2.70
Cross equation correlation	0.778	17.86		
Number of survey collectors	35			
Number of respondents	529			
Log-likelihood at convergence	−550.74			
Log-likelihood at zero	−673.43			
Akaike information criterion (AIC)	1,127.50			

Aggregate distributional effect of random parameters across the respondents

	Above zero	Below zero
Income indicator (1 if the respondent's annual household income is between $50,000 and $150,000, 0 otherwise) [*Lower fuel expenses*]	34.43%	65.57%
Income indicator (1 if the respondent's annual household income is between $50,000 and $150,000, 0 otherwise) [*Lower CO_2 emissions*]	44.70%	55.30%
Vehicle safety features indicator (1 if the respondent never owned a car with an advanced safety feature, 0 otherwise)	36.07%	63.93%

Table 6
(Pseudo-)elasticities of the explanatory variables included in the model of cost and environmental perceptions.

Variable	Lower fuel expense	Lower CO_2 emissions
Socio-demographics		
Inverse of square of the age of the respondent	–	−0.001
Current living area indicator (1 if the respondent lives in city center, 0 otherwise)	0.157	–
Income indicator (1 if the respondent's annual household income is between $50,000 and $150,000, 0 otherwise)	−0.069	−0.027
Opinions and Preferences		
Vehicle safety features indicator (1 if the respondent never owned a car with emergency automatic braking, lane keeping assist/lane centering, adaptive cruise control, left turn assist, adaptive headlights or blind-spot monitoring, 0 otherwise)	–	−0.072
Speed limit opinion indicator (1 if the respondent agrees or completely agrees with the statement: "Speed limits on high speed freeways should only be suggestive", 0 otherwise)	0.090	–
Mileage indicator (1 if the respondent annually drives less than 5,000 miles, 0 otherwise)	0.070	0.113

associated with the operation of flying cars are presented in Tables 9 and 10, respectively.

A number of sociodemographic characteristics are found to affect individuals' concern-specific perceptions. Table 7 shows that the interactions of flying cars with roadway vehicles and other flying cars or air vessels constitute major sources of concern for older individuals. In contrast, Table 9 shows that younger individuals are less likely to be concerned with the flying car performance during poor weather conditions. Both findings possibly capture the more conservative perspectives of older individuals towards the innovative, yet largely unknown capabilities of flying cars. In a similar manner, female respondents are overall more concerned about the implications from the interactions of flying cars with roadway vehicles as well as from the interactions with other flying cars or air vessels. Interestingly, the specific variable (female respondent indicator) increases the likelihood of concerns arising from the aforementioned interactions, by 0.167 and 0.15, respectively (as shown by the pseudo-elasticities in Table 8). Such attitudinal pattern of females is in line with previous findings relating to their perceptions of automated transportation technologies (see also Schoettle and Sivak, 2014) and possibly reflects their higher level of cautiousness against the implications of advanced transportation technologies. The income level of individuals' households constitutes another significant determinant. For example, Table 7 shows that individuals from medium- or high-income households (annual income from $50,000 to $150,000) are less likely to be concerned about the interaction of flying cars with other in-air vessels, whereas 52.26% of the respondents from high income households (annual income greater than $75,000) consider the learning process associated with the flying car operation as a more likely source of concern. Overall, the likely significant experience of medium- and high-income individuals with air trips as well as potential perceptual similarities between the flying cars and the conventional airplanes may affect their level of concern against various flying car operations.

Moving to the behavioral and attitudinal determinants of individuals' concerns, the accident history is found to result in mixed perceptions towards the in-air interactions and the learning process of the flying car operation. The majority (66.80%, as shown in Table 7) of respondents who were involved in more-than-one non-severe accidents over the last 5 years are more likely to be concerned about the in-air interactions of flying cars; whereas, the remaining one third (33.20%)

Table 7
Estimation results of the grouped random parameters bivariate probit model of individuals' concerns regarding the interactions of flying cars on the roadway and airway.

Variable	Interaction with other vehicles on the roadway		Interaction with other flying cars or vessels on the airway	
	Coeff.	***t*-stat**	**Coeff.**	***t*-stat**
Constant	–	–	0.473	2.60
Socio-demographics				
Gender indicator (1 if the respondent is female, 0 otherwise)	0.572	3.30	0.644	4.22
Square of the age of the respondent	0.0002	3.03	0.0003	2.26
Income indicator (1 if the respondent's annual household income is between $50,000 and $150,000, 0 otherwise)	–	–	−0.223	−1.90
Opinions and Preferences				
Vehicle safety features indicator (1 if the respondent never owned a car with an advanced safety feature, 0 otherwise)	–	–	0.235	1.93
Aggressive driving indicator (1 if the respondent thinks that s/he normally drives not aggressively, 0 otherwise)	0.143	1.40	–	–
Standard deviation of parameter distribution	0.244	2.90	–	–
Driving speed indicator (1 if the respondent normally drives faster than 65 mph on an interstate with a 65 mph speed limit and little traffic, 0 otherwise)	0.177	1.65	–	–
Red light reaction indicator (1 if the respondent accelerates and crosses the signal when approaching a traffic signal which is green initially but turns yellow, 0 otherwise)	–	–	−0.291	−1.48
Standard deviation of parameter distribution	–	–	0.267	1.90
Driver preference indicator (1 if the respondent generally prefers to drive herself/himself when there are more than two licensed drivers in a vehicle on a trip, 0 otherwise)	–	–	−0.006	−0.05
Standard deviation of parameter distribution	–	–	0.330	3.65
Accident history indicator (1 if the respondent has had more than one non-severe accidents in the last 5 years, 0 otherwise)	–	–	0.362	1.64
Standard deviation of parameter distribution	–	–	0.833	3.05
Mileage indicator (1 if the respondent annually drives greater than 20,000 miles, 0 otherwise)	0.462	1.85	–	–
Cross equation correlation	0.914	37.77		
Number of survey collectors		35		
Number of respondents		514		
Log-likelihood at convergence		−423.56		
Log-likelihood at zero		−574.62		
Akaike information criterion (AIC)		883.1		

Aggregate distributional effect of random parameters across the respondents

	Above zero	**Below zero**
Aggressive driving indicator (1 if the respondent thinks that s/he normally drives not aggressively, 0 otherwise)	72.03%	27.97%
Red light reaction indicator (1 if the respondent accelerates and crosses the signal when approaching a traffic signal which is green initially but turns yellow, 0 otherwise	13.80%	86.20%
Driver preference indicator (1 if the respondent generally prefers to drive herself/himself when there are more than two licensed drivers in a vehicle on a trip, 0 otherwise)	49.30%	50.70%
Accident history indicator (1 if the respondent has had more than one non-severe accidents in the last 5 years, 0 otherwise)	66.80%	33.20%

of respondents are less likely to be concerned about the in-air interactions of flying cars. Learning of flying car operations is found to bifurcate the perceptions of individuals with at least one, non-severe or severe, accident over the last 5 years, with almost half of these individuals being more likely to be concerned (49.75%, as shown in Table 9). Intuitively, the involvement of individuals in accidents with conventional vehicles may increase their level of cautiousness against various possible causes of flying car accidents, such as the interactions with other vessels or the inadequate knowledge of flying car operations. The latter may also affect the perceptions of individuals who are unfamiliar with advanced safety features; the non-ownership of a vehicle with such features increases (by 0.058, as shown by the pseudo-elasticities in Table 8) the likelihood of concerns stemming from the in-air interaction of flying cars.

The self-reported non-aggressive driving behavior of individuals is found to heterogeneously influence perceptions towards the on-ground interactions of flying cars. The vast majority (72.03%, as shown in Table 7) of respondents who perceive their driving behavior as non-aggressive are more likely to be concerned about the implications from the interactions of flying cars with other vehicles in the ground transportation network; while the opposite is observed for the remaining 27.97% of the respondents. Greater degree of cautiousness during the driving task, which is habitually exercised by non-aggressive drivers (Paleti et al., 2010), may enhance their tendency for low-risk ground interactions of flying cars. With respect to the effect of specific driving behavior patterns, speeding behavior (for example, driving with speed greater than the speed limit on an interstate highway) is found to increase the likelihood of concern (by 0.055, as shown in Table 8) associated with the on-ground interactions of flying cars. In contrast, the speeding behavior in the vicinity of a traffic signal (as exhibited by drivers who accelerate and cross the traffic signal when the traffic signal turns from green to yellow) has mixed effect on individuals' concerns; the vast majority (86.2%, as shown in Table 7) of these respondents are less likely to be concerned about the in-air interactions of flying cars. Due to their risk-taking behavior, these individuals may not consider the implications of the in-air interactions as possible issues that can disrupt the unobstructed navigation of flying cars.

Furthermore, individuals with high driving confidence – as indicated by their willingness to drive themselves even in the presence of other licensed drivers – are associated with mixed perceptions of the in-

Table 8
(Pseudo-)elasticities of the explanatory variables included in the model of individuals' concerns regarding the interactions of flying cars on the roadway and airway.

Variable	Interaction with other vehicles on the roadway	Interaction with other flying cars or vessels on the airway
Socio-demographics		
Gender indicator (1 if the respondent is female, 0 otherwise)	0.167	0.150
Square of the age of the respondent	0.0006	0.0005
Income indicator (1 if the respondent's annual household income is between $50,000 and $150,000, 0 otherwise)	–	−0.056
Opinions and Preferences		
Vehicle safety features indicator (1 if the respondent never owned a car with emergency automatic braking, lane keeping assist/lane centering, adaptive cruise control, left turn assist, adaptive headlights or blind-spot monitoring, 0 otherwise)	–	0.058
Aggressive driving indicator (1 if the respondent thinks that s/he normally drives not aggressively, 0 otherwise)	0.043	–
Driving speed indicator (1 if the respondent normally drives faster than 65 mph on an interstate with a 65 mph speed limit and little traffic, 0 otherwise)	0.055	–
Red light reaction indicator (1 if the respondent accelerates and crosses the signal when approaching a traffic signal which is green initially but turns yellow, 0 otherwise)	–	−0.078
Driver preference indicator (1 if the respondent generally prefers to drive herself/himself when there are more than two licensed drivers in a vehicle on a trip, 0 otherwise)	–	−0.001
Accident history indicator (1 if the respondent has had more than one non-severe accidents in the last 5 years, 0 otherwise)	–	0.080
Mileage indicator (1 if the respondent annually drives greater than 20,000 miles, 0 otherwise)	0.123	–

Table 9
Estimation results of the grouped random parameters bivariate probit model of individuals' concerns about flying car performance in poor weather and learning to operate a flying car.

Variable	Flying car performance in poor weather (storm, high wind, rain, snow, etc.)		Learning to operate/use a flying car	
	Coeff.	*t*-stat	Coeff.	*t*-stat
Constant	1.68	8.06	0.497	3.88
Socio-demographics				
Inverse of square of the age of the respondent	−293.72	−2.71	–	–
Current living area indicator (1 if the respondent lives in city center, 0 otherwise)	–	–	0.397	2.20
Income indicator (1 if the respondent's annual household income is greater than $75,000, 0 otherwise)	–	–	0.016	0.12
Standard deviation of parameter distribution	–	–	0.284	3.54
Opinions and Preferences				
Speed limit opinion indicator (1 if the respondent disagrees or completely disagrees with the statement: "Speed limits on high speed freeways should only be suggestive", 0 otherwise)	−0.297	−1.87	−0.297	−2.00
Driver preference indicator (1 if the respondent is not sure (varies) about driving herself/himself when there are more than two licensed drivers in a vehicle on a trip, 0 otherwise)	0.344	1.81	–	–
Accident history indicator (1 if the respondent has had at least one non-severe or severe accident in the last 5 years, 0 otherwise)	–	–	−0.001	−0.01
Standard deviation of parameter distribution	–	–	0.213	2.25
Cross equation correlation	0.641	8.21		
Number of survey collectors	35			
Number of respondents	550			
Log-likelihood at convergence	−502.57			
Log-likelihood at zero	−572.65			
Akaike information criterion (AIC)	1029.1			
Aggregate distributional effect of random parameters across the respondents				
	Above zero		Below zero	
Income indicator (1 if the respondent's annual household income is greater than $75,000, 0 otherwise)	52.26%		47.74%	
Accident history indicator (1 if the respondent has had at least one non-severe or severe accident in the last 5 years, 0 otherwise)	49.75%		50.25%	

air interactions of flying cars, with 50.7% (as shown in Table 7) of these individuals being less likely to be concerned about the implications of such interactions. In opposite, the variable reflecting varying willingness of individuals to undertake the driving task in the presence of other licensed drivers increases (by 0.059, as shown by the pseudo-elasticities in Table 10) the likelihood of concerns arising from the flying car performance during poor weather. Especially for drivers with limited driving familiarity, the inclement weather constitutes a major cause of driving discomfort and driving errors (Ahmed and Ghasemzadeh, 2018), which may also result in concerns about the operation of flying cars under such conditions. In similar fashion, experienced drivers (whose annual mileage exceeds 20,000 miles) are

Table 10
(Pseudo-)elasticities of the explanatory variables included in the model of individuals' concerns about flying car performance in poor weather and learning to operate a flying car.

Variable	Flying car performance in poor weather (storm, high wind, rain, snow, etc.)	Learning to operate/use a flying car
Socio-demographics		
Inverse of square of the age of the respondent	−0.001	–
Current living area indicator (1 if the respondent lives in city center, 0 otherwise)	–	0.130
Income indicator (1 if the respondent's annual household income is greater than $75,000, 0 otherwise)	–	0.006
Opinions and Preferences		
Speed limit opinion indicator (1 if the respondent disagrees or completely disagrees with the statement: "Speed limits on high speed freeways should only be suggestive", 0 otherwise)	−0.060	−0.108
Driver preference indicator (1 if the respondent is not sure (varies) about driving herself/himself when there are more than two licensed drivers in a vehicle on a trip, 0 otherwise)	0.059	–
Accident history indicator (1 if the respondent has had at least one non-severe or severe accident in the last 5 years, 0 otherwise)	–	−0.0005

more concerned about the interactions of flying cars with other vehicles on the roadway network.

With respect to the impact of attitudinal characteristics, individuals with unfavorable opinions towards the suggestive enforcement of speed limits are less likely to be concerned about the flying car performance in inclement weather as well as about the learning process that may be required for the operation of flying cars. This group of individuals may consider the behavioral variations under various traffic conditions as major risk component for conventional vehicles as well as for flying cars. In this perceptual context, the automated capabilities of flying cars may restrain the exposed risk of individuals during the on-ground or in-air operation.

The cross-equation error term correlation was consistently found positive in both concern-specific models, thus implying the homogeneous effect of the captured unobserved characteristics on the dependent variables. The interactions on the ground and in the air are, in fact, conceptually interrelated, with the cross-equation error correlation possibly capturing individuals' similar expectations regarding the safety performance of flying cars in the surface and air transportation networks. Such perceived safety considerations, in conjunction with the perceived navigation comfort and the infrastructure-related uncertainties, may interact with individuals' concerns about the performance of flying cars in inclement weather, and about learning to operate a flying car. The interdependence of weather, safety, and operational barriers have been also highlighted in the recent report of NASA on the potential market of Urban Air Mobility (NASA, 2018).

5. Summary and conclusions

The innovative features of flying cars – arising from their hybrid operation in the air and on the ground transportation networks – differentiate them significantly from the conventional vehicles, as well as from the emerging autonomous vehicles, especially in the context of individuals' perceptions. The limited awareness regarding their capabilities and differences from other urban mobility systems may affect the perceptual patterns towards potential advantages or drawbacks of flying cars. This study seeks to shed more light on individuals' perceptions on the benefits and concerns from the future use of flying cars, which may potentially have a critical effect on their adoption by the commuting population, and on their establishment in the traffic fleet. Using data collected from an online survey, the fundamental components of public perception were identified, in terms of benefits and concerns arising from various travel time, environmental, cost or operational implications of flying cars. Even though the survey results can provide preliminary insights into the current expectations of individuals, the long-term deployment of flying cars is anticipated to be highly dependent on the personal, behavioral and attitudinal factors that shape public perceptions. To identify these determinants, the survey-based data were statistically analyzed through the estimation of grouped random parameters bivariate probit models. Such models allow simultaneous modeling of conceptually similar benefits or concerns and account for various misspecification issues stemming from the highly heterogeneous nature of the survey data.

The findings of the statistical analysis showed that various socio-demographic, behavioral, and attitudinal attributes affect individuals' perceptions towards the benefits and concerns from the future use of flying cars. Overall, the majority of older individuals, individuals with varying willingness to drive, and individuals with high household annual income were found more likely to expect lower or more reliable travel times upon the introduction of flying cars. Individuals who live in densely populated urban districts and individuals who travel extensively were found more likely to anticipate a decrease in the fuel expenses after the introduction of flying cars. In contrast, individuals from medium- or high-income households, and individuals unfamiliar with advanced vehicle features were found less likely to expect environmental benefits from the introduction of flying cars.

With regards to individuals' concerns, the interactions of flying cars with other vehicles on the ground transportation networks were identified as a major source of concern for women, older individuals, non-aggressive drivers, and individuals who travel extensively. Similarly, women, older individuals, and individuals with notable accident history were more likely to be concerned about interactions involving other flying cars or vessels in the airway. Drivers with varying willingness to drive were more concerned about flying cars' performance in inclement weather. Finally, learning how to operate a flying car was found to be the least concerning implication; individuals located in densely populated areas, individuals with high annual income, and individuals with notable accident history were more likely to be concerned about this operational element.

The findings of the statistical analysis can provide significant insights on the potential of flying cars to attract public interest, as well as into the operational challenges that may act as potential barriers for their successful penetration into the traffic fleet. Understanding the determinants of individuals' perceptions can assist policymakers, researchers, manufacturing companies, and regulators in the identification of target groups, for which policy actions should be undertaken. In this context, older individuals, individuals with limited knowledge or experience with advanced transportation systems, or individuals with notable accident history, may all constitute focus groups whose perceptions towards the implications of flying cars need to be investigated in depth. To increase the awareness of such focus groups about the capabilities of flying cars, media campaigns, training sessions, or targeted demonstrations of flying car operations can be carefully designed and implemented.

The outcomes of this study can be blended with preliminary findings from recent endeavors of manufacturing or governmental entities (e.g., NASA, 2018; Airbus, 2019) focusing on policy actions to be undertaken, in order to address the establishment constraints of flying cars. In this context, future policy interventions may aim at raising public awareness about the automated features of flying cars – in both ground and air operations – as well as on their minimal facility requirements for take-off and landing operations. Such comparative advantages may further attract the interest of population groups with an inclination towards short and reliable travel times. Increased awareness about the monitoring and management of undesirable circumstances on the ground and in the air (e.g., traffic conflicts, on-ground and in-air vehicle interactions, system failure, navigation during adverse weather conditions) may also contribute to the resolution of concerns originating from conservative drivers or individuals with previous accident experience.

It should be noted that the current public perceptions, as outlined in this study, are influenced by the public's limited awareness and absence of previous experience with flying cars. As individuals become more informed about flying cars and essentially experience flying operations, their attitudinal perspectives will possibly change. For instance, if the introduction of flying cars bears reliable, safe, cost- and environmentally-effective trips, public perceptions may shift towards a more favorable standpoint. On the contrary, possible occurrence of undesirable incidents (e.g., accidents, system failures, excessive user's cost) may adversely affect individuals' perceptions and bring the implementation of flying cars to a halt. This paper should thus be regarded as an empirical, yet introductory step towards understanding public perceptions about the future use of flying cars, especially since the findings may be subject to temporal instability arising from the future growth patterns of the flying car market.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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