Transportation Research Part A 181 (2024) 104000

Contents lists available at ScienceDirect

Transportation Research Part A

journal homepage: www.elsevier.com/locate/tra

Mode choice modeling for an electric vertical takeoff and landing (eVTOL) air taxi commuting service

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ARTICLE INFO

In memory of Robert J. Bowler, father of Laurie Garrow.

Keywords:
Air taxi
Urban air mobility
Mode choice
Value of time
Air traveler behavior

ABSTRACT

In this study, a stated choice experiment was conducted to better understand individuals' preferences for an air taxi commute service. Random taste parameter models with panel effects were used to model the choice among: (1) traditional auto, (2) transit, and (3) air taxi. We find that individuals who are male and are frequent ridesharing users are more likely to select the air taxi. A non-trader analysis of individuals who always selected the same mode across our eight stated choice scenarios showed that air taxi preferences are heterogeneous and polarized, with 14 percent always selecting air taxi and 14 percent never selecting air taxi. Among the traders, significant variation across individuals' value of time (VOT) was observed. Results based on a negative lognormal distribution show the median in-vehicle VOTs for the air taxi mode was about 25 USD/hour, but 10 percent had VOTs higher than 64 USD/hour. Our results highlight the need for future studies of potential market demand for eVTOL aircraft to incorporate the percentage of the population who will likely never consider using an air taxi, as well as the distribution of VOTs for those who will consider using this new mode.

1. Introduction and motivation

Advancements in electric propulsion and autonomy technologies are leading to the development of a new class of electric vertical takeoff and landing (eVTOL) aircraft (Langford & Hall, 2020). These new eVTOL aircraft are expected to be safer, quieter, and less expensive to operate and maintain than existing vertical takeoff and landing aircraft, i.e., helicopters (Uber, 2016). These aircraft could transform how we transport people and goods in our cities and regional markets by overflying ground traffic congestion and shortening door-to-door travel times for one or more trip purposes, including commute trips, trips to the airport, trips to major attractions such as sporting events, shuttles between business or medical facilities, and emergency response trips (e.g., see Vascik & Hansman, 2017; Straubinger et al., 2021).

Research into urban air mobility (UAM) and advanced air mobility (AAM) has exploded in the last five years.[1] Garrow et al. (2021)

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[1] As noted in Garrow et al. (2021), "On March 23, 2020, the U.S. National Aeronautics and Space Administration (NASA) began referring to its on-demand aerial activities as AAM instead of UAM to reflect a more inclusive vision for both urban and rural applications (Banke, 2020).".

https://doi.org/10.1016/j.tra.2024.104000
Received 15 October 2020; Received in revised form 2 January 2024; Accepted 8 February 2024
Available online 23 February 2024
0965-8564/

provide a review of UAM articles that were published from January 2015 to June 2020 and show that UAM publications have grown exponentially over this period—from a low of 5 in 2015 to a high of 120 in 2019.[2] UAM research has covered a wide range of topics. A review article by Straubinger et al. (2020) classifies UAM research areas into eight broad areas: air vehicles, regulation, infrastructure, operations, market actors, integration, acceptance, and modeling.

Given how new this field is, there is no unified vision for how UAM and AAM will evolve in urban and regional areas—nor a standard terminology for describing these new modes of transportation. In this paper, we focus on an application for an air taxi service for commute trips that would be able to offer door-to-door travel-time savings compared to traditional modes. Here, we define an air taxi as an eVTOL aircraft that carries two to four passengers and is flown by a certified pilot. It is envisioned that the air taxi service would be on-demand, and a passenger would reserve a seat on the air taxi by using a ridesharing app similar to those used by transportation network companies such as Lyft or Uber to connect operators with demand in real time.

Several studies have examined potential UAM demand for different trip purposes. To determine if an air taxi service would be able to compete with conventional ground modes, many studies have compared door-to-door travel times between UAM and conventional modes and examined the sensitivity of these door-to-door times to different parameters, such as access and egress times and aircraft cruise speeds. A study by Roland Berger (2018) found that air taxi trips need to be at least 15–25 km (about 9–16 miles) to provide travel-time savings over existing modes. Swadesir and Bil (2019) compared travel times, costs, and general convenience of using an air taxi service, bike, auto, and public transport in Melbourne, Australia, and found that demand for an air taxi service is sensitive to access and egress times to the vertiport, as well as the times to board and disembark the aircraft. Antcliff et al. (2016) compared travel times for urban and suburban commutes between ground and air taxis in Silicon Valley in California and found travel times for air taxis that were three to six times lower than cars for some commutes in this area. Kreimeier et al. (2016) assessed the viability of a UAM service in Germany for intercity travel and found that UAM market shares are highly sensitive to UAM prices, as well as access and egress times. Vascik et al. (2018) compared door-to-door travel times for 32 reference missions in the Boston, Dallas, and Los Angeles areas to identify operational constraints. Their analysis focused on high-income commuter neighborhoods, which they defined as those with annual household incomes of at least 200 K USD or as neighborhoods with average home valuations of at least 1 M USD in Los Angeles and Dallas and at least 900 K USD in Boston.

In most of these door-to-door studies, travel times and costs of each mode were computed, and a single value of time (VOT) was applied to determine the number of air trips for which the benefit of travel-time savings over conventional modes was present. A sensitivity analysis that varies the VOT estimate may be conducted, but the key point is that an average VOT for the population has typically been used in prior studies, not a distribution of VOT across the population.

In this study, a stated choice experiment was conducted to better understand individuals' preferences for an air taxi commute shuttle and to empirically determine the distribution of VOT in the survey populations. Random taste parameter models with panel effects were used to model the choice among traditional auto, transit, and air taxi. Incorporating systematic and unobserved heterogeneity in individuals' sensitivity to cost improved the overall model fit and revealed a significant proportion of the population has high VOT, which in turn will translate into higher willingness to pay to take an air taxi that saves time over other modes.

The balance of this paper contains five sections. Section 2 presents a conceptual model of demand for an air taxi commuter service and discusses related literature. Section 3 describes the survey and presents descriptive statistics. Section 4 covers the methodology, and Section 5 presents results. We conclude with a discussion of key findings, limitations, and direction for future research in Section 6.

2. Conceptual model of demand for an air taxi commuter service and related literature

Fig. 1 shows the conceptual model of demand for an urban air mobility commuter service adapted from Garrow et al. (2020) that guided our survey design. This conceptual model follows the decision-making framework of Domencich and McFadden (1975), which characterizes the choice process by four elements: the decision-makers' characteristics, the alternatives available to the decision-makers, the attributes of these alternatives, and a decision rule. For the air taxi commuting application, it is hypothesized that several characteristics of the decision-makers influence demand. These characteristics include the individuals' current commute, air travel, and ridesharing[3] patterns. Individuals' socioeconomic and demographic (SED) characteristics may also influence demand. These decision-maker characteristics, together with the characteristics of the available transportation alternatives, determine the individual's utility for each alternative. The decision-maker is assumed to choose the alternative with the highest utility, and different discrete choice models are used to model mode choice.

Systematic taste preferences can be incorporated by including interaction terms between observable characteristics of the decision-maker and observable attributes of the alternatives. Random taste preferences can be incorporated by using a mixed logit model to include a distribution of preferences across decision-makers.

Other studies examining new modes of transportation have found the factors included in our conceptual model of demand for an urban air taxi commuter service to be important. Researchers have examined a variety of new transportation modes, including electric ground vehicles (EVs), autonomous ground vehicles (AVs), ridesharing, carsharing, and air taxis. With respect to SED characteristics,

[2] As an update to this paper, we also identified 189 articles published in 2020 and 259 published from January to August of 2021.

[3] Ride-hailing and ridesharing are two terms commonly used to describe services by transportation network companies such as Uber and Lyft and can be used to distinguish between cases in which an individual reserves an entire vehicle to travel alone (i.e., ride-hailing) or a case in which an individual reserves a seat and shares a ride with one or more other passengers (i.e., ridesharing). For an air taxi commuter shuttle, we assume that individuals will be reserving a seat and, thus, use the term ridesharing throughout the paper.

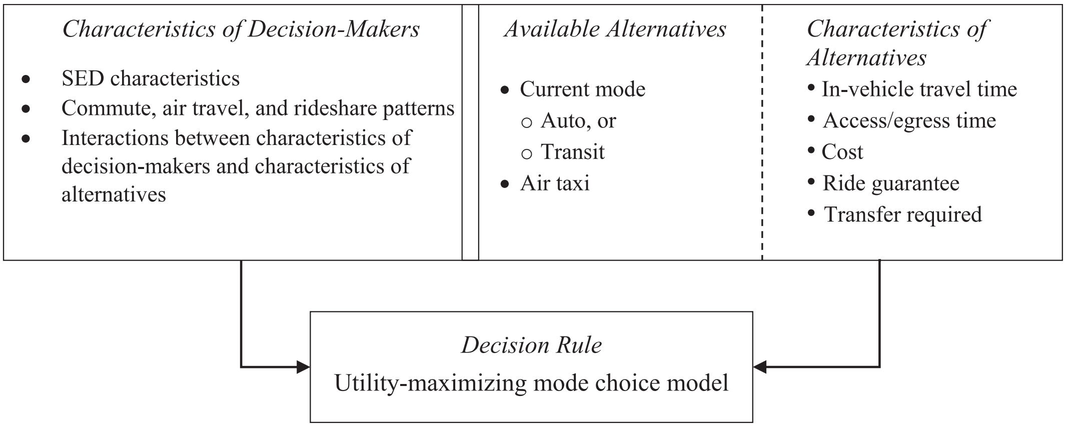

Fig. 1. Conceptual model of demand for urban air taxi commuter flights.
Adapted from Garrow et al. (2020).

several studies have found that interest in AVs, EVs, and sharing technologies is associated to a greater extent with individuals who are younger, more educated, have higher incomes, and are male (e.g., Dong et al., 2019; Hudson et al., 2019; Kopp et al., 2015; Liu et al., 2019; Potoglou et al., 2020; Shabanpour et al., 2018; Spurlock et al., 2019; Vij et al., 2020; Wang & Zhao, 2019).

With respect to current travel patterns, Alemi et al. (2019) conducted a survey in 2015 of 1,191 millennials and 964 Generation Xers from California and found an association between ridesharing and air travel. Respondents who reported higher numbers of long-distance business trips and had a higher share of long-distance trips made by airplane were more likely to have used ridesharing.

A ride guarantee is one of the more interesting attributes associated with a mode that may be particularly relevant to air taxis. Several public transit organizations have guaranteed-ride-home programs in which they provide partial or full reimbursement for an alternate form of transportation home in the event of an illness, emergency, or similar unforeseen event. For representative examples of guaranteed-ride-home policies from Atlanta, Boston, San Francisco, and Los Angeles—four of the cities we included in our survey—see A Better City TMA (2020), Spare the Air (2020), Georgia Commute Options (2020), and LA Metro (2022). Given that air taxis will not be able to operate in some weather conditions, the provision of a guaranteed ride to and/or from work may be important in commuters' mode choice decisions and is one of the factors we include in our stated choice experiment.

Prior studies of mode choice have found that individuals prefer alternatives with shorter travel times, lower costs, and fewer transfers. A large body of research has investigated VOT and applied mixed logit models to incorporate a distribution of customer VOT preferences; see Train (2009, Chapter 6) for a general overview of mixed logit models and Hess et al. (2005) for a discussion on using mixed logit models to estimate VOT.

With respect to VOT for air taxi trips, several survey-based studies have been conducted. Fu et al. (2019) modeled the choice among private car, public transportation, autonomous ground taxi, and autonomous air taxi using a stated choice survey of 248 respondents from the Munich, Germany, metropolitan area that included both daily commuting and noncommuting private trips. The authors estimated VOTs for these four modes as 27.55, 27.47, 32.57, and 44.68 €/hour, respectively, which correspond to[4] 33.89, 33.79, 40.06, and 54.96 USD/hour, respectively. Based on 2,607 residents from Dallas–Ft. Worth and Los Angeles (many of whom were drawn from the Uber customer database), Song et al. (2019) estimated a latent class model and found VOTs ranging from 11.15 to 36.78 USD/hour for different travel time components. Based on a joint stated and revealed preference survey of more than 5,000 individuals in the Greater Jakarta region of Indonesia, Ilahi et al. (2021) estimated multinomial and mixed logit models that considered multiple travel purpose and included existing modes as well as two emerging modes: on-demand ground transport and UAM. The authors found that UAM demand is sensitive to cost and that a 1 percent increase in travel cost for UAM would reduce the probability of choosing UAM by 2.07–9.55 percent.

Previous studies of air taxi mode choice based on *stated choice* surveys have explored systematic heterogeneity in the VOT (e.g., by interacting cost by income), but we are aware of none that have investigated unobserved heterogeneity in VOT by applying a distribution to the time or cost parameters. Our paper helps address this gap in the literature by using random taste parameter models with panel effects to account for both systematic and unobserved variation in individuals' VOT using a stated choice survey. Our paper complements work by Rimjha et al. (2021a, 2021b) that estimated mode choice for an air taxi service for commute trips and trips to airports based on *revealed preference* surveys and datasets. That is, Rimjha and colleagues first estimated a model based on existing modes and then incrementally added in a UAM alternative to conduct their analysis. The mode choice models by Rimjha and colleagues incorporated a negative lognormal distribution on cost to capture random taste preferences.

Our paper also complements work by several researchers who have added a UAM alternative to mode choice models that are part of traditional ground-based demand models. For example, Peksa and Bogenberger (2020) estimated demand for a UAM commuter

[4] An exchange rate of 1€ = 1.23 USD was used based on the average exchange rate in February to April 2018, when the survey data were collected (Pound Sterling Live, 2020).

network in Bavaria, Germany, by adding a UAM network with 11 vertiports into the existing ground transportation model developed in PTV-VISUM (PTV Group, 2022) for Munich and the surrounding area. The introduction of a UAM network resulted in network-level in-vehicle travel time savings across all modes of about 12,500 h per day for a base scenario. Rothfeld et al. (2021) also add a UAM mode to MATSim, an agent-based travel demand model calibrated for three geographies: the Munich Metropolitan Region, Île-de-France (i.e., the Paris area), and the San Francisco Bay Area. The authors found that the introduction of a UAM alternative would reduce the travel times by at least 1 min for a base case scenario for 3 percent of motorized trips in Munich, 7 percent in San Francisco, and 13 percent in Paris. Ploetner et al. (2020) added a UAM mode to an existing agent-based model for the Munich Metropolitan Area and examined the sensitivity of UAM demand to different UAM network designs and service levels. They found that 55 percent of UAM demand was concentrated on routes less than 10 km long and 84 percent on routes under 40 km, and that UAM market shares were around 1–4 percent, depending on the scenario and distance.

As seen from the literature review, researchers have shown much interest in quantifying potential UAM demand for different trip purposes, including commuters, but limited information has been published on individuals' willingness to pay for such a service. As Ploetner et al. (2020) note:

> "*to be able to estimate future UAM demand properly…a specific mode-choice model for urban air mobility for both commuters and other potential users (e.g., airport passengers) including all other relative alternative modes of transport (e.g., autonomous vehicles) have to be set up; this would require UAM-related stated preference surveys upfront.*"

To this end, our paper contributes to this gap in the literature by providing one of the first analyses of mode choice behavior for an air taxi service for commute trips under current transportation options (i.e., traditional auto and transit).

3. Survey

3.1. Overview

We conducted an internet-based stated choice survey from April to June 2018. Respondents from five U.S. Census–defined combined statistical areas (CSAs)—Atlanta, Boston, Dallas–Ft. Worth, Los Angeles, and San Francisco—were recruited through an online opinion panel service provider. These CSAs represent different transit usage, geographies, and morphologies. Boston and San Francisco have higher shares of commuting to work by transit than the other cities. Atlanta and Dallas–Ft. Worth are landlocked cities in the southeast and central U.S., respectively, that have low transit usage and exhibit development patterns that have expanded radially over time, resulting in CSAs with a circular shape. Boston, San Francisco, and Los Angeles are coastal cities in the northeast and west U.S. whose development patterns have been constrained by geographic features such as oceans and/or mountains, resulting in CSAs with a more elongated shape. These different development patterns can result in different distributions of commute distances. Additionally, in the context of UAM aircraft, average and maximum mission distances are key design parameters; thus, it is common to consider the range requirements for different cities when evaluating the potential of different aircraft designs (e.g., see Daskilewicz et al., 2018).

3.2. Alternatives, attributes, and choice sets

Four alternatives were included in the survey. Three of these alternatives (auto, transit, and rideshare) exist today, whereas the fourth (air taxi) is a potential future mode unfamiliar to the majority of respondents.[5] Consequently, we needed to provide a description of the air taxi service as part of the survey, and we included the following text:

NASA and many companies are spearheading research to develop an air taxi service for cities. The aircraft:

- *Are battery powered*
- *Carry two to four passengers*
- *Travel within a city at cruise speeds of 150 mph*
- *Could be used for getting to and from work faster*
- *Have efficient security checks with no lines*
- *Take off and land vertically like a helicopter*
- *Take off and land at locations in a city such as tops of buildings and parking decks*
- *Have a ride quality and cabin noise level similar to large aircraft*
- *Are much quieter than helicopters, both for the community and for the occupants of the aircraft*
- *Travel at about the altitude where traffic helicopters fly*
- *Are flown by certified pilots*
- *Do not fly in hazardous weather conditions (such as thunderstorms)*
- *Meet stringent safety requirements mandated by the U.S. Federal Aviation Administration*

[5] In an unpublished survey that we conducted for an aircraft manufacturer in Fall 2019 in three U.S. cities, we explicitly asked about respondents' familiarity with urban air mobility. In that survey, a total of 69 percent of the respondents indicated that they were unfamiliar with the concept of urban air mobility.

After this description, we provided images of representative eVTOL designs, including those of Airbus, Joby, Kitty Hawk, and Lilium (see City Airbus, 2018; Joby, 2018; Kitty Hawk, 2018; and Lilium, 2018 for representative images).

In describing the UAM service, we intentionally noted "NASA and many companies are spearheading research" in the positioning, as this is reflective of what is occurring within the U.S. The U.S. National Aeronautics and Space Administration (NASA) has been playing an important role in UAM development. Based on a metanalysis of unique authors who published UAM-related work in the American Institute of Aeronautics and Astronautics (AIAA) database published from 2015 to June 2020, Garrow et al. (2021) found that 31 percent were affiliated with NASA. We recognize that our description of the air taxi service is generally positive and that statements such as "are flown by certified pilots" and "take off and land at locations in a city such as tops of buildings and parking decks" are not universally accepted across aircraft manufacturers and countries as the most likely vision for the future, but these descriptions do consistently describe a common vision for an air taxi market in the U.S. (e.g., see Antcliff et al., 2019; Dietrich, 2020).

Furthermore, given that this is one of the first surveys to explore whether individuals would be interested in using an air taxi for commuting, describing the air taxi alternative in generally positive terms allows us to explore whether—even under the "most favorable" conditions—individuals are willing to consider air taxi as a commute mode. Stated another way, if we see from our survey that individuals do not choose air taxi even when it is portrayed positively, then an air taxi commuting service will likely not be viable under less favorable market conditions. In this context, our survey provides an initial assessment (possibly more favorable) of how many individuals would be willing to consider air taxi for commuting purposes at the time the service is initially introduced, given different cost, time, and other factors.

The number of individuals willing to adopt air taxi as a commuter mode would potentially increase over time as individuals become more comfortable with the technology. For example, two surveys by Al Haddad et al. (2020) and Leonard et al. (2021) asked respondents how long after air taxis entered the market would they consider using one. The survey by Al Haddad et al. (2020) found that of the 221 respondents, 3 percent would never use a UAM and 21 percent were uncertain of their adoption timeline for UAM, while 22 percent would adopt UAM during its first year, 37 percent in the second or third year of operation, 14 percent in the fourth or fifth year, and 3 percent during the sixth year. The survey by Leonard et al. (2021), based on about 2,800 respondents, found that 9.5 percent would never use an air taxi and 31 percent would use an air taxi in the first year of operation, 33 percent in the second or third year of operation, 18 percent in the fourth or fifth year of operation, and 10 percent in the sixth year of operation or later (Hill & Garrow, 2021). If the initial consumer base and interest in the air taxi service is small, then the costs of introducing and sustaining the air taxi service until adoption can increase to the point of achieving a profitable service will likely be prohibitive.

Five attributes were presented as part of our stated choice experiment: cost, in-vehicle travel time (IVTT), out-of-vehicle travel time (OVTT), a ride guarantee, and a transfer. These attributes are consistent with those included in other mode choice models used for air taxi applications (e.g., Fu et al., 2019; Ilahi et al., 2021; Rimjha, et al., 2021a, 2021b; Song et al., 2019). The key distinction across these prior surveys is that Fu et al. (2019) included additional attributes for UAM safety levels and multi-tasking possibilities.

Table 1 shows the range of levels used for each of the attributes in the survey. The levels used for cost and IVTT were customized based on whether the respondent's one-way travel time to work was less than 24 miles, 25–39 miles, 40–54 miles, or more than 55 miles.

Following the approach described in Binder et al. (2018), we set the range of prices of the eVTOL ride based on estimates reported in current literature. Uber is targeting eVTOL prices of 5.73 USD per passenger mile (pax-mile) at launch, 1.84 USD per pax-mile in the near term, and 0.44 USD per pax-mile in the long term (Holden, 2018). A study conducted for NASA forecasts the costs of five-seat eVTOL at 6.25 USD per pax-mile in the near term, but "in the long term, operational efficiency, autonomy, technology improvements may decrease costs by 60 percent" (which would bring costs down to 2.50 USD/pax-mile) (Hamilton, 2018). To put these costs in context, in recent studies the average operating cost of helicopters is reported to be 8.93 USD per pax-mile by Holden (2018) and 6–8 USD per seat mile[6] by Johnson et al. (2020), whereas the average cost per mile of auto ownership in 2017 was 0.592 USD (American Automobile Association [AAA], 2017).[7] Given that our goal is to determine if there might be a viable market for launching air taxi service before the lower long-term costs per passenger mile are realized, we set the prices in a range we believe would be aggressive but realistic in the short-term after launch, and targeted our sampling plan to higher-income individuals with long commutes—i.e., those with both the motivation and the means to pay a premium for a shorter commute. Specifically, we set the air taxi prices from about 0.50 to 1.50 USD per pax-mile in the survey.

Out-of-vehicle travel times include wait time (for ridesharing), access/egress times (for transit and air taxi), and transfer time (for transit). The ride guarantee applied to the transit and air taxi modes, and was described as follows (using the eVTOL alternative for illustrative purposes):

> *"In the event that the eVTOL option is not available (for example, due to bad weather), a ride guarantee makes sure you receive priority for taking a Lyft or Uber car. To compensate you for the inconvenience, the rideshare option would be discounted and you would pay less than what the cost of an eVTOL flight would have been."*

Transfers applied only to the transit option. Refer to Binder et al. (2018) for additional details.

[6] Within the airline industry, revenue passenger mile (RPM) and available seat mile (ASM) are more common definitions used. RPMs refer to miles flown by paying customers, and ASMs refer to actual seats available for sale.

[7] The cost per mile estimate includes the full cost of auto vehicle ownership; however, individuals may only consider the marginal cost of auto ownership (e.g., fuel and parking) when making a mode choice decision. Using an estimate for the full cost of auto vehicle ownership may bias the predictions in favor of non-auto modes.

Table 1
Range of levels used for attributes by one-way commute distance.

	0–24 miles	25–39 miles	20–54 miles	55+ miles
Cost for air mode ($)	5–10	5–20	10–40	20–45
Cost for non-air modes ($)	2.5–5	2.5–5	4–10	5–20
IVTT for air mode (min)	10–25	10–25	15–45	20–50
IVTT for non-air modes (min)	30–60	30–75	60–105	60–120
OVTT for non-auto modes (min)	10–20			
Ride guarantee for air and transit	Yes/No			
Transfer for transit	Yes/No			

Each respondent was shown eight different choice scenarios with two alternatives as part of each choice scenario: one reflecting their current commute mode (drive, transit, or rideshare) and the second reflecting the new mode (air taxi). A stated choice experiment using a D-efficient design with blocking was used to create the choice scenarios using macros in SAS (Kuhfeld, 2010). The design provides information on the combination of the levels associated with the attributes shown to a respondent in a single choice scenario and how many different scenarios need to be shown to a respondent. For situations in which the recommended design contains a large number of choice scenarios, it is common to divide the design into blocks. In our application, the recommended design included 32 choice scenarios and four blocks that contain eight choice scenarios were created. A respondent was shown one of these four blocks.

We recognize that by including only two alternatives in the choice set, our mode choice estimations are potentially confounding inertia effects with mode preferences. However, the dominance of the auto mode among the target demographic (upper income commuters) would have made these effects difficult to disentangle even with a more complex set of survey questions, so we restricted the choice scenarios to the current commute mode and the new mode to simplify the survey as presented to participants.

An example of a choice set shown to an individual who currently commutes by auto is shown in Fig. 2, and an example for an individual who currently commutes by transit is shown in Fig. 3.[8]

3.3. *Sample statistics*

The survey contained several sections that covered screening criteria, current travel patterns (both for commuting and air travel), attitude and opinions related to travel, personality and lifestyle traits, demographics, perceptions of the air taxi service, and the stated choice experiment. Table 2 shows the sociodemographic and typical commuting and air travel characteristics of the sample before screening criteria were applied. Only those individuals who were full-time workers, traveled to a work location outside the home at least two days per week, and had an annual income of 100 K USD or more were eligible to participate. In addition, a priority was placed on recruiting individuals who had one-way commute times in excess of 30 min. The initial focus on higher-income households with longer one-way commute times was designed to reflect those individuals who would be most likely to initially adopt a commuter air taxi service.

A total of 2,499 individuals completed the survey. The distributions shown in Table 2 were compared to population characteristics for the U.S. population, as well as the populations within each of the represented CSAs using census data. The sample data are similar to census data in terms of gender, number of children in the household, and the typical mode used to commute to work. Compared to census data, the sample has a higher percentage of two-adult households with higher educational attainment levels that are in the 25–64-year age range; this is consistent with the qualification criteria that individuals are required to be working full-time and earn at least 100 K USD to qualify for the study. Vehicle ownership is higher in the sample, with just 1.2 percent of households not owning a vehicle, compared to 9.5 percent based on census data for these regions. Respondents were much more likely to have used rideshare modes, with 77 percent having done so compared to 40 percent in the 2017 National Household Travel Survey (NHTS; FHWA, 2018). This rideshare experience is relevant because phone apps similar to those used by current automobile rideshare providers have been envisioned for air taxi service. Almost one in five respondents owns or leases a hybrid vehicle, which is also important from the standpoint that these respondents have experience with ground vehicles partially powered by batteries, which is another of the technologies envisioned for air taxi aircraft.

As part of the analysis, we also examined if and how SED characteristics varied across the cities in the sample using a chi-square analysis. While the complete details of this analysis are outside the scope of the current paper, the major differences can be summarized as follows. Atlanta respondents were slightly more likely to be within the ages of 18–24 and have no children, and Boston respondents were more likely to be female, have no children, take transit to work, travel by air less frequently, and never have taken rideshare. Dallas respondents were more likely to drive to work, have two vehicles, and be within the ages of 35–44 and earn 100–149 K USD per year. Los Angeles respondents were more likely to be males from households with two adults and no children, drive to work, have longer average one-way commute times, and own a hybrid vehicle, whereas those in San Francisco were more likely to earn between 100 and 149 K USD per year, take transit to work, rideshare at least once a week or more, and own a hybrid vehicle.

These differences across cities are consistent with our *a priori* expectations, e.g., Los Angeles is infamous for long commute times and for having some of the most congested interstate systems in the nation (Romero, 2016), which is likely reflected in longer average

[8] The images shown in Fig. 2 and Fig. 3 are reprinted from the Creative Commons attribution licenses (Kaito, 2018; iconsDB.com, 2018; Vicons Designs, 2018).

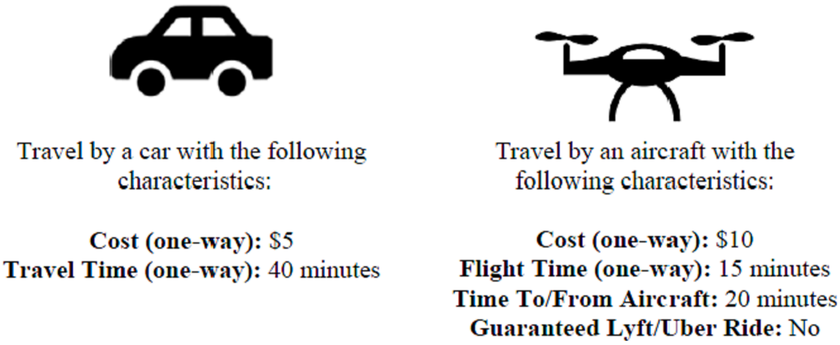

Fig. 2. Example of a choice set that contains auto and air taxi.
Kaito, 2018; iconsDB.com, 2018

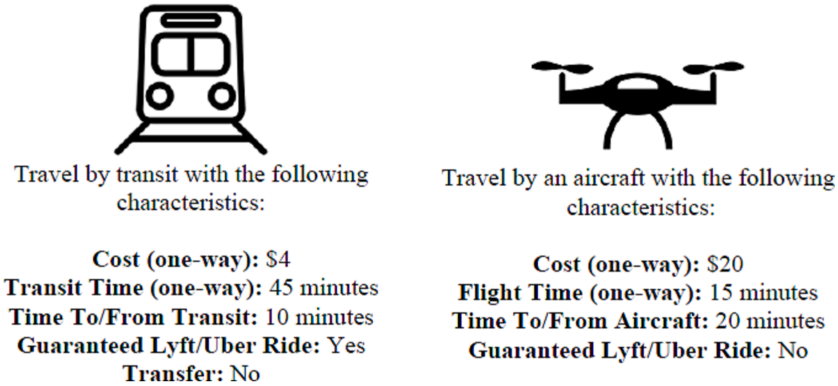

Fig. 3. Example of a choice set that contains transit and air taxi.
Kaito, 2018; Vicons Designs, 2018

one-way commute times. Among the cities in the sample, San Francisco has one of the better transit systems and has a reputation for being an incubator of new technologies (Rampton, 2014), which is likely reflected in the higher usage of ridesharing in this area. Finally, California has a reputation for being a leader in environmentally friendly policies (Hubbard, 2021), which is likely reflected in the higher ownership of hybrid vehicles in San Francisco and Los Angeles.

Although the sample is not representative of the population in every way, the primary purpose of this study is to uncover relationships among variables rather than purely to describe a population (Babbie, 2009; Groves, 1989, Chapter 1). For example, if the sample were used to estimate the true share of income in the population, the lack of a fully representative sample would be problematic, but a model based on the sample can properly model commuting air taxi usage given income.

3.4. Non-trader analysis

Consistent with the approach of other researchers, including Correia et al. (2019), we distinguished between traders and non-traders in our analysis. Non-traders "may have a major influence on the estimated marginal utility coefficients, which are used to derive the value of travel time" (Hess et al., 2010, as quoted in Correia et al., 2019). A non-trader is defined as a respondent who always chooses the same alternative across all of the choice sets. Among the 2,499 respondents in our sample, 348 (13.7 percent) always selected a traditional mode and 358 (14.3 percent) always selected the air taxi mode. Intuitively, this percentage of non-traders may seem high, but it is consistent with other studies. For example, based on a survey that measured preferences for AVs, Correia et al. (2019) conducted a stated choice experiment that included eight scenarios and found that 29 percent exhibited non-trading behavior.

Multiple reasons have been noted in the literature for non-trading behavior, e.g., "(1) a respondent has an extreme preference for one alternative; (2) a respondent gets bored or does not take the survey seriously; or (3) a respondent makes a political or strategic decision" (Correia et al., 2019). Given that the underlying causes for non-trading behavior cannot be determined from our survey, we estimated models that included all respondents (traders and non-traders) as well as those models that only included traders.

4. Methodology

We estimated various logit-based discrete choice models, including the multinomial logit (MNL), and a mixed logit (ML) model that

Table 2
Sociodemographic and typical commuting and air travel characteristics of the sample.

Characteristic	Category	Sample Number (%)
Annual individual income in USD (N = 2,499)	$100–149.9 K	1,375 (55.0)
	$150–199 K	598 (23.9)
	$200 K or more	526 (21.0)
Gender (N = 2,499)	Female	1,173 (46.9)
	Male	1,326 (53.1)
Age (N = 2,473)	18–24	101 (4.1)
	25–34	395 (16.0)
	35–44	652 (26.4)
	45–54	607 (24.5)
	55–64	559 (22.6)
	65+	159 (6.4)
Number of adults in household (N = 2,478)	1 adult	381 (15.3)
	2 adults	1,631 (65.8)
	3 or more adults	466 (18.8)
Number of children in household (N = 2,499)	No children or missing data	1,367 (54.7)
	1 child	464 (18.6)
	2 children	487 (19.5)
	3 or more children	181 (7.2)
Highest educational level (N = 2,499)	Some college with no degree or less education	267 (10.7)
	Associate's degree	140 (5.6)
	Bachelor's degree	1,070 (42.8)
	Master's degree	667 (26.7)
	Professional or doctorate degree	355 (14.2)
Number of household vehicles (N = 2,499)	No vehicles	31 (1.2)
	1 vehicle	668 (26.7)
	2 vehicles	1,247 (49.9)
	3 or more vehicles	553 (22.1)
Owns a hybrid vehicle (N = 2,468)	Owns hybrid	449 (18.2)
	Does not own hybrid	2,019 (81.8)
Number of annual air trips (N = 2,499)	1 round trip (RT) per week or more	146 (5.8)
	1–3 RTs per month	434 (17.4)
	7–11 RTs per year	554 (22.2)
	1–6 RTs per year	1,079 (43.2)
	Fewer than 1 RT per year	286 (11.4)
Typical mode to work (N = 2,491)	Auto and other (e.g., motorcycle, vanpool)	2,093 (84.0)
	Transit	219 (8.8)
	Bike or walk	84 (3.4)
	Ride share	95 (3.8)
Rideshare usage (N = 2,499)	At least once a week	262 (10.5)
	2–3 times per month	475 (19.0)
	Once a month	270 (10.8)
	4–11 times per year	321 (12.8)
	2–3 times per year	346 (13.8)
	Once a year or less	258 (10.3)
	Never	567 (22.7)
Self-reported one-way travel time to work (N = 2,499)	1–19 min	446 (17.8)
	20–39 min	714 (28.6)
	40–59 min	667 (26.7)
	60–89 min	476 (19.0)
	90 + minutes	196 (7.8)

is a random taste parameter model with panel effects (McFadden, 1974; Train, 2009). In all of the discrete choice models we estimated, we model the mode choice, y_{nik}, for an individual, n, who chooses alternative i from one of the k choice-scenarios questions the respondents were shown on the survey as in Equation (1):

$$y_{nik} = \begin{cases} 1 & \text{if individual } n \text{ chooses mode } i \text{ from tradeoff question } k \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

The systematic utility V for individual n in choosing alternative i from choice set J_n is a linear function of $\boldsymbol{x}_{nik}$, written $V_{nik} = \boldsymbol{\beta}_i^{'}\boldsymbol{x}_{nik}$, where $\boldsymbol{x}_{nik}$ is a vector comprising the alternative characteristics and sociodemographic characteristics of the individuals, and $\boldsymbol{\beta}_i^{'}$ is the transpose of the vector of coefficients associated with all variables. This systematic utility is added to a random utility ε_{nik} to yield the total utility, $U_{nik} = V_{nik} + \varepsilon_{nik}$. If ε_{nik} is distributed independently and identically with a Gumbel (or extreme value type I) distribution, the probability of individual n choosing alternative i in choice scenario k_n, which we denote as P_{nik}, is given as in Equation (2):

$$P_{nik}(\boldsymbol{x}_{nik}) = \Pr(y_{nik} = 1 \mid \boldsymbol{x}_{nik}) = \frac{e^{V_{nik}}}{\sum_{j \in J_n} e^{V_{njk}}} = \frac{e^{\boldsymbol{\beta}_i^{'}\boldsymbol{x}_{nik}}}{\sum_{j \in J_n} e^{\boldsymbol{\beta}_j^{'}\boldsymbol{x}_{njk}}} \tag{2}$$

This probability function is for models where the vector of parameters $\boldsymbol{\beta}$ potentially varies over alternatives i, but is a known fixed value (i.e., the same constant value) for all individuals n. Later we will relax this restriction, but for models that are consistent with this assumption (i.e., the MNL model), we can convert the probability to a likelihood function for each observation by taking the vector of parameters $\boldsymbol{\beta}$ as variable, and the data $\boldsymbol{x}$ as given, writing:

$$L_{nik}(\boldsymbol{\beta}) = \Pr(y_{nik} = 1 \ |\boldsymbol{\beta}) = \frac{e^{V_{nik}}}{\sum_{j\in J_n} e^{V_{njk}}} = \frac{e^{\boldsymbol{\beta}_i^{'}\boldsymbol{x}_{nik}}}{\sum_{j\in J_n} e^{\boldsymbol{\beta}_j^{'}\boldsymbol{x}_{njk}}} \tag{3}$$

We use maximum likelihood estimators to solve for the parameter estimates by maximizing the joint likelihood function as in Equation (4):

$$L(\boldsymbol{\beta}) = \prod_{n=1}^{N}\prod_{k=1}^{K}\prod_{i\in J_n}(L_{nik}(\boldsymbol{\beta}))^{y_{nik}} \tag{4}$$

Or, equivalently, by maximizing the log-likelihood (LL) as in Equation (5):

$$LL(\boldsymbol{\beta}) = \sum_{n=1}^{N}\sum_{k=1}^{K}\sum_{i\in J_n} y_{nik}\ln L_{nik}(\boldsymbol{\beta}) \tag{5}$$

The MNL model, while one of the most frequently used discrete choice models in practice, has two main limitations that are of particular concern for our application. The MNL model does not incorporate a distribution of values of time, and it does not incorporate correlation across observations. That is, in our application, since we have K responses from each individual, the assumption that ε_{nik} is independent across observations is problematic, since we expect the responses from each individual to be correlated with each other. These limitations can be addressed using a mixed logit model that is a random taste parameter model that incorporates panel effects. In the ML model, one or more of the $\boldsymbol{\beta}$ parameters are no longer fixed values that represent "average" population values, but rather are random realizations from the density function $f(\boldsymbol{\beta}|\boldsymbol{\omega})$, where $\boldsymbol{\omega}$ is a vector that parameterizes the distribution of $\boldsymbol{\beta}$. The ML choice likelihoods are expressed as the integral of logit likelihoods evaluated over the density of distribution parameters, or as in Equation (6):

$$L^{mixed}(\boldsymbol{\omega}) = \prod_{n=1}^{N}\int\prod_{k=1}^{K}\prod_{i\in J_n}(L_{nik}(\boldsymbol{\beta}_n)f(\boldsymbol{\beta}_n|\boldsymbol{\omega}))^{y_{nik}}d\boldsymbol{\beta}_n \tag{6}$$

where $L_{nik}(\boldsymbol{\beta}_n)$ is a logit probability evaluated at the vector of parameter estimates $\boldsymbol{\beta}_n$ that are random realizations from the density function $f(\boldsymbol{\beta}_n|\boldsymbol{\omega})$, and $\boldsymbol{\omega}$ is a vector of parameter estimates associated with that density function. In a mixed logit model, L_{nik} takes the MNL form. Similar to the MNL model, we use maximum likelihood estimators to solve for the parameter estimates, but in this case, we maximize a simulated log-likelihood function:

$$\widehat{LL}(\boldsymbol{\omega}) = \sum_{n=1}^{N}\ln\sum_{r=1}^{R}\prod_{k=1}^{K}\prod_{i\in J_n}(L_{nik}(\boldsymbol{\beta}_n))^{y_{nik}} \tag{7}$$

where, instead of calculating L_{nik} once for a fixed vector of $\boldsymbol{\beta}$, an average value is calculated across R draws. Unfortunately, for datasets like this that have more than one response from each individual, this log likelihood does not collapse neatly. The simulated (average) likelihood must be computed over all K responses from each individual, to account for the stability of individual preferences (i.e. the likelihood for all the choices needs to be evaluated jointly for each random draw of $\boldsymbol{\beta}$ preferences). Nevertheless, this simulated log-likelihood remains tractable, and is statistically efficient for estimating the parameters of a random taste parameter model with panel effects.

We used Larch (Newman, 2020) and PyTorch (Paszke et al., 2019) to estimate the discrete choice models and evaluated the integral for the random taste parameter models with panel effects using 250 Latin hypercube draws based on the simulated log-likelihood function given in Equation (7). Estimation results were based on 19,064 observations for the dataset that included both traders and non-traders and 13,744 for the trader-only dataset.[9] We verified that the number of draws produced stable results.[10] We used a forward stepwise regression approach to determine which variables to include in the utility functions. Specifically, we started with a base utility specification that included constants and modal attributes such as time, cost, and a ride guarantee; we then entered in each of the SED variables one at a time and ranked them according to which best fit the data. Then, we sequentially added variables to the base

[9] Of the 2499 respondents, 95 were screened out because they frequently took ridesharing service to work and another 21 were screened out because they did not pass quality control checks. The total number of respondents used for mode choice modeling is 2,383. Given each respondent was shown 8 choice scenarios, the total number of observations for the dataset that includes traders and non-traders is 2,383 × 8 = 19,064. Similar logic applies to the calculation of observations used for the trader-only dataset.

[10] We estimated three models that used 250, 1000, and 5000 draws. With the exception of the insignificant parameter estimate for the transit alternative-specific constant (ASC) that varied from −0.0297 to −0.0334, all parameter estimates differed by less than 1.0 percent across the three models.

specification, starting with those variables that had the largest improvement in log-likelihood values from the stepwise regressions. We dropped those variables that were statistically insignificant and/or had counterintuitive signs from the final model specifications. Finally, we sequentially interacted each significant SED variable to incorporate systematic taste preferences in VOTs. Specifically, we evaluated systematic heterogeneity with respect to time, and with respect to cost, and with respect to time and cost simultaneously. We found the last of these to generate unstable parameter results during estimation, as the quantity of estimation data was probably not sufficient to support such a complex model. Given variation in preferences of either cost or time can result in heterogeneous representations of VOT, we chose to focus in the results section on the best fitting results that interacted SED variables with cost.

We investigated heterogeneity in VOT by estimating models that used a triangular or negative lognormal distribution for cost and/ or time variable. Given that the negative lognormal distribution on cost best fit the data and produced stable results, we also estimated the thresholds of a truncated lognormal distribution to explore the robustness of results on the tail of the distribution.

We also investigated heterogeneity in unobserved preferences for the modes by assuming ASCs were normally distributed. Theoretically, it is possible to identify and add mixture distributions for $J - 1$ alternatives included in this mode choice model given the structure of the data. However, there are very few observations in our dataset for which individuals chose transit, so adding in two mixtures was numerically unstable. Thus, we present results that added a normal distribution to the air taxi constant.

5. Results and discussion

This section discusses the results from the discrete choice analysis and is organized into four parts. The first part covers the baseline model that is a mixed logit model that incorporates panel effects and includes random taste variation for the air taxi mode. The second part discusses differences between models that include all observations versus those that include only responses from traders. The third part explores how VOTs vary across the population when various distributions are assumed for cost, and the fourth part extends these models to include systematic taste variation.

5.1. Baseline model

Table 3 summarizes estimation results for random coefficient models with panel effects that incorporated distributions for the air taxi constant and cost. Model 1 is the baseline model that includes only traders and assumes the air taxi constant is normally distributed.

With respect to characteristics associated with the individual, few of the sociodemographic characteristics we investigated were statistically significant. Men were more likely to choose an air taxi compared to women (coefficient of 0.0802), and those with children were relatively more likely to take transit or air taxi compared to auto (coefficient of −0.180 associated with auto). In terms of age, those ages 65 or older (who are still working full time) were more likely to take transit for commuting compared to other age groups and modes (coefficient of 1.66). In general, older individuals (between the ages of 35 and 64) were more likely to take air taxi than younger individuals (between the ages of 18 and 34). This is seen by the smaller coefficient associated with ages 35–64 with the age coefficient on auto (0.205) compared to ages 18–34 for auto (0.361). Many other individual characteristics, including household income (above the qualification criteria of 100 K USD), education level, and number of annual air trips typically taken, as well as current commute characteristics including travel times, typical congestion levels experienced, and auto availability (expressed as vehicles per adult in the household), were not statistically significant and/or ranked very low in the stepwise regression analysis. Our results are consistent with the ground transportation literature, which has found that interest in autonomous vehicles and on–demand transport is associated more with individuals who are younger and/or male (e.g., see Dong et al., 2019; Hudson et al., 2019; Vij et al., 2020).

Characteristics related to the individuals' prior exposure to new technologies were strong predictors of mode choice. Rideshare frequency was one of the variables that ranked highest in the forward regression. With respect to rideshare frequency, those who travel more frequently are more likely to take air taxi or transit. The coefficients associated with ridesharing frequency and auto are negative and generally more negative as frequency increases. Those who rideshare once a week or more, two to three times a month, about once a month, and between two and eleven times a year are more likely to take air taxi or transit compared to those who have never taken rideshare or only take rideshare once a year or less. Interestingly, current air travel frequency was not as strong a predictor as rideshare frequency in our data. Our finding that rideshare frequency is associated with intention to use air taxis is consistent with a survey conducted by Airbus of 1,540 individuals from Los Angeles, Mexico City, New Zealand, and Switzerland, which found that interest in UAM was higher among males and those who frequently use ridesharing services (Yedavalli & Mooberry, 2019).

Values of time are commuted as in Equation (8):

$$VOT_{i,n} = \frac{\delta V_{i,n} / \delta T_{i,n}}{\delta V_{i,n} / \delta C_{i,n}} = 60 \times \frac{\beta T}{\beta C} \tag{8}$$

where $V_{i,n}$ represents the systematic utility for alternative i and individual n; $T_{i,n}$ represents a travel time component (in minutes) for alternative i for person n (e.g., auto IVTT, air taxi OVTT); and $C_{i,n}$ represents the cost. The parameter estimates for time (in minutes) and cost (in dollars) are represented by βT and βC, respectively, and 60 is used to convert the expression from USD per minute to USD per hour.

The VOTs associated with Model 1 range from \$25 to \$28 USD/hour across the different modes. These values are in line with the study by Song et al. (2019) that was based on U.S. data and found a range of 11.15–36.78 USD/hour for various travel time

Table 3
Estimation results for random coefficient models that exclude interaction terms.

	Model 1 Traders	Model 2 All Data	Model 3Neg LN Traders	Model 4Trunc Neg LN Traders
Constants				
Auto (ref.)	0	0	0	0
Transit	−0.141 (−0.5)	−0.821 (−1.9)	−0.0521 (−0.2)	−0.0562 (−0.2)
Air taxi	−0.931 (−5.9)	−2.14 (−8.1)	−0.796 (−4.6)	−0.789 (−5.1)
Air taxi std. dev.	0.855 (25.)	2.31 (39.)	0.685 (14.)	0.679 (15.)
In-vehicle travel time				
Auto	−0.0731 (−41.)	−0.0720 (−38.)	−0.0741 (−39.)	−0.0741 (−41.)
Transit	−0.0647 (−15.)	−0.0691 (−14.)	−0.0713 (−14.)	−0.0710 (−15.)
Air taxi	−0.0694 (−22.)	−0.0703 (−20.)	−0.0716 (−22.)	−0.0714 (−23.)
Out-of-vehicle travel time	−0.0634 (−16.)	−0.0662 (−16.)	−0.0671 (−16.)	−0.0669 (−17.)
Cost	−0.158 (−35.)	−0.161 (−32.)		
Cost (Log-Normal)			−1.77 (−43.)	−69.1 (−0.3)
Cost (Log-Normal) std. dev.			0.735 (20.)	9.73 (0.6)
Cost – left truncation				−0.828 (−8.2)
Cost – right truncation				−0.0727 (−14.)
Ride guarantee	0.670 (17.)	0.675 (17.)	0.694 (17.)	0.695 (18.)
Male (air)	0.0802 (1.5)	0.301 (2.8)	0.144 (2.6)	0.139 (2.9)
Presence of children (auto)	−0.180 (−3.0)	−0.619 (−4.9)	−0.181 (−2.9)	−0.176 (−3.5)
Age				
18–34 (auto)	0.361 (2.7)	−0.177 (−0.7)	0.331 (2.3)	0.332 (2.8)
35–64 (auto)	0.205 (1.7)	−0.331 (−1.5)	0.114 (0.9)	0.112 (1.0)
65+ (transit)	1.66 (3.0)	2.94 (3.4)	1.72 (3.0)	1.70 (2.9)
Rideshare frequency				
1 × a year or less & never (ref.)	0	0	0	0
Once a week or more (auto)	−0.731 (−6.0)	−1.79 (−7.6)	−0.601 (−4.9)	−0.593 (−5.6)
Two or three × a month (auto)	−0.563 (−6.4)	−1.51 (−8.6)	−0.497 (−5.5)	−0.487 (−6.2)
About once a month (auto)	−0.434 (−4.1)	−1.20 (−6.0)	−0.380 (−3.5)	−0.375 (−4.0)
About 4 to 11 × a year (auto)	−0.235 (−2.5)	−0.782 (−4.2)	−0.219 (−2.2)	−0.220 (−2.7)
About 2 or 3 × a year (auto)	−0.240 (−2.6)	−0.499 (−2.8)	−0.238 (−2.5)	−0.227 (−2.7)
Once a month or less (tr.)	−0.361 (−2.2)	−0.915 (−2.8)	−0.297 (−1.6)	−0.294 (−1.9)
Model Statistics				
# obs; # parameters (z)	13,744; 20	19,064; 20	13,744; 21	13,744; 23
LL at zero $LL(0)$	−9,526.61	−13,214.16	−9,526.61	−9,526.61
LL at constants $LL(C)$	−9,514.63	−13,202.42	−9,514.63	−9,514.63
LL at convergence $LL(\beta)$	−7,508.67	−9,381.46	−7,393.23	−7,389.90
ρ_0^2; $\overline{\rho}_0^2$	0.2118; 0.2097	0.2900; 0.2885	0.2239; 0.2217	0.2243; 0.2219
ρ_c^2;$\overline{\rho}_C^2$	0.2108; 0.2090	0.2894; 0.2881	0.2230;0.2210	0.2233; 0.2211

Notes. Parameter estimate (t-stat); models estimated using 250 draws; × = times; Neg LN = negative lognormal; Trunc Neg LN = truncated negative lognormal; air = air taxi; tr. = transit; ref. = reference; LL = log-likelihood; $\rho_0^2 = 1 - \frac{LL(\beta)}{LL(0)}$; $\rho_c^2 = 1 - \frac{LL(\beta)}{LL(C)}$; $\overline{\rho}_0^2 = 1 - \frac{LL(\beta) - z}{LL(0)}$; $\overline{\rho}_C^2 = 1 - \frac{LL(\beta) - z}{LL(C) - 3}$. Koppelman and Bhat (2006) pages 81–82 were used as the reference for calculating adjusted rho-square values.

components, but lower than the study by Fu et al. (2019) that was based on data from Germany and found a range of 33.79–54.96 USD/hour.

5.2. Analysis of traders and non-traders

To compare the sensitivity of results to the exclusion of non-traders from the estimation dataset, we compared the baseline Model 1 that used responses from traders to a model that used responses from both traders and non-traders; this latter model is reported as Model 2 in Table 1. The results between Models 1 and 2 are similar in the sense that they provide same directional interpretation for the parameter estimates, with the exception of age. The relative importance or magnitude of parameter estimates varies across these models, but as shown in Table 4, the VOTs are similar across the models.

The key difference between Models 1 and 2 is in the parameter estimate associated with the air taxi constant. Since ASCs capture the average effect on utility of all factors that are not included in the model, we can interpret the standard deviation of the air taxi constant as the variation in the overall preferences for air taxi in the population due to factors left out of the model. As an example, consider two scenarios. In the first scenario, we assume that the majority of the survey respondents enjoy flying; in the second scenario, we assume that half of the survey respondents enjoy flying and half fear flying. The estimated standard deviation under the second scenario should be larger than under the first scenario as there is more variation in unobserved preferences related to enjoyment and fear of flying. Similarly, for Model 2 that includes traders who selected multiple modes, non-traders who only selected auto or only selected transit, and non-traders who only selected air, the coefficient associated with the standard deviation of the air taxi constant is much larger (coefficient of 2.31) versus when only data from traders are used (coefficient of 0.855).

As noted previously, multiple reasons have been noted in the literature for non-trading behavior. While it is difficult to distinguish among these effects, we can investigate the hypothesis that straight-lining behavior is related to one's like or dislike of flying by examining how often respondents agreed or disagreed with the following two statements related to air travel: (1) "I like traveling by airplane" and (2) "Traveling by air makes me nervous." Table 5 compares the distribution of responses to these two statements for respondents who always selected auto or always selected transit, respondents who always selected air taxi, and respondents who selected a mix of modes across the choice scenarios. Some differences are evident among traders and non-traders related to their like or dislike of flying. For example, those who always selected auto or always selected transit are less likely to agree or strongly agree with the statement "I like traveling by airplane." The percentages agreeing or strongly agreeing with this statement are 53 percent for non-traders who always selected auto or always selected transit, 68 percent for those who selected a mix of modes, and 79 percent for non-traders who always selected air taxi. The percentages agreeing or strongly agreeing with the statement "Traveling by air makes me nervous" are 31 percent for non-traders who always selected auto or always selected transit, 22 percent for those who selected a mix of modes, and 19 percent for non-traders who always selected air taxi. Thus, while we see some association between liking to travel by airplane and non-trading behavior (particularly for those who always selected the air mode), this alone does not fully explain the non-trading responses.

We can gain additional insights into underlying motivations among the population that never chose an air taxi from another question we asked on the survey. Specifically, for those respondents who never selected the air taxi, we asked: "Is there anything that would change your mind/any circumstances under which you would take an eVTOL aircraft?" If they answered "yes," we asked them to describe these circumstances. Of the 358 respondents who never selected air taxi in our survey, 78 (22 percent) indicated that there were circumstances under which they would consider taking an eVTOL aircraft. These text responses are provided in Table 6. More than one third of these respondents noted that they would consider using the air taxi if it had a proven safety record, and 26 percent indicated that they did not want to be the first one to use this new mode, but would consider it later (either because of safety issues or just in general once the operation was "proved to work"). A desire for lower costs, more time savings, and improvements in other convenience factors were noted by 23, 12, and 8 percent of these respondents, respectively. Convenience factors included statements related to the desire to have vertiports located closer to home and/or work locations, not having to make a transfer, having a guaranteed ride home, etc. About 19 percent of respondents indicated that an air taxi mode simply did not meet their current commute needs, e.g., the distance to work was not long enough, they needed a vehicle while at work, they could not take their dog to the office, etc. Finally, only 6 percent indicated they never selected an air taxi due to a fear of flying and 3 percent indicated they currently enjoyed their commute by driving. Other responses included concerns over what the ride would feel like and the desire to see these aircraft in person before taking the air taxi.

While this analysis provides some insights into the motivations for never selecting an air taxi on the choice survey, it is important to note that only 21 percent of the non-traders who never selected an air taxi indicated they would be open to using one in the future. For the remaining 78 percent, it is unclear how many are not trading because they do not like to fly versus survey fatigue or other reasons. Given the large number of non-traders seen in this survey, it would be valuable for the research community to investigate this issue in more depth and design surveys that could help distinguish between different underlying causes for non-trading behaviors.

5.3. Models that apply a distribution for the cost variable

Models 3 and 4 in Table 3 summarize the results from random taste parameter models with panel effects when various distributions are assumed for cost. Specifically, Model 3 assumes that the cost parameter has a negative lognormal distribution, and Model 4 assumes a truncated negative lognormal distribution. The mean and standard deviation parameters shown for Models 3 and 4 represent the respective moments of the underlying normal distribution, not the log normal distribution itself. The general interpretations related to individuals' characteristics, ridesharing frequency, and technology-related attitudes are similar to the baseline model described previously; thus, we focus the discussion here on results related to the value of time for OVTT and IVTT.

First, incorporating heterogeneity in individuals' willingness to pay improves the overall model fit. Where Model 1 has a log-likelihood value of −7,508.67 and a ρ_c^2 value of 0.2108, Model 3 has corresponding values of −7,393.23 and 0.2230, respectively. Second, using a truncated negative lognormal distribution only marginally improves the model fit and leads to identification issues; Model 4 has a log-likelihood value of −7,389.90, which is an sufficient level of improvement for a likelihood ratio test to reject Model 3. For these reasons, we focus the interpretation of results on Model 3.

Fig. 4 shows the value of time distribution and confidence intervals for Model 3, calculated via numerical simulation. The mean in-vehicle VOTs for the air taxi mode is 33.05 USD/hr and the 95 % confidence interval is 29.01–37.43 USD/hr. The median in-vehicle

Table 4
Values for time for models 1 and 2.

	Model 1 Traders	Model 2 All data
Out-of-vehicle travel time (OVTT)	24.08	24.67
In-vehicle travel time (IVTT) auto	27.76	26.83
In-vehicle travel time (IVTT) transit	24.57	25.75
In-vehicle travel time (IVTT) air taxi	26.35	26.20

Note. VOT in USD/hour.

Table 5
Association between straight-lining and affinity for air travel.

	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
I like traveling by airplane					
Always select auto or always select transit	14 %	11 %	22 %	38 %	15 %
Always select air taxi	3 %	7 %	11 %	44 %	35 %
Select a mix of modes	2 %	9 %	21 %	46 %	22 %
Traveling by air makes me nervous					
Always select auto or always select transit	22 %	29 %	17 %	15 %	17 %
Always select air taxi	40 %	27 %	12 %	17 %	4 %
Select a mix of modes	29 %	37 %	15 %	14 %	5 %

Note. Row percentages total to 100 and represent the percentage of respondents who "straight-lined" by either never selecting an air taxi or always selecting an air taxi and the percentage of respondents who did not straight-line and selected a mix of the air taxi and other modes.

Table 6
Factors noted by respondents for never selecting an air taxi.

Factor	**Percent of respondents (N = 78)**
Safety concerns	36 %
Adoption timeline (would consider later)	26 %
Cost too high	23 %
Constraints on current commute	19 %
Time-savings too low	12 %
Convenience-related factors	8 %
Fear of flying	6 %
Like driving	3 %

Note. Respondents could indicate more than one factor so column percentages do not sum to 100.

VOTs for the air taxi mode is 25.22 USD/hr and the 95 % confidence interval is 22.37–28.23 USD/hr. Importantly, by incorporating a distribution for the value of time we see that 10 percent have an in-vehicle VOT for the air taxi mode higher than 64.69 USD/hr (95 % confidence interval 55.45–74.87 USD/hr).[11] Results for the other value of time components show similar patterns.

From a policy perspective, the significantly better fit achieved with Model 3 is important, as the results provide clear evidence that when designing air taxi systems, it will be important to incorporate a distribution of values of time in the population. Ours is one of the first surveys related to the air taxi market that provides evidence of this underlying distribution of individuals' value of time. The key takeaway is that there appears to be a nontrivial number of individuals with higher incomes and high VOTs that could be targeted as part of an initial air taxi launch. Longer-term, of course, communities will want to ensure that air taxi service does not become a mode exclusively used by higher income households; however, the presence of individuals with high VOTs bodes well for aircraft manufacturers and service providers seeking to launch air taxi service and reduce the timelines for when that service becomes profitable.

5.4. Extensions to include systematic taste variation in VOT

The models discussed thus far have incorporated unobserved taste variation by assuming a distribution for the cost parameter. As part of the analysis, we also investigated whether there were systematic taste preferences in VOTs by interacting each significant SED characteristic with IVTT components. Due to the fact that many of the interaction terms were not significant at the 0.05 level, we report results for four models: Model 5 interacts age with IVTT, Model 6 interacts rideshare frequency with IVTT, Model 7 interacts presence of children with IVTT, and Model 8 includes all of these interaction terms and removes the insignificant terms.

Likelihood ratio tests were used to compare models with incorporated interaction terms with the baseline model (Model 3 in Table 3). Models that included interaction effects for age (Model 5), rideshare frequency (Model 6), the presence of children (Model 7), and significant interaction effects for age, rideshare frequency, and presence of children (Model 8) improved the model fits and rejected the null hypothesis that the baseline and interaction models were the same. The results for these four interaction models are summarized in Table 7, and the associated VOTs and confidence intervals for the air taxi in-vehicle travel time components are shown in Figs. 5–7.

The inclusion of interaction terms provides modest improvements in model fit, e.g., ρ_c^2 is 0.2230 in the baseline model and 0.2234–0.2239 for the interaction models. The directional interpretation and magnitude of parameter estimates is also similar across these models. VOT estimates are similar between Models 3 and 8 when no interaction terms are included. VOTs associated with the

[11] The conclusion that 10 percent of travelers have at least this high of an in-vehicle VOT for the air taxi mode is of course conditioned on the assumption that values of travel time are log-normally distributed over the population.

auto mode are lower for younger individuals and for households that have children. The mean (median) IVTTs for auto are 36.55 (27.90) USD/hr compared to 31.75 (24.73) USD/hr for those ages 18–34 and 34.05 (26.52) USD/hr for households that have children. VOTs associated with the air taxi mode are lower for younger individuals and for those who rideshare once a month or more. The mean (median) IVTTs for air taxi are 33.05 (25.22) USD/hr compared to 30.89 (24.06) USD/hr for those ages 18–34 and 32.16 (25.05) USD/hr for those who rideshare once a month or more. Results related to ridesharing are particularly interesting because while overall, we see that individuals who are frequent rideshare users are more likely to use air taxis, that they have a slightly lower value of time than those who are infrequent users or have never used rideshare. The propensity to use rideshare may be correlated with other factors not captured in our data, including things like typical daily activity patterns, and these results suggest this may be an important avenue for further research.

6. Discussion, limitations, and directions for future research

In this paper, we used random taste parameter models with panel effects to model mode choice among traditional auto, transit, and air taxi for commute trips. Consistent with other studies that have examined new modes of transportation, most notably demand for EVs and AVs, we find that individuals who are male and frequent ridesharing users are more likely to select the air taxi. Importantly, we find evidence that air taxi preferences are heterogeneous and polarized, with a significant portion of survey respondents showing no interest in using air taxis. This is important, as UAM demand models should incorporate a factor to account for the percent of the population that is unwilling to travel in an air taxi and use a distribution for VOT preferences instead of an average VOT.

As with any study, there are limitations. Given that we sampled individuals with annual incomes above 100 K USD, our results may not generalize to lower-income households. While our intent was to survey individuals with commutes greater than 30 min, the survey execution resulted in households with shorter commutes being included in our survey who may not be representative of individuals

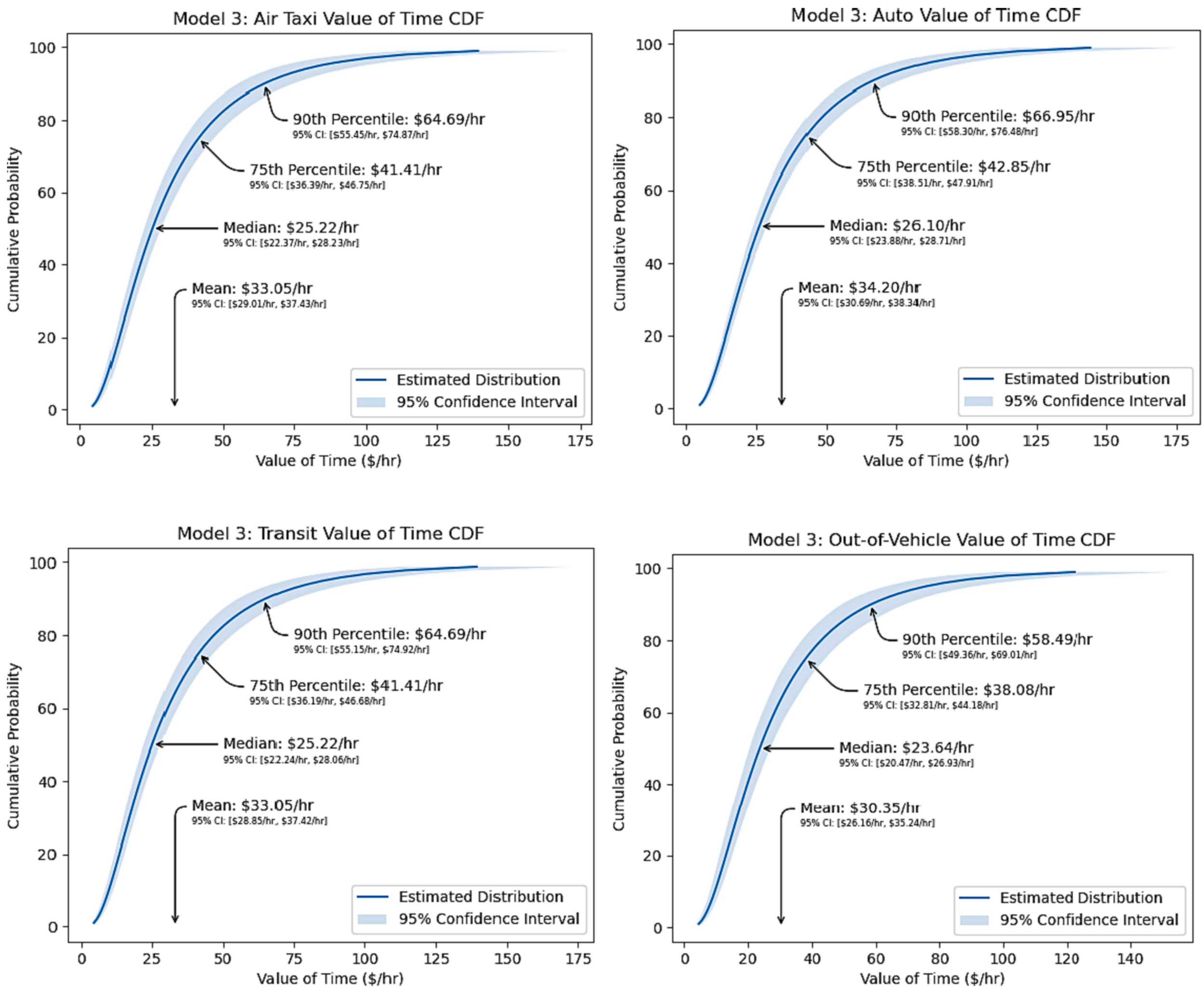

Fig. 4. Values of time for model 8 with no interaction terms.

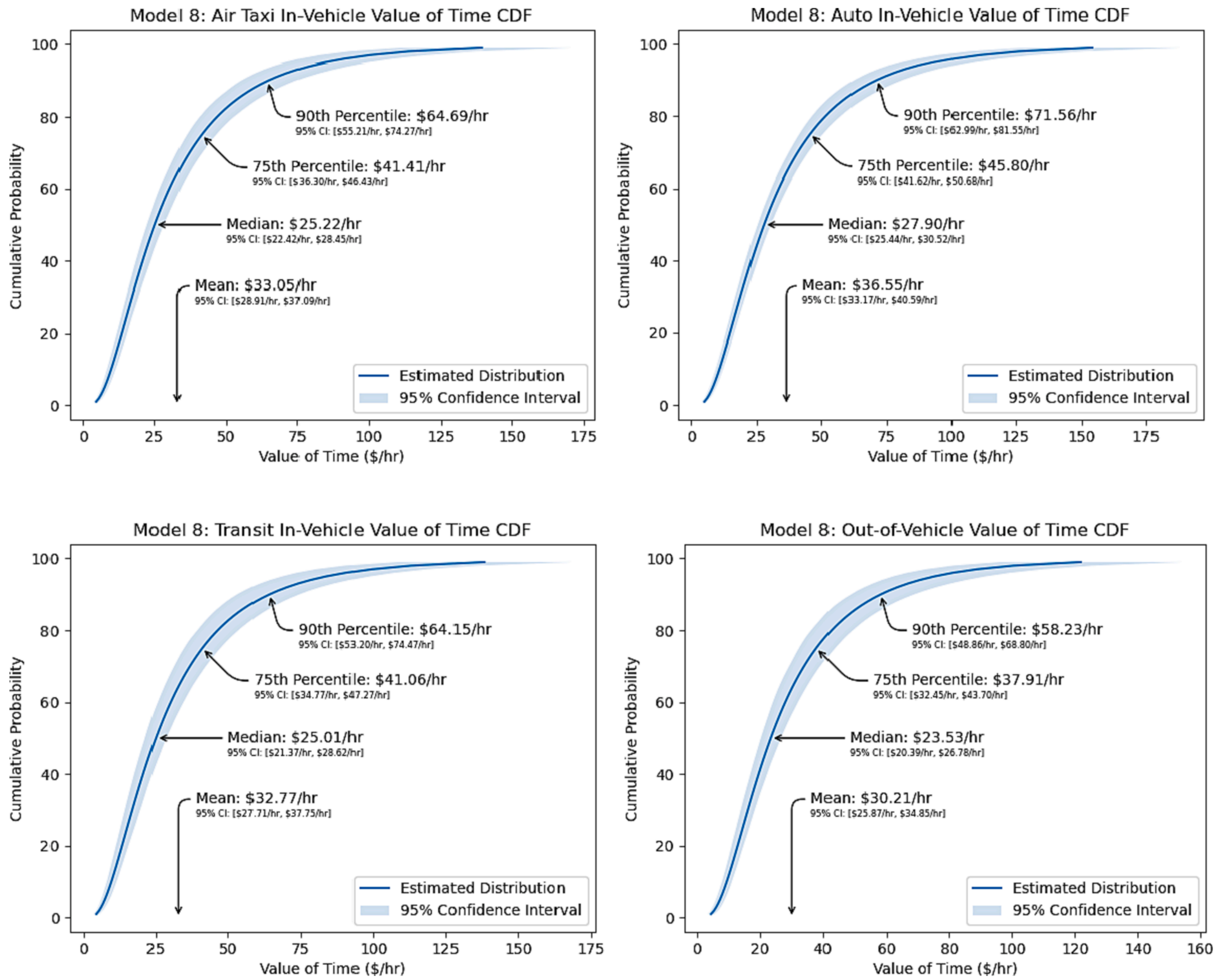

Fig. 4. (*continued*).

who would consider air taxi for commute purposes. Nonetheless, our survey does contain a large percentage of individuals with long commute times: 27 percent reported one-way commute times of 40–59 min, 19 percent with times of 60–89 min, and 8 percent with times of 90 min or more.

We also note that while we included participants from these different cities with differing geographies in our study, but due to overall sample size limitations we found we had insufficient quantities of data to simultaneously identify the effects of heterogeneity in value of time across travelers and also heterogeneity over geographies. We chose to focus on the former, leveraging the variances in travel times and costs that emerge from geography to help provide more robust results for our models. However, with larger sample sizes an explicit study of the effects of geography would also be of interest, as such a study may uncover market-specific factors that this work cannot.

It is also important to note that given this is one of the first surveys to explore whether individuals would be interested in using an air taxi for commuting, we described the air taxi alternative in generally positive terms to allow us to explore whether—even under the "most favorable" conditions—individuals are willing to consider air taxi as a commute mode. In this context, our survey provides an initial assessment (possibly more favorable) of how many individuals would be willing to consider air taxi for commuting purposes at the time the service is initially introduced given different cost, time, and other factors.

Future research includes several potential directions. Recent work by Glerum et al. (2016) proposed a methodology for relating the market shares obtained from a stated choice experiment that includes a single new mode to observed market shares for the traditional modes. Conceptually, this approach involves including a common choice scenario among all respondents that is used to match the survey market shares to the population market shares of interest. Incorporation of this approach in future surveys of UAM is ideal, as it would allow predictions from the stated choice survey to be less sensitive to the underlying design of the choice scenarios.

Our stated choice survey focused on understanding mode choice under "initial" market conditions, but many studies within the ground transportation literature have focused on the timing of adoption. To date, we are aware of only one study within the UAM area, by Al Haddad et al. (2020), that has focused on this adoption issue. A valuable direction for future research would be to explore models

Table 7
Estimation results for random coefficient models that include interaction effects.

	Model 5 Neg LN Age 18–34	Model 6 Neg LN Rideshare	Model 7 Neg LN Children	Model 8 Neg LN Age, RS, Children
Constants				
Auto (ref.)	0	0	0	0
Transit	−0.130 (−0.4)	0.0589 (0.1)	−0.141 (−0.5)	−0.358 (−1.4)
Air taxi	−0.875 (−5.4)	−0.810 (−4.7)	−0.885 (−4.6)	−1.00 (−7.1)
Air taxi std. dev.	0.686 (16.)	0.687 (15.2)	0.685 (15.)	0.606 (14.)
IVTT				
Auto	−0.0778 (−40.)	−0.0773 (−35.)	−0.0781 (−32.)	−0.0792 (−34.)
Transit	−0.0732 (−15.)	−0.0772 (−10.)	−0.0746 (−15.)	−0.0710 (−16.)
Air taxi	−0.0759 (−22.)	−0.0789 (−20.)	−0.0766 (−18.)	−0.0790 (−22.)
IVTT interactions				
Auto IVTT × age 18–34	0.0179 (4.3)			0.0199 (5.5)
Transit IVTT × age 18–34	0.00762 (1.5)			
Air taxi IVTT × age 18–34	0.0206 (2.7)			0.0158 (3.1)
RS once a month or more × IVTT auto		0.00830 (2.5)		
RS once a month or more × IVTT transit		0.0114 (1.1)		
RS once a month or more × IVTT air		0.0187 (3.1)		0.0130 (2.7)
Auto IVTT × presence of children			0.00854 (2.6)	0.00682 (2.3)
Transit IVTT × presence of children			0.00818 (1.8)	
Air taxi IVTT × presence of children			0.0110 (1.7)	
OVTT	−0.0674 (−18.)	−0.0671 (−18.)	−0.0673 (−18.)	−0.0668 (−18.)
Cost	−1.77 (−44.)	−1.78 (−44.)	−1.77 (−45.)	−1.77 (−46.)
Cost std. dev.	0.738 (20.)	0.738 (20.)	0.736 (20.)	0.707 (19.)
Ride guarantee	0.695 (18.)	0.697 (18.)	0.696 (18.)	0.693 (17.)
Male (air)	0.143 (2.6)	0.144 (3.0)	0.146 (3.0)	0.147 (2.7)
Presence of children (auto)	−0.183 (−3.2)	−0.181 (−3.4)	−0.366 (−2.1)	−0.489 (−3.1)
Age				
18–34 (auto)	−0.108 (−0.4)	0.329 (2.6)	0.329 (2.4)	
35–64 (auto)	0.113 (1.0)	0.111 (1.0)	0.113 (0.9)	
65+ (transit)	1.73 (3.2)	1.77 (2.9)	1.76 (2.9)	1.66 (3.1)
Rideshare frequency				
Never or once a year or less (ref.)	0	0	0	0
Once a week or more (auto)	−0.597 (−5.2)	−0.626 (−3.1)	−0.600 (−5.2)	−0.231* (−2.0)
Two or three × a month (auto)	−0.496 (−5.9)	−0.524 (−2.8)	−0.497 (−6.0)	−0.231* (−2.0)
About once a month (auto)	−0.384 (−3.8)	−0.411 (−2.1)	−0.383 (−3.8)	−0.231* (−2.0)
About 4 to 11 × a year (auto)	−0.222 (−2.5)	−0.222 (−2.6)	−0.220 (−2.4)	−0.208 (−2.6)
About 2 or 3 × a year (auto)	−0.243 (−2.8)	−0.241 (−2.7)	−0.240 (−2.8)	−0.235 (−3.0)
Once a month or less (transit)	−0.290 (−1.8)	−0.444 (−0.9)	−0.308 (−2.1)	
Model Statistics				
# obs; # parameters (z)	13,744; 24	13,744; 24	13,744; 24	13,744; 20
LL at zero $LL(0)$	−9,526.61	−9,526.61	−9,526.61	−9,526.61
LL at constants $LL(C)$	−9,514.63	−9,514.63	−9,514.63	−9,514.63
LL at convergence $LL(\beta)$	−7,383.84	−7,387.70	−7,389.26	−7,384.85
ρ_0^2; $\overline{\rho}_0^2$	0.2249; 0.2224	0.2245; 0.2220	0.2244;0.2218	0.2248;0.2227
ρ_c^2; $\overline{\rho}_C^2$	0.2239; 0.2217	0.2235; 0.2213	0.2234;0.2211	0.2238;0.2220

Notes. Parameter estimate (t-stat); models estimated using 250 draws; IVTT = in-vehicle travel time; OVTT = out-of-vehicle travel time; RS = rideshare; × = times; Neg LN = negative lognormal; tr. = transit; ref. = reference; *constrained to be the same. LL = log-likelihood; $\rho_0^2 = 1 - \frac{LL(\beta)}{LL(0)}$; $\rho_c^2 = 1 - \frac{LL(\beta)}{LL(C)}$; $\overline{\rho}_0^2 = 1 - \frac{LL(\beta) - z}{LL(0)}$; $\overline{\rho}_C^2 = 1 - \frac{LL(\beta) - z}{LL(C) - 3}$. Koppelman and Bhat (2006) pages 81–82 were used as the reference for calculating adjusted rho-square values $\overline{\rho}_C^2 = 1 - \frac{\mathrm{LL}(\beta) - z}{\mathrm{LL}(C) - 2}$.

for incorporating adoption timing for UAM and to explore potential competition with AVs. Another research need is to examine demand for other use cases (such as trips to the airport) and understand relationships among demand and service parameters, such as wait times and reliability.

CRediT authorship contribution statement

Sreekar-Shashank Boddupalli: Data curation, Formal analysis. **Laurie A. Garrow:** Conceptualization, Data curation, Formal analysis, Funding acquisition, Writing – original draft. **Brian J. German:** Conceptualization, Funding acquisition, Writing – review & editing. **Jeffrey P. Newman:** Formal analysis, Methodology.

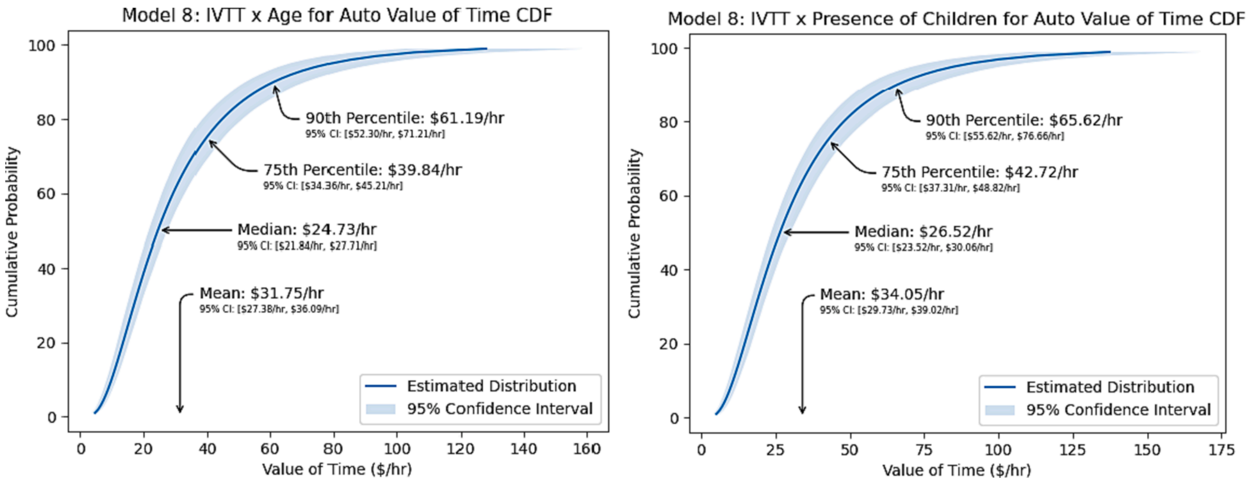

Fig. 5. Values of time for model 8 for auto mode with interaction terms.

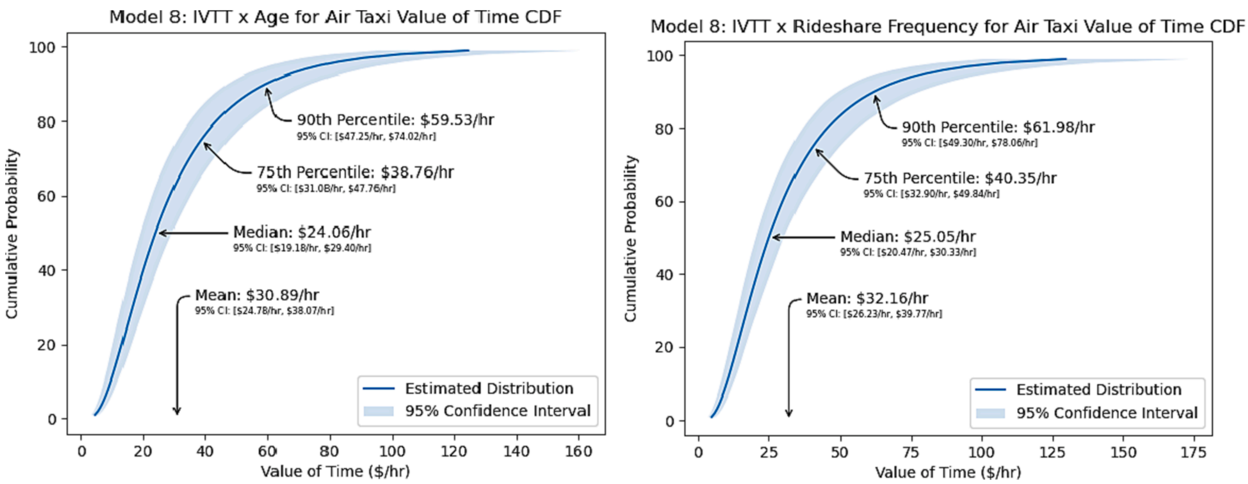

Fig. 6. Values of time for model 8 for air taxi mode with interaction terms.

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.

Acknowledgements

This paper is dedicated in memory of Robert J. Bowler, father of Laurie Garrow, who passed away on May 29, 2023. This research was supported through a contract with the U.S. National Institute of Aerospace (NIA) through prime contract NNL13AA08B, subcontract T13-6500-GT, and task order 601047; the NIA received funding from NASA to support this research. The authors are grateful to Pat Mokhtarian who helped with the survey design, Caroline Leonard who checked the accuracy of tables, and Sharon Dunn, who copy edited the manuscript.

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