

Heterogeneous Preferences for Air Metro and Air Taxi Services: A Sociotechnical Analysis of Urban Air Mobility Adoption Intentions

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ABSTRACT

Urban air mobility (UAM) promises an efficient, sustainable, and safe alternative to ground-based transportation, yet relatively little is known about the preferences and characteristics of potential users. This study examines preferences for air taxi (an on-demand private mode) and air metro (a fixed-route public transportation mode) alongside comparable ground-based alternatives, employing a comprehensive set of contextual characteristics (service and trip attributes) and individual-level characteristics (attitudes and demographics) as determinants of adoption. We employ a rank-ordered stated preference survey with a blocked structure and estimate a corresponding rank-ordered probit (ROP) model. A two-stage analytic framework jointly captures the effects of contextual characteristics, latent attitudinal constructs, and demographics while accounting for unobserved heterogeneity. Results indicate that adoption depends heavily on service attributes, particularly convenience and travel quality. Aerial modes are especially well-suited for long-distance inter-city trips and time-sensitive medical transport. Attitudes toward technology and travel directly shape UAM preferences, while UAM noise sensitivity influences adoption through interactions with UAM noise levels. Adoption patterns vary substantially across user groups and modes, with demand for air metro concentrated among a distinct market segment from the more commonly studied air taxi. The findings provide important insights for UAM service design, vertiport placement, and positioning strategies.

Keywords: Urban Air Mobility (UAM), Air Taxi, Air Metro, Stated Preference, Ranked Choice, Transportation Technology Adoption

1. INTRODUCTION

The image of the “flying car” has captured the public imagination for decades, symbolizing futuristic progress and the potential to revolutionize travel (Branch, 1964; Anders et al., 1994; Cwerner, 2006; Pan and Alouini, 2021). Recent advancements in battery technology have brought this long-standing “dream” into the realm of possibility through the development of vertical take-off and landing (eVTOL) aircraft technology. Indeed, a growing number of companies are actively developing and testing such eVTOL technologies with near-term rollout plans, including intentions for commercial service during the 2028 Los Angeles Olympic and Paralympic games (LA28 Olympics, 2025). In particular, Archer, the air taxi partner of Team USA, plans to provide urban air mobility (UAM) services during the event with safety levels rivaling those of commercial airlines while producing less noise and emissions than traditional helicopters (LA28 Olympics, 2025). Beyond the Olympics, a wide range of aerial human mobility options are in development, promising to expand the scope of urban transportation beyond surface-level movement and provide a potentially safe, efficient, and sustainable alternative to the milieu of surface options already available (Garrow et al., 2021; Federal Aviation Administration, 2023). While eVTOL aircraft currently constitute the dominant technological platform enabling UAM services, the broader UAM ecosystem encompasses multiple service concepts most notably on-demand air taxi services and fixed-route, shared air metro systems. These service concepts are distinguished by their operational characteristics rather than underlying vehicle technology.

Even though the development of UAM human mobility technology has seen substantial progress in recent years, comparatively less effort has been devoted to understanding the preferences and characteristics of potential users of such services. It is generally accepted that, just as for surface modes, individual-level adoption decisions of UAM services will reflect a complex interaction of service attributes, trip characteristics, and individual attitudes. Accordingly, a growing body of research has begun to examine the influence of selected factors on potential users’ adoption intentions (see, for example Al Haddad et al., 2020; Hwang and Hong, 2023; Lee et al., 2023; Karami et al., 2024). Much of this work, however, focuses on a limited subset of UAM service attributes, and is often restricted to specific applications such as on-demand air taxi services (see Zaps and Chankov, 2022; Boddupalli et al., 2024; Karimi et al., 2024).

In this study, we further contribute to the extant literature on UAM adoption by employing a comprehensive set of contextual characteristics (service and trip attributes) and individual-level characteristics as potential determinants of UAM adoption. Among individual-level characteristics, we consider not only demographic variables but also accommodate the impact of individual attitudes and lifestyle preferences. In doing so, and based on well-established Theory of Planned Behavior (TPB) and Technology Acceptance Model (TAM) frameworks (Davis, 1989; Ajzen, 1991; Venkatesh and Davis, 2000), we expressly recognize that the adoption of emerging and unfamiliar technologies such as UAM are substantially shaped by individual attitudes and intrinsic life preferences. In addition, we expand the examination of UAM adoption beyond air taxi (an on-demand private mode) to include air metro services (a fixed-route public transportation mode), quantifying stated preferences for both of these distinct UAM services when presented alongside surface travel modes. Methodologically, we employ a rank-ordered stated preference data collection approach and a corresponding rank-ordered probit analysis framework, enabling the efficient econometric estimation of the effects of a comprehensive set of determinant factors. Overall, our study of UAM adoption provides important insights for UAM service design (including placement of vertical take-off and landing sites, or vertiports) and UAM positioning strategies.

The rest of this paper is structured as follows. The next section provides an overview of the existing literature on UAM adoption patterns. Section 3 presents the analytic approach and mathematical formulation used to analyze UAM adoption. Section 4 discusses data collection and sample characteristics. Section 5 presents the model estimation results and interpretations, discusses model fit, and outlines the method used to compute expected modal shares associated with shifts in explanatory variables. Section 6 discusses the planning and policy implications of the results. Finally, Section 7 concludes by summarizing the findings and presenting potential directions for future work.

2. LITERATURE OVERVIEW

As just discussed, previous studies of UAM adoption have examined the influence of two main types of variables influencing UAM perceptions and adoption: (1) contextual characteristics (including the service attributes of each modal alternative and the trip context) and (2) individual-level characteristics (including demographics and attitudes). Contextual characteristics correspond to the operational and experiential conditions that may be encountered during UAM trips, while individual-level characteristics shape how travelers perceive and evaluate service attributes to inform their mode choice decisions. A summary of the contextual characteristics (service attributes and trip context) and attitudinal factors considered in prior stated preference studies of UAM adoption is provided in Table 1 (we do not include demographic characteristics in this table for presentation conciseness, though we discuss these in Section 2.2). The upper panel of Table 1 summarizes studies examining general UAM adoption intentions, while the lower panel presents studies that employ specific stated preference (SP) experiments to model mode choices between multiple competing alternatives.¹

2.1 Contextual Characteristics

Many UAM adoption studies consider the impacts of “traditional” travel attributes, consistent with well-established findings for ground-based (GB) mode choice behavior. As shown in Table 1, service attributes such as travel time, waiting time, distance to pick-up/drop-off locations, and cost, have been widely examined in prior SP surveys, with adoption increasing when UAM offers benefits over existing surface modes. Among these attributes, in-vehicle travel time is a primary determinant of UAM adoption intentions and preferences (for example, see Fu et al., 2019; Al Haddad et al., 2020; Cho and Kim, 2022; Hwang and Hong, 2023; Qu et al., 2024), consistent with widespread findings in the GB literature (Bhat and Sardesai, 2006; Frank et al., 2008; Ranjan and Sinha, 2025). In particular, given relatively higher speeds of UAM compared with GB modes, the reduction in in-vehicle travel time is one of the principal advantages of UAM (Fu et al., 2019; Kim et al., 2023; Adamidis et al., 2025). Also consistent with mode choice among GB modes, previous findings indicate that both waiting times due to infrequent service and long distances to vertiport pick-up/drop-off locations negatively impact UAM adoption (for example, see Hwang and Hong, 2023; Lotz et al., 2023; Adamidis et al., 2025). Similarly, regarding cost, studies consistently show that higher prices are associated with lower projected usage rates (Fu et al., 2019; Al Haddad et

¹ While not included in Table 1, the reader is also referred to several studies that do not explicitly examine UAM adoption but instead focus on specific perceptions regarding UAM. For instance, Connors (2019), and Yedavalli and Mooberry (2019), investigate UAM noise perceptions in different environmental conditions; Ragbir et al. (2020) consider how perceptions of UAM vary with external factors such as weather conditions or surrounding terrain; Mostofi et al. (2024) examines general perceptions of UAM rather than potential user adoption intentions; and Stolz et al. (2021) and Reimer et al. (2025) provide market research into interior UAM design preferences but do not study user adoption considerations.

al., 2020; Hwang and Hong, 2023; Lotz et al., 2023). Among these traditional service attributes, almost all earlier studies have considered in-vehicle time and cost, though fewer have considered waiting times and distance to drop-off locations, as may be clearly observed from Table 1.

Interestingly, as may be observed from Table 1, while traditional travel measures (including in-vehicle travel time, waiting time, distance to pick-up/drop-off location, and cost) have been more prevalent in SP experiments of mode choice, the more salient attributes in the UAM context have been more prevalent in UAM adoption intention studies. The first such attribute listed in Table 1 is UAM flight altitude, which, to our knowledge, has not been considered in the literature until the current study. In terms of UAM availability, aerial services that continue to operate in adverse weather garner increased trust from some potential users (Kim et al., 2023), while other individuals are less willing to fly in a UAM vehicle in rainy or inclement conditions (Ragbir et al., 2020). In addition, guaranteeing a GB backup option when UAM services are unavailable due to weather has been shown to increase adoption propensity (Boddupalli et al., 2024). Much of the existing literature on the next attribute, noise level, has focused on community-level perceptions of UAM-related noise, finding that higher noise levels and longer noise durations increase annoyance (Connors, 2019; Yedavalli and Mooberry, 2019; Mostofi et al., 2024). In contrast, we are not aware of any adoption intention or SP study that considers noise as a service attribute within individual-level models, although aggregate-level market research indicates that higher in-vehicle noise levels reduce the overall appeal of UAM services (Stolz et al., 2021; Reimer et al., 2025). Conversely, a good UAM in-flight experience can encourage UAM usage; previous studies correlate comfortable seating, wi-fi connectivity, and space for luggage with favorable user perceptions and, in some studies, these in-flight attributes have been shown to increase UAM adoption propensity (Johnson et al., 2022; Kim et al., 2023; Lotz et al., 2023). Sharing a cabin with other passengers, another attribute of UAM in-flight experience, is not always a deterrent (Hwang and Hong, 2023), with some studies finding that shared services are preferred over private services, though whether this is a result of the positive security/safety benefits of being in company in an emerging aerial mode context or whether this is due to lower prices from sharing is still an open question (Brunelli et al., 2023; Qu et al., 2024; Riza et al., 2024).

Moving on to other attributes in Table 1, environmental sustainability has also been shown to influence UAM adoption. Previous studies have found that improvements in environmental performance relative to GB modes, such as lower emissions, increase preferences for UAM (Lotz et al., 2023; Karami et al., 2024). In contrast, other studies have found limited or no relationship between environmental sustainability and UAM adoption (Zaps and Chankov, 2022; Lee et al., 2023). These inconsistent results suggest that the role of environmental sustainability factors is context dependent and warrants further investigation.

Many existing studies have also identified UAM crash-related safety levels as a critical factor for adoption. The impact of crash-related safety is most commonly examined through respondents' safety perceptions, measured by responses to subjective statements regarding the crash risk of UAM vehicles. These studies consistently find that higher perceived crash risk reduces willingness to adopt UAM (Al Haddad et al., 2020; Johnson et al., 2022; Karami et al., 2024). Although less common, some SP experiments incorporate UAM crash-related safety levels explicitly defined relative to familiar GB modes, finding that decreased crash-related safety levels discourage adoption in a similar manner (Fu et al., 2019). Accordingly, Table 1 distinguishes between studies examining objective UAM crash-related safety levels as a service attribute and those examining subjective safety perceptions as individual attitudes (which are also discussed in more detail in the following subsection). Additional in-vehicle personal safety measures (separate

from crash-related safety risk), such as in-flight monitored cameras, regular communication of flight information, and restraining devices may also improve personal safety confidence (Al Haddad et al., 2020; Johnson et al., 2022), though UAM pre-board security screenings (similar to those required for commercial air travel) appear to have only a relatively small positive effect (Kim et al., 2023). Within this context, automation emerges as an important factor, influencing adoption patterns both directly, as a service attribute that shapes willingness to use UAM, and indirectly, through its effect on crash-related safety perceptions. For instance, some earlier studies have indicated that full autonomy may improve crash-related safety perceptions and increase UAM adoption (Fu et al., 2019; Hwang and Hong, 2023), with respondents exhibiting greater safety concern with GB autonomous vehicles than aerial autonomous services (Fu et al., 2019; Yavuz, 2024). In contrast, other previous studies have found that potential users have limited trust in automated technology, especially in aerial contexts, and so are hesitant to adopt automated UAM services. In this case, the physical presence of a pilot appears to improve confidence, leading to more widespread adoption (Johnson et al., 2022; Lotz et al., 2023; Kim and Zhang, 2025). Collectively, these results highlight the importance of perceived safety and trust of potential users shaping early UAM adoption.

Along with UAM service attributes, the trip context (trip purpose and trip distance) also plays a role in shaping UAM adoption patterns. Previous studies find that preferences for aerial modes vary across trip purposes, observing increases in adoption for business, leisure trips, and airport access (For example, see Zaps and Chankov, 2022; Coppola et al., 2024; Qu et al., 2024; Kim and Zhang, 2025), while preferences for routine commuting are lower (Fu et al., 2019; Johnson et al., 2022; Hwang and Hong, 2023). Fewer studies have considered the effects of trip distance, through those that have considered this aspect of trip-making observe that adoption tends to increase with trip distance, with elevated UAM preferences for inter-city UAM trips compared with shorter intra-city trips (Brunelli et al., 2023; Hwang and Hong, 2023; Qu et al., 2024). These findings highlight that UAM adoption is likely to be shaped not only by service attributes, but also by the trip context.

2.2 Individual-Level Characteristics

Some earlier studies have identified attitudinal factors that shape UAM adoption decisions, often based on the Theory of Planned Behavior (TPB) and Technology Acceptance Model (TAM) frameworks (Davis, 1989; Ajzen, 1991; Venkatesh and Davis, 2000). Within these frameworks, perceptions of usefulness and ease of use, attitudes, and subjective norms shape behavioral intentions alongside contextual characteristics (see the third column of Table 1). For example, high levels of technological savviness and personal innovativeness promote UAM adoption (Johnson et al., 2022; Karami et al., 2024; Yavuz, 2024). These effects are associated with increased perceived usefulness in the context of TAM, and more favorable attitudes towards UAM within the TPB (Karami et al., 2024; Mostofi et al., 2024; Yavuz, 2024). Similarly, favorable views of automation or prior experience with autonomous systems increase adoption (Al Haddad et al., 2020; Brunelli et al., 2023). This relationship also has also been modeled as driving adoption via perceived usefulness, aligning closely with the role of tech-savviness within behavioral models of technology adoption (Al Haddad et al., 2020). Additionally, attitudes relating to current travel experiences can shape mode selection, with an inverse relationship between ground-mode satisfaction and UAM adoption (Brunelli et al., 2023; Karimi et al., 2024; Adamidis et al., 2025). This relationship can be attributed not just to the limitations of current modes, but to the productive use of travel time and the enjoyment which travelers expect during UAM trips (Johnson et al.,

2022; Karimi et al., 2024; Adamidis et al., 2025). These anticipated benefits contribute to more favorable attitudes toward UAM, consistent with the TPB framework for modeling behavioral intention.

Individuals' attitudes can also shape the perception of objective UAM service attributes such as noise and crash-related safety. For instance, noise sensitivity is a well-documented individual trait with certain individuals exhibiting higher responsiveness to noise levels (Miedema and Vos, 1999; Schutte et al., 2007; Shepherd et al., 2010; Aalmoes and Sieben, 2021). The sensitivity to transportation noise may be further amplified by crash-related safety concerns or fears associated with a given mode (Miedema and Vos, 1999). Beyond noise perceptions, an individual's attitudes toward risk or prior experiences with traffic crashes also shape adoption decisions. Prior studies show that elevated crash-related safety concerns reduce willingness to adopt UAM by negatively impacting perceived usefulness (Al Haddad et al., 2020; Johnson et al., 2022; Karimi et al., 2024). Such effects are particularly relevant among those who are risk-averse or have air travel anxieties (Al Haddad et al., 2020; Johnson et al., 2022; Karimi et al., 2024).

In addition to these attitudinal factors, individual sociodemographic characteristics have also been shown to shape UAM adoption patterns (although these are excluded from Table 1 for presentation conciseness). Gender is a well-documented driver of UAM preferences, with men displaying a larger preference for aerial modes than women (Yedavalli and Mooberry, 2019; Al Haddad et al., 2020; Boddupalli et al., 2024; Karimi et al., 2024). Age too plays a role, with younger respondents demonstrating a higher preference for UAM (Yedavalli and Mooberry, 2019; Karimi et al., 2024; Adamidis et al., 2025; Jang et al., 2025), though several studies identify age interactions with other contextual characteristics and individual-level variables. Specifically, long-distance trips, air taxi business service, and high-income status are key elements which contribute to elevated UAM preferences among older or middle-aged respondents (Fu et al., 2019; Hwang and Hong, 2023; Boddupalli et al., 2024). Findings on education level are mixed, with some studies indicating a positive association with UAM adoption (Yedavalli and Mooberry, 2019; Jang et al., 2025), and others reporting opposite effects (Johnson et al., 2022). Besides the interaction effects with age, a higher income generally leads to a higher propensity to adopt UAM (Al Haddad et al., 2020; Brunelli et al., 2023; Karimi et al., 2024). Residential location also has been found to impact adoption, with previous studies indicating that rural residents are less likely to be early adopters of UAM (Yedavalli and Mooberry, 2019; Johnson et al., 2022).

2.3 Study in Context

Despite the growing body of research on determinants of UAM adoption, several gaps remain. In this context, the current study advances the literature in five key ways. First, the study explicitly examines adoption of air metro services in addition to air taxi services, quantifying the demand and determining likely adopters for a fixed route, shared aerial mode. As may be observed from the second column of Table 1, almost all earlier studies have exclusively investigated the case of on-demand air taxi services. While a few studies have begun to differentiate these two UAM modes, existing studies remain limited to (1) shared aerial services for the sole use case of airport access (Brunelli et al., 2023; Coppola et al., 2024; Jang et al., 2025; Kim and Zhang, 2025), (2) examinations of adoption intentions in which respondents evaluated individual UAM modes separately, rather than selecting between multiple UAM alternatives or between UAM and GB alternatives (Riza et al., 2024), and (3) multimodal studies that include both UAM and GB modes but do not differentiate between UAM service modes during the modeling stage (Hwang and Hong, 2023). Our study extends this work by explicitly differentiating between air metro and air taxi

services within a comprehensive multimodal (GB-inclusive) choice framework. Second, we leverage a blocked survey structure to account for a wide range of salient attributes in the UAM context, such as UAM flight altitude, UAM availability, and noise level. While previous studies have examined a limited set of such salient attributes, these have been confined primarily to studies of UAM adoption intentions rather than considered within SP experiments (see Table 1). Our data, on the other hand, provide insights into a comprehensive set of 13 different service attributes and two trip context variables (see the last row of Table 1). We also explore potential interactions of service attributes, trip contexts, and individual-level demographics (for example, a potential higher travel time sensitivity for emergency medical transport). Importantly, by including such a comprehensive set of variables as well as variable interactions, we are better able to shed light on the effects of contextual characteristics, especially those such as environmental sustainability and level of automation that have shown inconsistent effects in the existing literature (see Zaps and Chankov, 2022; Hwang and Hong, 2023; Lotz et al., 2023; Kim and Zhang, 2025). Additionally, the survey scenarios were designed to vary service attribute levels across not only aerial modes but also GB modes. This systematic variation allows differences in sensitivity to service attributes between aerial and GB alternatives to be identified. Third, we integrate individual attitudes and perceptions into the modeling structure to account for their influence on UAM adoption. This is accomplished through the inclusion of three latent constructs capturing (a) tech-savviness, (b) UAM noise sensitivity, and (c) positive travel perceptions. While several previous studies have considered similar attitudinal effects (see the final column of Table 1), we also consider interactions between these constructs and contextual characteristics as well as individual demographics (for example, those with high individual-level UAM noise sensitivity may be particularly averse to high noise levels). Fourth, this study employs a ranked preference design rather than a first-choice design, providing more information about respondents' relative preferences across modes for efficient econometric estimation, which enables us to tease out the effects of multiple variables (and their interactions) simultaneously in ways that would not be possible with a traditional first-choice design (see Nair et al., 2019). The analytic structure also accommodates correlations among the utilities ascribed across modes, capturing unobserved factors that may cause individuals to rank certain alternatives similarly. For example, an individual who is more sociable may be more inclined toward both the air metro and GB public transportation alternatives because they are shared modes, while the opposite would be true for someone who values their privacy during travel. In addition, to improve data collection efficiency and increase the sample size available for estimation, two SP choice occasions were collected from each respondent, with the resulting panel structure accommodated through the estimation of correlations between the two choice occasions. These correlations reflect the influence of unobserved factors that may lead individuals to respond similarly across choice occasions, such as a tendency to favor modes they habitually use. Finally, we go beyond simple model estimation to quantify the impacts of both contextual and individual-level characteristics on UAM adoption by calculating average treatment effects (ATEs) within the proposed modeling framework. These ATEs translate the model coefficients into more interpretable measures of how specific contextual and individual-level characteristics influence mode choice, providing a quantitative foundation for concrete policy and planning recommendations related to UAM service design and positioning.

3. METHODOLOGY

3.1 Analytic Framework

As discussed above, we focus on the mode choice between aerial and GB modes using a ranked SP design. Thus, the main outcome of interest is rank-ordered, with five alternatives corresponding to (1) air taxi, (2) air metro, (3) ridehailing, (4) public transportation, and (5) private vehicle. A visual depiction of the model structure used to predict the ranking of these alternatives is shown in Figure 1, with the mode choice outcome shown on the far right. Note that two choice scenarios were presented to each individual. In each scenario, each mode was described by a selection of service attributes (e.g., travel time, cost, level of automation), with attributes varying across scenarios according to predefined levels, and a specific trip context (including trip purpose and distance) was specified. As shown in the figure (and discussed in more detail in Section 4), several sets of variables were used to predict the rank-ordered outcome. First, contextual characteristics (shown on the lower left in the figure) presented in each scenario were assumed to impact the utilities of each alternative directly. Second, a set of individual- and household-level demographic characteristics (shown on the upper left) were specified to influence the utilities of each outcome directly, but also considered as determinants of a set of unobserved continuous latent constructs (shown in the center of the figure). Three latent constructs (tech-savviness, UAM noise sensitivity, and positive travel perceptions) were identified based on exploratory and confirmatory factor analysis (see further details in Section 4.3), using a set of ordinal indicators (the individual indicators have been omitted in Figure 1 for simplicity). The ordinal indicators themselves were based on Likert Scale responses to subjective statements designed to capture attitudes toward technology, UAM noise disruptions, and travel. Finally, the latent constructs were assumed to also impact the utilities of each ranked alternative.

To accomplish this estimation, we adopted a two-stage analytic approach, mimicking Bhat's (2015) Generalized Heterogeneous Data Model (GHDM) while supporting a simpler, two-stage estimation process. The approach belongs to the class of two-step optimization estimators, which, under general regularity conditions, is a consistent and asymptotically normal (CAN) estimator (see Newey and McFadden, 1994), while also reducing the computational complexity of a joint estimation of the two stages. In particular, in the first stage, the latent constructs were estimated (independent of the main rank-ordered outcome) based on their loadings on the ordered indicators, and the effects of demographics on each latent construct were imputed using a linear regression specification for the continuous latent constructs. The imputed regression results were then used to predict the unobserved latent construct values based on each individual's demographics. This first stage mirrors the structural equation modeling (SEM) component of the GHDM as well as the portion of the measurement equation modeling (MEM) component relating to the indicators of the latent constructs. Additionally, within this first stage, each of the three latent constructs are allowed to covary, accommodating unobserved sources of variation that may affect multiple attitudinal constructs of the same individual (Γ in Figure 1).

The second stage then uses the estimated latent construct scores alongside individual/household demographics and contextual characteristics to estimate a rank-ordered probit (ROP) model for the main ranked choice outcome. This stage mimics the part of the MEM portion of Bhat's (2015) GHDM framework pertaining to the estimation of the main outcomes. Importantly, unlike the GHDM, the two stages are performed sequentially rather than simultaneously. As a result, latent construct scores are first estimated independently, and subsequently incorporated into the ranked choice model. But, we still retain the possibility of jointness in the utilities across the modal alternatives due to unobserved factors through the

specification of a covariance matrix across alternatives in the rank-ordered outcome ($\tilde{\Lambda}_l$ in Figure 1). In addition, due to the panel structure of the data where a single individual provides two ranked responses, covariances are estimated between the utilities of the same alternative across the two choice occasions of the same individual (Ω in Figure 1). These covariations account for any unobserved individual-level factors which impact both choice occasions, such as intrinsic habits or modal familiarity. Methodological details are presented in the following section.

3.2 Mathematical Formulation

3.2.1 First Stage Estimation of Latent Constructs

First, for the mathematical notation for the first-stage component of the model, let l be the index for the latent constructs ($l = 1, 2, \dots, L$) and label each latent construct as z_l^* . In our analysis $L = 3$, corresponding to the three latent constructs shown in the central portion of Figure 1. We will suppress the index for the individual, simply for ease of presentation. Each latent construct may be written as a function of covariates as:

$$z_l^* = \alpha_l' \mathbf{w} + \eta_l \quad (1)$$

where $\mathbf{w}$ is a $(D \times 1)$ vector of observed variables, α_l is a corresponding $(D \times 1)$ vector of coefficients, and η_l is a random error term. The error vector η_l is assumed to be standard normally distributed. Also, define the $(L \times D)$ matrix $\alpha = (\alpha_1, \alpha_2, \dots, \alpha_L)'$, and the $(L \times 1)$ vector $\eta = (\eta_1, \eta_2, \dots, \eta_L)'$. Then, the $(L \times 1)$ vector of latent constructs may be written as $\mathbf{z}^* = (z_1^*, z_2^*, \dots, z_L^*)'$ and, in matrix form, we may write the equations for the latent constructs as:

$$\mathbf{z}^* = \alpha \mathbf{w} + \eta. \quad (2)$$

In order to accommodate unobserved factors that may also jointly influence multiple latent variables, we allow a multivariate normal (MVN) correlation structure for η . $\eta \sim MVN_L[\mathbf{0}_L, \Gamma]$, where $\mathbf{0}_L$ is an $(L \times 1)$ column vector of zeros, and Γ is an $(L \times L)$ correlation matrix.

Next, consider a set of N ordinal indicators used to identify the latent constructs, and denote the index for the indicators as n ($n = 1, 2, \dots, N$). Then, let J_n be the number of categories for the n^{th} ordinal indicator ($J_n \geq 2$) and let j_n be the corresponding index ($j_n = 1, 2, \dots, J_n$). Also, for each ordinal indicator, let $\tilde{\tau}_n^*$ be the underlying latent variable whose horizontal partitioning leads to the observed selection. Then, we can apply the usual ordered response formulation to write:

$$\tilde{\tau}_n^* = \tilde{\mathbf{d}}_n' \mathbf{z}^* + \tilde{\varepsilon}_n \quad (3)$$

with $\tilde{\psi}_{n, a_n-1} < \tilde{\tau}_n^* < \tilde{\psi}_{n, a_n}$, assuming that the individual chooses the a_n^{th} ordinal category. $\tilde{\mathbf{d}}_n$ is an $(L \times 1)$ vector of loadings of each latent construct on the ordinal indicator, the $\tilde{\psi}$ terms represent thresholds to be estimated, and $\tilde{\varepsilon}_n$ represents the standard normal random error for the ordinal indicator. For each indicator, the thresholds are ordered $\tilde{\psi}_{n,0} < \tilde{\psi}_{n,1} < \tilde{\psi}_{n,2} \dots < \tilde{\psi}_{n,J_n-1} < \tilde{\psi}_{n,J_n}$, with $\tilde{\psi}_{n,0} = -\infty$, $\tilde{\psi}_{n,1} = 0$, and $\tilde{\psi}_{n,J_n} = +\infty$. Let $\tilde{\Psi}_n = (\tilde{\psi}_{n,2}, \tilde{\psi}_{n,3}, \dots, \tilde{\psi}_{n,J_n-1})'$ and $\tilde{\Psi} = (\tilde{\Psi}_1', \tilde{\Psi}_2', \dots, \tilde{\Psi}_N')'$.

Then, to develop a matrix representation across the indicators, stack the N underlying continuous variables $\tilde{\tau}_n^*$ into an $(N \times 1)$ vector $\tilde{\tau}^*$, and the N error terms $\tilde{\varepsilon}_n$ into an $(N \times 1)$ vector $\tilde{\varepsilon}$. Define the $(N \times L)$ matrix $\tilde{\mathbf{d}} = (\tilde{\mathbf{d}}_1, \tilde{\mathbf{d}}_2, \dots, \tilde{\mathbf{d}}_N)'$, and stack the N lower thresholds $\tilde{\psi}_{n,a_n-1}$ into an $(N \times 1)$ vector $\tilde{\Psi}_{low}$ and the N upper thresholds $\tilde{\psi}_{n,a_n}$ into another vector $\tilde{\Psi}_{up}$. Then, in matrix form, the equation for the indicators for the individual may be written as:

$$\tilde{\tau}^* = \tilde{\mathbf{d}}\mathbf{z}^* + \tilde{\varepsilon}, \quad \tilde{\Psi}_{low} < \tilde{\tau}^* < \tilde{\Psi}_{up}. \quad (4)$$

The first estimation stage identifies the loading vector $\tilde{\mathbf{d}}$, while also simultaneously estimating the vector α corresponding to the regression of the latent constructs on the covariates $\mathbf{w}$. For additional discussion of the necessary identification conditions to estimate both the vectors $\tilde{\mathbf{d}}$ and α , see Bhat (2015). The system is first estimated using a maximum likelihood approach, then estimated values of the continuous latent constructs are constructed for each individual in the sample as $\hat{\mathbf{z}}^* = \hat{\alpha}\mathbf{w}$, where $\hat{\alpha}$ are the estimated coefficients. These constructed values are then used to predict the rank-ordered mode choice outcomes in the second stage of estimation, as discussed next. For the estimation of this first-stage of the model, a variety of latent constructs were specified and tested both in terms of their internal fit as well as their explanatory power in the second stage. This process is described in detail in Section 4.3 along with a discussion of the final latent constructs retained in the model.

3.2.2 Second Stage Estimation of Rank-Ordered Outcomes

For the main rank-ordered mode choice outcomes considered, each individual is asked a set of two SP questions (as discussed in Section 3.1). Let t be the index for the choice occasion of the individual ($t = 1, 2, \dots, T$), with $T = 2$ for all individuals in the current context. The index for the individual is again omitted for brevity. Then, for the rank-ordered outcome, let I be the number of alternatives available for ranking and let i be the corresponding index ($i = 1, 2, 3, \dots, I$). In our context, $I = 5$ for the five available alternatives for ranking, see the main outcome on the right side of Figure 1. We can then apply the usual underlying random utility structure for each alternative i :

$$U_{it} = \mathbf{b}'\mathbf{x}_{it} + \varsigma_{it}, \quad (5)$$

where $\mathbf{x}_{it}$ is an $(A \times 1)$ vector of exogenous variables, including the estimated values of the continuous latent constructs estimated in the prior stage and interactions between these latent constructs and other exogenous variables. $\mathbf{b}$ is an $(A \times 1)$ vector of corresponding coefficients and ς_{it} is a random normal error term. We assume that ς_{it} is independent and identically distributed across individuals, but allow for a general covariance structure across the alternatives for each choice occasion for each individual. To do so, stack the error terms ς_{it} into the $(I \times 1)$ vectors $\varsigma_t = (\varsigma_{1t}, \varsigma_{2t}, \dots, \varsigma_{It})'$. Then, $\varsigma_t \sim MVN_I(\mathbf{0}_I, \Lambda)$. Note that we restrict the covariance matrices for the two choice occasions to be equal, as there is no reason to believe that unobserved factors influencing multiple alternatives would differ between the choice occasions. Also, standard normalizations are applied for identification. Taking the utility differentials with respect to the last alternative (in our empirical analysis, the last alternative corresponds to the ground-based private

vehicle), only the elements of the covariance matrix $\tilde{\Lambda}_I$ of $\tilde{\zeta}_{it} = \zeta_{it} - \zeta_{It}$ ($i \neq I$) are estimable, with one of the diagonal elements of $\tilde{\Lambda}_I$ set to 1 for identifiability. Also, for future use, define

$\tilde{\zeta}_{it} = (\tilde{\zeta}_{1it}, \tilde{\zeta}_{2it}, \dots, \tilde{\zeta}_{(I-1)it})'$ ($I-1 \times 1$ vector) and $\tilde{\zeta}_I = (\tilde{\zeta}_{1I}, \tilde{\zeta}_{2I}, \dots, \tilde{\zeta}_{TI})$ ($(I-1) \times T$ vector). Define the $(I-1)T \times (I-1)T$ (with $T=2$ in our empirical context) covariance matrix of $\tilde{\zeta}_I$ as $\Theta = \begin{bmatrix} \tilde{\Lambda}_I & \Omega \\ \Omega & \tilde{\Lambda}_I \end{bmatrix}$,

where Ω captures the covariation across choice occasions of the individual in the differenced utility space. For stability and parsimony, we assume Ω to be diagonal. This restricts the covariance matrix so that covariance is allowed between the same alternative (differenced from the last alternative) across choice occasions, but not between different alternatives (differenced from the last alternative again) across the choice occasions. For instance, we allow for unobserved factors that influence the utility of the air taxi alternative in the differenced utility space across choice occasions but not those that influence the air taxi alternative in the one choice occasion and the public transit alternative in another choice occasion in the differenced utility space. Next,

partition the matrix Θ as $\Theta = \omega \Theta^* \omega$, where $\omega = \begin{bmatrix} \tilde{\omega} & 0 \\ 0 & \tilde{\omega} \end{bmatrix}$, where $\tilde{\omega}$ is the diagonal matrix of the

standard deviations of Λ_I and Θ^* is the correlation matrix corresponding to Θ . A typical normalization that is adopted in the literature is that one of the $\tilde{\omega}$ elements is normalized to one. While innocuous regarding the scale of which alternative (in differenced form from the last alternative) is normalized to one, the model coefficients produced from alternative normalizations will be different (though the final probabilities of the ranked alternatives remain unchanged). Instead, we use the more clean normalization proposed recently by Bhat and Robbennolt (2026) that produces a single set of model coefficients. In this alternative normalization procedure, $\sum_{i=1}^{I-1} s_i^2 = 1$, where s_i represents the scale of the utility of alternative i (as differenced from the utility of the last alternative). In our notation from above, s_i ($i = 1, 2, \dots, I-1$) also corresponds to the elements of $\tilde{\omega}$.

To proceed, define a contrast matrix $((I-1) \times I)$ $\mathbf{M}_I$ for each choice occasion based on the observed ranking r_t . Specifically, let the first ranked alternative be r_t^1 , the second r_t^2 , and so on until the last-ranked alternative r_t^I . Then, based on this ranking, the following utility inequalities should hold: $U_{r_t^2} - U_{r_t^1} < 0, U_{r_t^3} - U_{r_t^2} < 0, \dots, U_{r_t^I} - U_{r_t^{I-1}} < 0$. Then, for each choice occasion, we can stack the $(I-1)$ utility differentials based on the observed rank ordering, into a

vector $\mathbf{u} = \left((U_{r_t^2} - U_{r_t^1}), (U_{r_t^3} - U_{r_t^2}), \dots, (U_{r_t^I} - U_{r_t^{I-1}}) \right)'$. These inequalities may also be identified

in the contrast matrix $\mathbf{M}_I$. To do so, fill the matrix with zeros. Then, in the first row (corresponding to the first inequality shown above), place a value of negative one in the column corresponding to the first-ranked alternative, and a value of one in the column corresponding to the second-ranked alternative. In the second row (corresponding to the second inequality shown above), place a value of negative one in the column corresponding to the second-ranked alternative, and a value of one in the column corresponding to the third-ranked alternative. Continue this procedure for each row

and corresponding inequality. Next, define a larger contrast matrix $\mathbf{M} = \begin{bmatrix} \mathbf{M}_1 & \mathbf{0} \\ \mathbf{0} & \mathbf{M}_2 \end{bmatrix}$ of size $((I-1)T \times IT)$ ($I = 5$ and $T = 2$) based on the observed choices for the individual in each period. Also define a mask matrix $\tilde{\mathbf{D}}$ of size $I \times (I-1)$ using an identify matrix of size $(I-1)$ and supplementing with additional rows of zeros at the I^{th} row (note that $I=5$ in our empirical analysis). Also, define matrix $\mathbf{D} = \begin{bmatrix} \tilde{\mathbf{D}} & \mathbf{0} \\ \mathbf{0} & \tilde{\mathbf{D}} \end{bmatrix}$ of size $(IT \times (I-1)T)$ ($I = 5$ and $T = 2$). Using this contrast matrix, $\mathbf{M}$, and the mask matrix $\mathbf{D}$, we can characterize the distribution of the differenced utility vector $\mathbf{u}$ from that of $\mathbf{U}$. Specifically, $\mathbf{u} \sim MVN_{(I-1)*T}(\mathbf{M}\mathbf{b}\mathbf{x}, \mathbf{M}\mathbf{D}(\omega\Theta^*\omega)\mathbf{D}'\mathbf{M}')$.

Let the set of parameters to be estimated be $\delta = \left[\mathbf{b}', (\text{diag}(\tilde{\omega}))', (\text{Vechup}(\Theta^*))' \right]'$, where $\text{diag}(\tilde{\omega})$ corresponds to the diagonal elements of $\tilde{\omega}_1$, and $\text{Vechup}(\cdot)$ row-vectorizes the unique and non-zero upper diagonal elements of a matrix. Then, the likelihood function for the individual may be written as:

$$L(\delta) = F_{((I-1)*T)}(\mathbf{0}; \mathbf{M}\mathbf{b}\mathbf{x}, \mathbf{M}\mathbf{D}(\omega\Theta^*\omega)\mathbf{D}'\mathbf{M}') \quad (6)$$

where $F_{((I-1)*T)}(\mathbf{0}; \boldsymbol{\mu}, \mathbf{v})$ is the $((I-1)*T)$ -dimensional multivariate normal cumulative distribution function computed at the truncation point vector of $\mathbf{0}$, with mean $\boldsymbol{\mu}$ and covariance matrix $\mathbf{v}$. The likelihood function for the entire sample of decision-makers is obtained as the product of the individual-level likelihood functions.

Finally, because the estimated values of the latent constructs, $\hat{\mathbf{z}}^*$, are used as exogenous variables in the second stage of estimation, the covariance matrix of the parameters must be corrected. We apply the procedure suggested by (Murphy and Topel, 2002; Terza, 2016) to obtain the corrected asymptotic standard errors of this second stage estimator.

4. DATA DESCRIPTION

4.1 Survey Characteristics

The data for this study were collected using an online survey distributed predominantly, although not exclusively, within Texas between March, 2025 and October, 2025. The sampling approach was largely convenience based, with distribution through social media and flyers, as well as through the email networks of community and neighborhood associations in Austin, Dallas, Houston, San Antonio, Lancaster, and Waco, enabling participation from respondents across the state. In addition to the 890 responses collected within Texas, 173 responses originated from outside of Texas, reached by partners at the University of California Irvina and Iowa State University who aided in sample distribution. As an incentive, the first 150 participants were provided with a \$10 e-gift card, and all subsequent participants were entered into a lottery for one of an additional 100 \$10 e-gift cards. This approach resulted in an overall sample size of 1,063 respondents. Additional residence-based neighborhood attributes from the 2023 American Communities Survey (ACS) Community Business Profile (CBP) database (United States Census Bureau, 2023) were appended based on respondent zip code. After cleaning and appending neighborhood data, the final sample size for analysis comprised 1,057 respondents.

The survey design and development benefited from discussions and feedback received from key industry and public agency stakeholders, including Movability (a Central Texas Transportation Management Association), Capital Metro (the Austin public transportation provider), the Austin Justice Coalition, the Austin Urban Technology Movement (community non-profit organizations), the City of Austin, and the Texas Department of Transportation. These stakeholders provided insights into how UAM is being developed and envisioned, and key information that would aid in the assessment of adoption intentions. Informed by these discussions, the survey instrument contained sections designed to elicit information on exogenous variables (see Section 4.2), a set of indicators to develop individual-level latent constructs embodying attitudes and life-style preferences (discussed in Section 4.3), and responses to the human UAM SP experiments (constituting the main endogenous outcomes; see Section 4.4).

4.2 Exogenous Variables

As outlined in Section 3.1, the exogenous variables used to predict the ranked mode choice outcomes include both contextual characteristics (service attributes and trip context) corresponding to the SP scenarios, and individual-level characteristics (demographic characteristics). Table 2 summarizes the contextual characteristics included in the experimental design along with their corresponding levels which varied across scenarios. Because UAM services constitute an emerging technology that may be unfamiliar to many respondents, background information and descriptions were provided to add context to the UAM attributes and their associated levels. For instance, to help participants understand the different levels of noise, we presented noise-level comparisons to familiar sounds (for example, noise equivalent to “a heavy truck or motorcycle,” “moderate car traffic,” or “a quiet outdoor environment”). Similarly, to help participants visualize different UAM flight altitudes, we used images generated from a virtual reality simulation providing the view from the vehicle at each altitude (see the images embedded in Table 2 in the row labeled “UAM Flight Altitude”).

To effectively examine the large number of service attributes identified as potentially influential, a blocked survey structure was employed. In each scenario, the five following key modal service attributes were always presented: (a) in-vehicle travel time (based on speed in the experimental design and a specified scenario trip distance), (b) waiting time, (c) distance to pick-up/drop-off locations, (d) cost, and (e) UAM flight altitude (please see the attribute listing in Table 2). In addition, each scenario presented a subset of three additional service attributes, selected from a larger list of the following eight service attributes: (i) UAM availability, with variation in the availability of the two UAM modes based on weather conditions (clear weather or not), (ii) noise level, with variation in the noise level for the UAM modes (iii) UAM in-flight experience, (iv) environmental sustainability, (v) UAM crash-related safety (relative to ground vehicles), (vi) in-vehicle personal safety monitoring, (vii) UAM pre-boarding security screening, and (viii) level of automation (please see the attribute listing in Table 2). Two trip context variables, the trip purpose and trip distance (provided at the end of Table 2), were also included in every scenario.

In total, each scenario comprised ten variables (eight service attributes and two trip context variables), as discussed above, with the attribute level combination set across these variables developed based on an orthogonal design to construct 64 unique scenarios, with emphasis on isolating the main effects and two-level interactions. The scenarios also generated realistic attributes for each mode, while providing good variation in the attribute levels between scenarios. Additionally, attribute level combinations were tailored to maintain consistency across modal alternatives (such as providing a consistent flight altitude for both aerial modes). The 64 scenarios

were then grouped into 32 blocks of two scenarios each such that both scenarios within a block presented the same set of attributes (but with varying levels). Subsequently, a randomization feature in the survey platform was invoked to present a single block of two SP scenarios to each participant.

In addition to these scenario design-related exogenous variables, demographic characteristics were also collected. These included individual demographics (gender, age, level of education, race, ethnicity, and employment status; shown in the left panel of Table 3) and household demographics (household income, housing type, housing tenure, residential location, household composition, household size, number of motorized vehicles in household, and state of residence; shown in the right panel of Table 3). Descriptive statistics of these variables are summarized in Table 3 alongside corresponding American Community Survey (ACS) 2023 one-year estimates for the state of Texas. While the survey sample and state-level population are not directly comparable due to the inclusion of out-of-state respondents in the sample, ACS estimates are included as a reference point for evaluating sample composition given that a majority of respondents (83.6%) were Texas residents. Relative to state-level ACS estimates, the sample overrepresents men and young people (18-23 and 25-34 age groups), those holding a bachelor's degree or higher, White individuals, and students and individuals in the "other" employment category (including those who selected volunteer, homemaker/caregiver, unemployed, or "other" to represent their employment status). In contrast, older individuals (55-64 and 65+ age groups), Hispanic individuals, and those in the "other" race category (including mixed race individuals, and races not represented by the other categories) are underrepresented within the sample. At the household level, there is an overrepresentation of high-income households (with incomes greater than \$100,000), while medium income households (\$35,000-\$100,000), households living in single family (detached) homes, and single adult households are underrepresented. Finally, residential location and state of residence were classified based on respondents' zip codes, with population density value appended from the ACS CBP dataset. To categorize population densities, the sample was grouped approximately into thirds, with respondents categorized as residing in low-density areas (less than 6,600 persons per square mile), medium-density areas (6,600–15,999 persons per square mile), or high-density areas (16,000+ persons per square mile). Data is not readily available from the ACS regarding other gender identities, residential location, or the presence of children under 13 years in the household.

The skews observed within the sample are expected due to the largely convenience-based sampling approach. In particular, the overrepresentation of high-income and highly educated individuals aligns with the distribution process of the sample, as these individuals tend to be more able to engage with community organizations (Dutta-Bergman, 2003; Sandstrom and Alper, 2019). While the sample may not completely mirror the true demographic population of the state of Texas, this does not necessarily imply that the individual-level relationships between mode choice and explanatory variables cannot be generalized to the population at large to inform the design and future positioning of UAM services. Importantly, the sampling strategy employed corresponds to exogenous sampling, as respondents were not selected based on their UAM adoption preferences (the endogenous variable). In other words, inclusion in the sample is independent of adoption behavior, meaning the sample is not biased toward individuals who already prefer or reject UAM. In the exogenous sampling case, an unweighted approach provides more efficient parameter estimates (Solon et al., 2015; Robbennolt et al., 2026). Thus, we apply an unweighted estimation approach in this study, leveraging the adequate variation across the range of exogenous variables to estimate generalizable individual-level adoption trends.

4.3 Latent Constructs

In the SEM component of the analytic framework, we incorporate latent constructs to account for unobserved individual attitudes and lifestyle preferences that are expected to influence UAM adoption patterns. These latent constructs are extracted using the responses to a series of attitudinal statements presented to respondents, asking respondents to indicate their agreement or disagreement with each statement on a five-point Likert Scale ranging from “strongly disagree” to “strongly agree.”² The observed responses to these statements serve as indicators of the underlying latent constructs.

In our analysis, we include three latent constructs likely to impact UAM adoption patterns: tech-savviness, UAM noise sensitivity, and positive travel perceptions. Additional constructs designed to explain individuals’ green lifestyle propensity, attitudes toward control during travel, adventurousness, air travel anxieties, and UAM safety perceptions were also tested. The final set of three latent constructs was determined by an analysis of “within construct” and “between construct” variance, as well as the relationships between latent constructs and the ranked outcomes. Constructs related to green lifestyle propensity and control during travel did not demonstrate sufficient internal consistency, with weak and inconsistent factor loadings across associated indicators (each of these had a loading that differed by a factor greater than 2, indicating unstable measurement behavior). On the other hand, constructs representing adventurousness, air travel anxieties, and safety perceptions demonstrated acceptable loadings but did not have statistically significant effects on the ranked outcomes after accounting for the effects of the retained latent constructs. This result is likely due, at least in part, to the high correlation (0.733) of tech-savviness and adventurousness constructs, which capture different but closely related aspects of an underlying affinity for new experiences and technologies. In addition, the lack of significant effect for the safety perceptions construct may reflect the explicit inclusion of UAM crash-related safety levels as an exogenous variable within the survey design.

The final first-stage model retained three latent constructs that a) demonstrated reliable loading patterns (with all loadings for each retained latent construct differing by a factor less than 1.4), b) represent distinct and theoretically relevant attitudinal characteristics, and c) yield significant effects on the ranked SP outcomes. The resulting first-stage component of the model achieved a root mean square error of approximation (RMSEA) of 0.042 and a standardized mean square residual (SRMR) of 0.031. The low RMSEA and SRMR values indicate that the retained measurement structure provides a good representation of the observed covariance relationships among the indicators. Together with the strong and statistically significant factor loadings (as discussed in Section 5.1), the theoretical interpretability of the retained constructs, and their explanatory power in the subsequent rank-ordered choice model, these results support the conclusion that the latent constructs provide reliable and substantively meaningful attitudinal dimensions for explaining UAM adoption preferences. Indicator distributions of the latent constructs for the final measurement model are shown in Figure 2. Each latent construct is discussed in more detail below.

² To mitigate response bias, UAM-specific attitudinal statements were presented using both positive and negative framings, with each version presented to half of the sample. For example, the first indicator of UAM noise sensitivity was phrased, “I am concerned about UAM making too much noise in residential areas” as well as, “I am not too concerned about UAM making too much noise in residential areas.” The third indicator of tech-savviness and both indicators of UAM noise sensitivity were collected in this manner, and half of the responses were subsequently reverse coded to ensure consistency in interpretation. The unified responses, shown in Figure 2, were used in latent construct estimation. All remaining indicators were presented using a single wording.

The first latent construct represents an individual's tech-savviness, with higher values indicating a greater inclination to engage with emerging technologies and automation. Attitudes toward technology have been widely shown to influence adoption of emerging transportation modes (see, for example, Asmussen et al., 2020; Zhang and Kamargianni, 2023; Geržinič et al., 2025), and have also been linked to prospective UAM adoption behavior in prior research (Johnson et al., 2022; Karami et al., 2024; Mostofi et al., 2024; Yavuz, 2024). Within the TAM and TPB behavioral frameworks, tech-savviness is often found to increase perceived usefulness of UAM as well as improving attitudes towards the technology (Al Haddad et al., 2020; Karami et al., 2024; Mostofi et al., 2024). Individuals with higher technological savviness are therefore expected to exhibit a greater openness toward UAM, and rank it more highly in general in the SP experiments. As shown in the top panel of Figure 2, responses for tech-savviness are roughly uniformly distributed, though respondents display a higher level of disagreement to the indicator "I would be comfortable flying in a self-flying vehicle" relative to other indicators of technology affinity.

The second construct, UAM noise sensitivity, captures respondents' sensitivity to UAM-related noise in residential contexts and during nighttime hours, with higher values indicating greater annoyance (for presentation conciseness, we will refer to this construct simply as UAM noise sensitivity, without the repeated explicit tie to noise in residential areas and around the home location of the individual). As mentioned previously, noise sensitivity has been identified in prior literature as an individual-level trait (Miedema and Vos, 1999; Schutte et al., 2007; Shepherd et al., 2010; Aalmoes and Sieben, 2021), with sensitivity levels elevated for those who exhibit anxiety or fear relating to the associated mode (Miedema and Vos, 1999). While not commonly included as a distinct variable within the traditional TAM (which instead generally focuses on perceived usefulness and perceived ease of use), UAM noise sensitivity aligns closely with the attitudinal component of TPB that explicitly recognizes the importance of beliefs about the negative consequences of performing a behavior. In the UAM context, we capture noise sensitivity as a context specific attitudinal belief, capturing the extent to which anticipated noise disruptions contribute to negative attitudes towards UAM technology. Incorporating this construct allows us to examine the role of general noise sensitivity and perceptions in shaping adoption intentions, while controlling separately for in-vehicle noise levels as a service attribute. Within the sample, UAM noise sensitivity responses appear somewhat skewed toward higher sensitivity, particularly for the second indicator related to noise levels near the home during nighttime operations (see the middle panel of Figure 2).

The final construct represents positive travel perceptions, measuring the degree to which individuals enjoy the act of traveling and perceive travel time as useful. This construct reflects general satisfaction with existing mobility options. This construct aligns with the perceived usefulness component of TAM, capturing the extent to which individuals view their current travel as providing value beyond merely reaching a destination. As such, it is expected that individuals with more positive perceptions of their current travel experiences will display lower propensities to adopt UAM services (Brunelli et al., 2023; Karimi et al., 2024; Adamidis et al., 2025). Conversely, individuals who are frustrated with existing modal options or dissatisfied with their current travel experiences are likely to have lower scores on this construct, which may increase their receptiveness to UAM. Responses related to positive travel perception (see the final panel of Figure 2) suggest that most individuals view their current travel experiences favorably, with a small minority expressing negative perceptions of their travel time.

4.4 Endogenous Outcome

The endogenous outcome in this study is an ordered ranking of preference across five modal alternatives presented to each individual in each of two SP scenarios. The five alternatives include: (1) air taxi (an on-demand private service), (2) air metro (a public aerial service with fixed routes, set departure times, and shared vehicles), (3) GB ridehailing services, (4) GB public transportation, and (5) GB private vehicle. This design provides a realistic comparison between preferences, including both on-demand and fixed-route alternatives for both aerial modes and GB modes. Each respondent was asked to rank all five alternatives in each of the two SP scenarios, yielding a total of 2,114 ranked observations ($1,057 \text{ respondents} \times 2 \text{ choice occasions}$). Table 4 presents the overall stated ranked mode preferences across both scenarios.

The “First Rank” column of Table 4 indicates that air taxi is the second most frequently selected first-choice mode (22.2%), followed by air metro (12.4%). At an aggregate level, these results suggest that interest in UAM modes is quite substantial, with an aerial mode selected as a first-choice in 34.6% of the SP experiments. At the same time, aerial modes also appear among the least-preferred alternatives for comparable shares of respondents. As shown in the final column of Table 4, air taxi and air metro account for 21.3% and 13.6% of fifth-ranked choices, respectively. This pattern of polarization suggests substantial variation in preferences across scenarios or heterogeneity in individual attitudes toward modal alternatives. Turning to GB modes, shares for ridehailing are highest in the intermediate (third and fourth) ranks, peaking at 30.4% for the fourth-rank position. Public transportation is the least preferred alternative overall, with 38.0% of responses ranking it last. Finally, private vehicle is the most commonly selected first-ranked alternative, accounting for 51.2% of first-rank preferences. These descriptive patterns provide high-level insights into relative modal preferences, revealing both enthusiasm and hesitancy towards UAM services. However, they do not, on their own, explain the sources of these preferences.

5. RESULTS

The final rank-ordered model specification was developed through a systematic evaluation of various combinations of explanatory variables, including testing different functional forms and interaction effects. Continuous/count variables such as travel time, cost, age, household size, and number of motorized vehicles in household were tested in both continuous, piecewise-linear, and dummy variable forms, and all except age turned out to be best included in continuous (linear) form in the final specification. Categorical variables were initially tested in their most disaggregate dummy variable form, and then combined based on statistical tests and behavioral interpretability. Interaction effects between contextual and individual-level characteristics were also systematically tested. Latent constructs were incorporated directly, with additional interactions considered to capture the influence of attitudes on the perceptions of specific service attributes as well as interactions with individual characteristics. During the model estimation process, we used a t-statistic threshold of 1.28 corresponding to an 80% confidence level to retain variables for both the first-stage latent construct estimation, and second-stage ROP outcome.³ However, the vast

³ Some additional justification is warranted regarding our use of an 80% confidence level (0.20 level of significance). Specifically, the selection of a confidence level involves balancing the risks of incorrectly including variables that have no true impact and incorrectly excluding meaningful variables. As recommended by the American Statistical Association (see Wasserstein and Lazar, 2016; Wasserstein et al., 2019), researchers should exercise context-specific judgement to employ appropriate statistical thresholds, rather than applying any confidence level across all contexts. In this analysis, due to the modest sample size (while there are a good number of choice occasions, the sample includes a more limited number of distinct respondents, reducing the efficiency of individual- and household-level effects) and

majority of the variables included in the final specification are statistically significant at much higher levels of confidence than this threshold, with only two variables falling below a 90% level of confidence.

The final estimation results are shown in Tables 5 and 6. A “--” entry in these tables indicates that the corresponding exogenous variable does not have a statistically significant impact on the outcome column. The population density variable was not found to have a statistically significant impact on the outcomes and is therefore omitted. Similarly, we also tested for differential effects of Texan and non-Texan respondents in all model components, including interacting a dummy “Texan” variable with contextual characteristics. However, these interaction effects did not result in any statistically and behaviorally meaningful relationships⁴, and were therefore excluded from the final model specification. As a result, regional effects associated with state of residence are captured only by alternative-specific “Texan” dummy variables, discussed in Section 5.2.2. The results for the impacts of the demographic variables on the latent constructs are presented in the following section, followed by the results of the ROP model for the effects of exogenous variables and latent constructs on the mode rankings in Section 5.2.

5.1 Latent Constructs

The top panel of Table 5 presents the loadings of the latent constructs on their respective indicator variables, with results exhibiting the expected signs as discussed in Section 4.3. The “Correlations Between Latent Variables” panel of Table 5 reports the correlations among latent constructs (Γ in Figure 1). Tech-savviness is negatively correlated with UAM noise sensitivity, perhaps because technological inclination makes individuals more accepting of UAM-related noise. In contrast, tech-savviness is positively correlated with positive travel perceptions, presumably a reflection of the enhanced ability of tech-savvy individuals to use their travel time more productively through technological tools and platforms (see Dannemiller et al., 2021). Finally, the estimated correlation between UAM noise sensitivity and positive travel perceptions is negative, but not statistically significant.

The bottom panel of Table 5 presents the effects of individual and household level demographic variables on the three latent constructs. The analysis indicates that men (compared with women and other genders) tend to exhibit higher levels of tech-savviness. Elevated tech-savviness among men likely reflects greater interest in, and engagement with, emerging technologies, as well as a tendency to view technological innovation as a source of novelty or personal enrichment. These patterns may be rooted in part in persistent gendered gaps in technology access and education (Galyani Moghaddam, 2010; Mushtaq and Riyaz, 2020), as well as higher levels of hedonism among men (Schwartz, 1992; Vianello et al., 2013; Brakus et al., 2022). Women, on the other hand, have been found to exhibit greater caution toward emerging mobility technologies due to heightened perceptions of risk and lower perceived usefulness,

selective availability of certain service attributes (due to the blocked survey design intended to allow for a large number of attributes to be considered), we prioritize including variables that are theoretically meaningful at a slightly lower level of confidence even if this entails a slightly increased chance of including variables with no true impact. This deliberate tradeoff allows us to identify relationships with a relatively high significance in the current dataset that may guide future investigations benefiting from larger sample sizes. Also, as noted above, only two variables turn out to be significant at the 80% confidence level and not the 90% confidence level.

⁴ The limited statistical power of interaction effects between the “Texan” indicator variable and service attributes/trip context is likely attributable to the relatively small sample size of non-Texas respondents (173 individuals, 16.4% of the overall sample). As mentioned in Section 7, future studies based on larger and more geographically balanced samples may offer additional insight into potential regional heterogeneity in UAM adoption patterns.

particularly in the context of autonomous vehicle technologies (Acheampong and Cugurullo, 2019; Asmussen et al., 2020; Dannemiller et al., 2021; Asmussen et al., 2022). The results also indicate that men tend to be less sensitive to UAM noise relative to women. While this finding contrasts with earlier literature suggesting that general noise sensitivity is largely independent of gender (Schutte et al., 2007; Shepherd et al., 2010), the result may reflect the specific context of UAM-related noise in residential environments, as captured by the indicators in this study. The elevated sensitivity of women to noise near the home may be linked to their central role in managing household routines and caregiving, where noise disruptions can have a negative impact. Consistent with this interpretation, prior work has identified a greater sensitivity among women to transportation and construction-related noise specifically near the home (Michaud et al., 2022).

An additional and strong attitudinal determinant is age, with increasing age associated with lower levels of tech-savviness. The reduction in tech-savviness with age is consistent with well-established findings, reflecting lower exposure to rapidly evolving digital technologies and greater difficulty adapting to new systems compared to younger individuals (Blazanin et al., 2022; Mohan et al., 2024; Xu et al., 2025). Age also shapes UAM noise sensitivity, with individuals in the 65 and older age group exhibiting a decreased sensitivity to UAM-related noise disruptions. This pattern has been attributed to less acute hearing among seniors, and lifecycle differences in the importance of environmental quality which make seniors less sensitive to residential disruptions (Miedema and Vos, 1999; Ni and Huang, 2022; Zhu and Chen, 2023).

Individuals with higher levels of formal educational attainment tend to exhibit increased tech-savviness and more positive perceptions of travel. Elevated tech-savviness among this group likely reflects greater exposure to technology in both educational and professional settings (see van Laar et al., 2017; Nair and Bhat, 2021). In addition, more positive perceptions of travel may be attributable to increased levels of schedule flexibility among highly-educated individuals, which can reduce time-related stress and enable productive use of travel time (Anderson et al., 2024; Hwang et al., 2025). The results also indicate that Black respondents exhibit more positive perceptions of both technology and travel relative to White individuals. Respondents in the “other” race category likewise tend to be more tech-savvy, while Hispanic respondents tend to hold more positive perceptions of travel. Improved technology perceptions among these racial groups may reflect existing transportation disparities that make transportation technologies feel more empowering compared with existing conditions. Similarly, positive travel perceptions among Black and Hispanic respondents may be related to experiences of time poverty (Kwate, 2017; Gee et al., 2019; Hess et al., 2020), which can increase the value placed on travel as a productive reprieve that enables transitions between competing responsibilities. The final individual-level variable affecting the latent constructs is full-time employment status, which has a negative effect on UAM noise sensitivity. As shown in Table 5, the UAM noise sensitivity construct in this study is derived from indicators relating specifically to disruptions in residential areas. Given this residential location emphasis, individuals such as part-time workers, students, retired individuals, and others not employed in full-time work may report higher UAM noise sensitivity due to a greater portion of time spent at home.

At the household level, individuals from lower-income households exhibit a reduced inclination toward technology, a well-documented trend attributable to higher levels of technology access and exposure among those from high-income households (Kalba, 2008; Lavieri et al., 2017; Dannemiller et al., 2021; Nair and Bhat, 2021). Respondents in lower-income households also exhibit lower levels of UAM noise sensitivity than those in higher-income categories, potentially reflecting a greater baseline exposure to transportation noise in economically disadvantaged

neighborhoods (Collins et al., 2020; Letellier et al., 2023). This finding is also consistent with previous studies identifying reduced noise level sensitivities among low-income groups in the context of commercial aircraft and helicopter noise (Michaud et al., 2022).

Moving onto other household-related variables, homeowners and individuals in households with young children (less than 13 years of age) tend to manifest more positive travel perceptions than non-homeowners and individuals in households without children, respectively. The latter result may be attributable to travel time being viewed as a period of peace within the day, offering a respite from the household responsibilities associated with caring for children (Craig and Mullan, 2010; Asmussen et al., 2022). As a result, individuals in households with young children may evaluate travel time more positively, not solely based on duration or efficiency, but in terms of its mental benefits as a structured break from domestic responsibilities. On the other hand, larger households tend to exhibit less positive travel perceptions, potentially due to the increased logistic complexity of coordinating travel among larger households (Ho and Mulley, 2015).

5.2 Main Outcomes

Table 6 presents the estimation results for the main ROP mode choice outcome. The coefficients represent the impact of variables on the utility of each alternative. The constants in the first row of the table do not have any meaningful interpretation, and are simply estimated to best match predicted and observed ranked proportions, given the estimated effects of the exogenous variables and latent constructs.

A couple of notes before we proceed to a discussion of the results. First, we tested extensively for alternative-specific effects of service attributes (such as in-vehicle travel time, waiting time, and cost), but many of these were not statistically significant. The ones that came out to be important are included in the table, and are discussed along with other effects. Second, for the service attributes that were not presented to all individuals, we tested if individuals may have responded differently if they were not at all shown the attribute relative to being shown the attribute. But invariably, we found that the “not shown” case was not different from the base case used for the service attribute. For instance, in the case of the service attribute of UAM availability, the base used is “UAM always available” and a separate dummy variable for “not shown” came out to be statistically insignificant with respect to zero. The implication here would be that, when UAM availability levels were not shown, individuals presumed that the UAM service would always be available. Thus, the dummy variable effect for “UAM available only in clear weather” reflects the difference from the base case of “UAM always available.”

5.2.1 Effects of Contextual Characteristics

Service Attribute Effects: The first section of Table 6 presents the effects of the service attributes, along with any interaction effects with trip context (trip purpose and distance) variables. The results reveal that, as expected, a longer in-vehicle travel time (IVTT) reduces the attractiveness of each mode, aligning with previous findings for both aerial and GB travel (Frank et al., 2008; Fu et al., 2019; Cho and Kim, 2022; Ranjan and Sinha, 2025). However, the negative impact of IVTT is stronger for aerial modes than GB alternatives (a coefficient of -0.1449 for the aerial modes relative to -0.0918 for the GB modes). This suggests that prospective users have a greater disutility associated with longer UAM travel times, likely because IVTT reductions are viewed as one of the principal advantages of UAM modes. Consequently, longer travel times may undermine one of the main motivations for adopting UAM over GB alternatives. The impact of IVTT is further shaped by trip context. For errand trips, the disutility associated with IVTT declines substantially

across all modes, resulting in a small IVTT impact for UAM modes (the net effect is $-0.1449 + 0.0756 = -0.0693$) and almost no impact for GB modes (net effect of $-0.0918 + 0.0756 = -0.0162$). Errands are primarily task-oriented, and often involve flexible, multi-stop travel patterns (Wallius et al., 2026), and so flexibility and convenience dominate relative to travel time. In contrast, the importance of IVTT is elevated for aerial medical trips, indicating a much stronger emphasis on minimizing travel time for emergency situations when using aerial modes (net effect of $-0.1449 + -0.0771 = -0.2220$). This reflects the urgency associated with medical emergencies, and the expectation that aerial transportation should provide fast and efficient transportation when time is critical. Overall, IVTT has a negative effect for non-errand trips for all travel modes, although its impact is larger for UAM modes, with this negative effect peaking for medical emergency trips by UAM.

Similarly, longer waiting times reduce the attractiveness across all modes. Individuals do not show a meaningful distinction between no wait time and a very short wait of 5 minutes, suggesting that some level of brief delay is generally acceptable. However, preferences begin to decline for wait times of 10-15 minutes and continue to decrease in attractiveness for wait times of 30 minutes. Specifically, a 10-minute wait time (compared to having no wait time, for any trip purpose and any trip length) is considered about as onerous as 20 minutes of additional IVTT for non-errand, non-medical emergency (NENME) trips by UAM (notice that the coefficient for a 10-minute wait time is -0.0509 , while the coefficient for an additional hour of UAM IVTT for NENME trips is -0.1449). A 30-minute delay is viewed as more burdensome, equating to approximately 50 minutes of additional IVTT for UAM NENME trips. These findings indicate that travelers place a substantial penalty on out-of-vehicle waiting time, valuing reductions in waiting time more highly than equivalent reductions in IVTT. This result is consistent with a large body of research on GB modes demonstrating that out-of-vehicle time is perceived as more burdensome than time spent inside a vehicle (Wardman et al., 2016; Hamadneh et al., 2023).

In addition to IVTT and waiting times, distance to pick-up/drop-off locations also play a role. Shorter access/egress distance to pick-up/drop-off locations increase the attractiveness of any mode, consistent with previous findings for both aerial and GB mode choice (Lam and Xie, 2002; Durand et al., 2016; Hwang and Hong, 2023; Adamidis et al., 2025). This pattern is also consistent with prior work showing that vertiport placement near the home is associated with higher levels of UAM adoption, while more distant locations are considered less attractive (Lotz et al., 2023). To provide context regarding the magnitude of this effect, reducing access/egress distance from more than a mile to within 0.5-1 miles is comparable to around a 20-minute reduction in IVTT for NENME trips by UAM. But a caveat here. For the UAM modes, this attractiveness of having vertiports within 0.5-1 mile is more than offset if UAM services are accompanied by high noise levels (equivalent of a heavy truck or a motorcycle) for those individuals with high UAM noise sensitivity (that is, for women, individuals younger than 65 years of age, non-full-time-employed individuals, and individuals from medium- or high-income households), as we discuss further in the next section. The appeal of door-to-door service, however, is very pronounced, dominating any noise-level related issues even for noise-sensitive individuals. The convenience of door-to-door UAM transportation corresponds approximately to a one-hour reduction in IVTT for NENME trips by UAM compared with an access/egress distance of more than a mile.

As expected, higher costs reduce the attractiveness of any mode, with the cost sensitivity varying based on household income level; individuals from lower-income households exhibit greater sensitivity to travel cost than individuals from higher-income households. Additionally, respondents exhibit a reduced sensitivity to the cost of inter-city trips (~120 miles one-way), with

all income levels exhibiting a higher willingness to pay for longer-distance travel. Notably, the reduction in cost sensitivity associated with inter-city trips (~120 miles one-way) is most pronounced among lower-income households. As a result, the effective cost sensitivities of the low- and middle-income groups become nearly identical in the inter-city travel context (for low income individuals: $-0.2383 + 0.1320 = -0.1063$, while for middle-income individuals: $-0.2083 + 0.1020 = -0.1063$). One possible explanation is that long-distance trips occur relatively infrequently and are therefore more likely to be planned and budgeted for in advance, allowing lower-income households to pay higher travel costs than they would for more routine intra-city trips. Consequently, cost considerations appear to play a somewhat smaller role in inter-city (~120 miles one-way) travel decisions than in shorter-distance (~10 or 40 miles) travel contexts, particularly among lower-income travelers. Together, the IVTT and cost coefficient values provide the basis for the estimation of value of travel time savings (VTTs) across trip contexts and income groups. These results are discussed in detail in Section 6.1.

Turning to UAM-specific service attributes, results relating to UAM availability, UAM in-flight experience, and environmental sustainability provide additional insights into user preferences. UAM availability emerges as an important factor, with utility decreasing dramatically when aerial services are only available during clear weather conditions. This suggests that respondents' desire for consistent availability outweighs potential fears related to UAM travel during inclement weather. This impact of inconsistent availability of UAMs is large, equating to approximately 1.4 hours of additional IVTT for UAM NENME trips. Preferences for UAM alternatives also decrease when the cabin interior is described as cramped. It may be that UAM is perceived as a premium mode, leading individuals to expect higher-quality travel conditions as a baseline, as also indicated by the fact that there was no statistically significant difference between the base category of "spacious interior with room for belongings" and when this UAM attribute was not shown to respondents. The negative utility associated with cramped UAM interiors mirrors the reduced passenger satisfaction observed in studies of current air travel when cabin space is cramped (Ahmadpour et al., 2014; Sezgen et al., 2019). Cramped spaces are considered about as onerous as a 1.2 hour increase in IVTT for UAM NENME trips, suggesting that in-flight experience is a highly valued aspect of UAM utility.

With respect to environmental sustainability, UAM mode utilities increase when aerial operations have a low environmental impact. Although the magnitude of this effect is smaller than those associated with UAM availability or UAM in-flight experience, its impact is still substantial, with low environmental impact being valued about as much as a 35-minute reduction in IVTT for UAM NENME trips. This suggests that prospective users are conscious of, and responsive to, the broader environmental consequences of UAM technology. From a methodological perspective, it is important to mention that this relatively strong and statistically significant effect emerges as a result of the comprehensive modeling approach. During the model specification process, many of the effects of service attributes varied (producing statistically insignificant effects and even changing signs in some cases) when ignoring other service attributes, trip contextual variables, and attitudinal effects. These variations imply that accommodating a comprehensive set of factors is important to uncover the direction and magnitude of UAM service attributes, and hence for the design and operational features of UAM services. For instance, our results show clear evidence that environmental sustainability can be an important determinant of UAM adoption, while earlier literature accommodating only a more limited set of factors (see, for example, Zaps and Chankov, 2022; Lotz et al., 2023; Karami et al., 2024) has shown mixed results.

Results related to UAM crash-related safety reveal a negative effect on UAM modal utilities when aerial travel is presented as more prone to crashes on a per-mile basis than GB alternatives. This finding is consistent with prior research highlighting the central role of crash-related safety in UAM adoption (Fu et al., 2019). Further insight is provided by the fact that when UAM crash-related safety was not presented, respondents did not evaluate UAM modes statistically differently from the base case of “fewer crashes per mile than ground vehicles,” suggesting that prospective users assume (as a baseline) that UAM services would involve fewer crashes than ground vehicles. But when expressly told that this would not be the case in the SP experiments, a strong negative response was expressed for the UAM modes (equating to around 50 minutes of additional IVTT for UAM NENME trips).

Finally, fully autonomous operation is found to reduce preferences for both aerial and GB modes, indicating that the absence of a human operator in the vehicle introduces discomfort. This effect is large; travel in an autonomous UAM vehicle is considered around 1.6 times as undesirable as an hour increase in IVTT for UAM NENME trips. Notably, when automation is not specified during the choice experiment, utilities are similar to the case when a human pilot is present in the vehicle, suggesting that individuals assume some level of human oversight of UAM operations as a baseline presumption. Despite lower preferences for automation across modes, the reduction in utility is smaller for aerial modes than for GB alternatives (though, admittedly, this reduction is not statistically significant). This result suggests that automation appears to be somewhat more accepted in aerial contexts. One possible explanation is that air travel is already associated with system-level control and high degrees of automation, where safe operation depends on complex systems rather than solely on a human operator. This perception may extend to emerging UAM services, leading automation to be viewed as an extension of existing aviation practices (Bennett and Vijaygopal, 2021; Fondevila-Gascón et al., 2025). In contrast, GB travel is more strongly associated with individual control and personal agency, and as most users have much more experience driving themselves (compared with piloting an aircraft), they may be less comfortable deferring control to automated systems in GB contexts (Annaç Göv, 2023; Fondevila-Gascón et al., 2025).

Trip Context: In addition to the interaction effects of service attributes with trip context variables, as discussed earlier, modal selection is also impacted directly by trip purpose, as shown at the top of the second page of Table 6. The results indicate a decreased utility for public transportation when trips are made for errands or emergency medical transport. The limited flexibility of public transportation and the need to carry items such as groceries may reduce its suitability for errands (Schneider et al., 2021; Wallius et al., 2026), while its shared nature likely contributes to the reduced preferences for emergency medical trips. For leisure trips, there is an elevated preference for the ridehailing mode, attributable to a wide range of benefits specific to ridehailing, including the quick and easy digital access, alleviation of parking concerns, and the safe consumption of alcohol (MacLeod et al., 2020; Tarabay and Abou-Zeid, 2020; Tirachini, 2020).

Trip distance also emerges as an influential factor, with utilities for aerial modes significantly reduced for the shortest trip length of around 10 miles. This finding suggests that prospective users view travel by aerial modes as most beneficial for longer trips such as for long intra-city trips (~40 miles one-way) and inter-city trips (~120 miles one-way). Although we control for the impacts of travel time savings and pick-up and drop-off locations within the modeling framework, respondents’ preferences may be driven by a mental barrier to entry involved with UAM adoption that goes beyond service attributes. The effort required to learn how to use this

(relatively) unfamiliar mode, particularly for a first-time user, may outweigh its benefits for short trips, discouraging adoption (see Dällenbach, 2020). In addition, users may perceive air travel as unnecessary for a short trip when simpler and more familiar GB alternatives are available.

5.2.2 Effects of Individual-level Characteristics

Latent Constructs: The “Latent Constructs” panel in Table 6 provides the effects of the three latent constructs and their interactions on the model utilities. As expected, individuals with a high level of tech-savviness exhibit elevated preferences for aerial modes. Tech-savviness also affects preferences for GB modes, with more technologically inclined individuals exhibiting reduced preferences for public transportation, consistent with the results of Julsrud and Denstadli, (2017) who found that smartphone users held more negative perceptions of public transportation than less tech-savvy individuals who did not use technology during their travel.

Those with elevated sensitivity to UAM-related noise are less inclined to rank UAM modes highly when noise levels are described as equivalent to those of a heavy truck or motorcycle (although this effect is significant only at the 80% confidence level). This response reflects both personal and environmental considerations. At an individual level, increased sensitivity to noise may make travelling in louder vehicles less appealing. At the same time, these individuals are more sensitive to the broader impacts of UAM noise within residential environments, leading to reduced preferences for more disruptive modes. Notably, neither UAM noise levels alone nor the UAM noise sensitivity latent construct independently have a significant impact on mode choice. Instead, the results suggest that preferences are shaped by the interaction between the specific UAM operating conditions and individual sensitivities. As discussed in Section 5.2.1, however, the relative magnitudes of the estimated effects indicate that convenience may outweigh these concerns at the individual level. The disutility associated with high UAM noise levels among UAM noise-sensitive individuals (coefficient of -0.0749) exceeds the utility gain associated with locating a vertiport within 0.5–1 mile of the traveler (coefficient of 0.0565 relative to a vertiport located more than one mile away). In contrast, door-to-door service provides a larger utility benefit (coefficient of 0.1557), more than offsetting the negative effect of high noise levels on adoption among UAM noise-sensitive individuals (net effect of $-0.0749 + 0.1557 = 0.0808$). These findings suggest that noise concerns shape the individual-level adoption decisions of UAM noise-sensitive individuals but do not dominate them, with convenient access to UAM services exerting a stronger influence on modal preferences. These findings add nuance to prior research that has identified community-level resistance to UAM noise disruptions (Goyal et al., 2018; Kähler et al., 2022), illuminating the factors which shape adoption at the individual level.

Finally, individuals with more positive perceptions of travel are less inclined towards UAM alternatives, suggesting a greater level of satisfaction with their current travel experience. Conversely, these results indicate that individuals who perceive travel as burdensome or unproductive may be more receptive to UAM alternatives. In particular, the potential for engaging in alternative activities such as work, rest, or recreation during travel may increase the utility of the UAM modes for currently dissatisfied individuals. While the significance of this result reaches only the 80% confidence level, it suggests that current travel experiences have the potential to play an important role in adoption.

Demographics: The demographic effects listed in Table 6 provide the direct effects of individual- and household-level demographics after accounting for the indirect effects of demographic characteristics mediated by the latent constructs. Overall, relatively few demographic variables

exhibit direct effects, suggesting that much of the influence of demographics on mode preferences is indirect through individual attitudes.

Gender and age both exhibit direct effects. Even beyond the tech-savviness effect on UAM mode preference, men exhibit an elevated utility for the air taxi mode. One possible explanation is that men are more likely to associate vehicles with status and identity (Sovacool and Axsen, 2018; Robbennolt et al., 2025). In this context, a technologically advanced and private mode such as an air taxi may be perceived by men as premium, enhancing its appeal. On the age front, individuals within the 35-64 age group exhibit lower preferences for the air metro mode specifically, with no corresponding effect observed for air taxi services. This finding suggests that middle-aged respondents exhibit a reduced interest in shared aerial mobility options relative to other age groups. At the same time, this group is more responsive to improvements in crash-related safety, showing higher preferences for aerial modes when they are presented as having fewer crashes per-mile than GB alternatives. Compared to younger and older individuals, this middle-age group is likely to be in a life cycle with more responsibility (such as having dependent children or dependent parents), which may make them more safety-centered (Orit Taubman and Noy, 2011; Cox and Cicchino, 2022).

Level of education also plays a role, with college-educated individuals exhibiting elevated preferences for public transportation relative to those with lower levels of formal education, presumably a reflection of greater environmental awareness and a higher propensity to engage in sustainable behaviors (Liu et al., 2020; Robbennolt et al., 2025). The only direct racial effects relate to Black respondents, who exhibit a reduced preference for public transportation. This finding is, however, not inconsistent with widely observed patterns of higher transit usage among Black populations in the United States (Purifoye, 2020; Swistara, 2020; Yang, 2025), because the overall mode choice decision is based on trade-offs between situational constraints and general mode preferences.

Regarding household characteristics, individuals from higher-income households exhibit lower preferences for public transportation, consistent with well-documented trends in the literature (Neff and Pham, 2007; Taylor and Morris, 2015; Smith et al., 2025). Housing type also shapes modal utilities, with those living in single family housing exhibiting reduced preferences for air metro, ridehailing, and public transportation alternatives. These patterns may reflect a stronger preference for privacy within the context of both housing and travel, which reduces the attractiveness of shared modes as well as ridehailing services involving unfamiliar drivers. Household motorized vehicle ownership further reinforces these patterns, with access to a greater number of vehicles associated with reduced preferences for aerial modes and public transportation. This indicates that the more private vehicles an individual has access to, the more likely they are to rely on private vehicle modes such as driving and ridehailing.

Finally, respondents' state of residence also influences baseline modal preferences. Specifically, the "Texan" dummy variable has a negative impact on UAM, ridehailing, and public transportation modal alternatives, as shown in the final panel of Table 6, indicating a stronger baseline preference among Texans for private vehicles compared to all other modes. This finding is consistent with a state-level culture of "car pride" (Moody and Zhao, 2019), which centers private vehicles as status symbols and means of individual expression (Chappell, 2012; Wilkins, 2016). In addition, the largely private vehicle-oriented urban form and transportation infrastructure that dominates Texas metropolitan areas may further reinforce preferences for private vehicles (Moody and Zhao, 2020). These results suggest that regional context, through both cultural norms and the built environment, can shape UAM adoption and mode selection.

5.2.3 Correlations

The final panel of Table 6 presents the covariance elements, including the scales of the differenced covariance matrix (the elements of the $\tilde{\omega}$ matrix in Section 3.2.2) and the elements of the correlation matrix Θ^* that provides both the correlations among the alternatives in differenced utility space (differenced from the last alternative, which is the private vehicle alternative in our methodological set-up) at each choice occasion as well as panel correlation effects across the two choice occasions from the same individual for each alternative. These scales and correlation elements are not readily interpretable unless some assumptions are made. In our case, we assume that the intrinsic utility variance across individuals associated with the private vehicle is negligible relative to other non-private and emerging technology modes, given the familiarity and control associated with the private vehicle mode. Also, the private vehicle mode tends to be uniquely positioned in the perceptual map of individuals so that there is perhaps little correlation between the private vehicle mode and other modes not owned by the individual. Within this context, the elements of $\tilde{\omega}$ and Θ^* may be viewed as corresponding to the non-private vehicle modes.

With that reasonable assumption, the scale elements indicate that there is more unobserved heterogeneity in the utility for the public transit alternative compared with the others, likely because of significant differences in perceptions of public transportation (based on location, personal history, and expectations about comfort, crowding, and reliability) that are not accounted for in the exogenous variables and latent constructs. In contrast, there is relatively less overall unobserved heterogeneity impacting the utility of ridehailing which is more easily characterized by the included attributes. The UAM modes fall between these, with a larger scale for air metro indicating that this type of service may still be somewhat more unfamiliar to respondents, leading to greater variations in their perceptions of it.

Next, all of the correlation elements between the utilities of the non-private vehicle modes at each choice occasion are positive. This suggests that individuals preferring any mode over private vehicle are also more likely to have a greater utility for each of the other non-private vehicle modes. Further, the highest correlation is between the alternatives for air taxi and air metro (correlation of 0.8501, t-statistic of 14.794), indicating a very strong correspondence between the unobserved preferences for these two UAM modes. High correlations are also found between air metro and ridehailing, as well as between ridehailing and public transit. As these modes all require a higher willingness to relinquish control and require some comfort in shared or semi-shared transportation vehicles, the close connection is rather intuitive. Conversely, the lowest correlation is between air taxi and public transportation. Finally, we find positive panel correlations across the choice occasions of the same individual for air taxi and ridehailing (but not for air metro and public transportation).

5.2.4 Model Fit

To assess the fit of the proposed modeling framework, we compare our second stage rank-ordered model with a corresponding independent and identically distributed model that does not account for heteroscedasticity across alternatives and does not accommodate correlations across the utilities of the modes or individuals' choice occasions. Although the significant scales and correlations discussed previously already indicate the need to consider correlation terms, this comparison formally tests their inclusion. To compare these specifications, several disaggregate fit measures, shown in Table 7, are computed. We compute the log likelihood at convergence, $L(\hat{\theta})$, for both models, as well as the log-likelihood of the constants only model, $L(c)$, which

includes only the thresholds for the five ranked outcomes. The Bayesian Information Criterion (BIC) statistic is calculated as:

$$BIC = -L(\hat{\theta}) + 0.5 (\# \text{ of model parameters}) \log(\text{sample size}) \quad (7)$$

and the adjusted likelihood ratio index is:

$$\bar{\rho}^2 = 1 - \frac{L(\hat{\theta}) - M}{L(c)} \quad (8)$$

where M is the number of parameters (excluding constants) estimated in the model. Together, these measures of fit favor the model with correlations, as indicated by the lower BIC and higher adjusted likelihood ratio index values for this specification. Additionally, as the independent model is nested within the final specification, we also conduct a log-likelihood ratio test. With the value shown in Table 7 computed as

$$-2 \left[L(\hat{\theta})_{Independent} - L(\hat{\theta})_{With\ Correlations} \right]. \quad (9)$$

The resulting test statistic substantially exceeds the critical value of the chi-squared distribution, providing additional support for the inclusion of correlation terms within the model framework. Finally, we also evaluate the model fit intuitively by calculating the average probability of correct prediction for each specification. To do so, we estimate the probability of the observed rank-ordered outcome, then compute an average across individuals to quantify the probability of correct prediction. As shown in Table 7, the model with correlations has a higher probability of correct prediction, representing a 29.0% increase in the correct prediction probability compared to the independent model. While these probabilities of correct prediction may seem small due to the large number of possible rank-ordered combinations, both specifications represent substantial improvements over the 0.008 probability correct prediction of a naïve model of five ranked alternatives. Together, these disaggregate fit measures indicate that the model with correlations is the preferred specification, and that accounting for unobserved correlations enhances model fit and predictive performance.

5.2.5 *Average Treatment Effects*

While the main estimation results provide insights into the direction and level of significance of exogenous variables' impacts on modal utilities, they do not convey the magnitude of those impacts in an intuitive way. To address this, we calculate average treatment effects (ATEs) to quantify the change in expected mode shares associated with shifts in explanatory variables. ATEs capture both direct and indirect effects by measuring the change between a base and treatment case. For example, to evaluate the impact of gender, we begin by setting the gender of all individuals in the sample to "Male" without changing any other variables, constituting the base case. Then we compute, for each individual, the probability that each mode is ranked first, averaging these probabilities across individuals to get predicted modal shares. The same process is then repeated for the treatment level of the exogenous variable, setting the gender of the entire sample to "Female." The percent ATE is then calculated as the percentage difference in the shares from the base case to the treatment case, capturing both the magnitude and direction of gender's impact on the mode choice outcome. For variables with more than two levels, we select meaningful base and treatment cases based on the model specification, often comparing the highest and lowest levels. For service attributes, we present ATEs based on mode-specific changes to service

attributes. These effects examine the impacts of service changes to air taxi and air metro alternatives individually, as well as jointly, to provide a sense of sensitivity differences between modes. The final ATE effects for a select group of exogenous variables are presented in Table 8, with each of the final five columns representing the percent change in share for each mode. For instance, the ATE for gender's impact on air taxi (see the bottom panel of Table 8) is listed as "67.9%" indicating that men are about 67.9% more likely to choose air-taxi as their first ranked alternative compared with women. In the following section, we discuss the implications of the results based on both imputed values of in-vehicle travel time savings (VTTS) as well as the ATE calculations.

6. IMPLICATIONS

6.1 Implications for In-Vehicle Value of Time Savings

Figure 3 presents the UAM in-vehicle VTTS by household income for different trip purposes and different trip distances. Understanding this variation is particularly important for UAM design and development, given the current uncertainty surrounding pricing. Current estimates for UAM fares vary widely across uncertain operational conditions (Goyal et al., 2018; Lee et al., 2023), as well as between higher near-term estimates (Hae Choi and Park, 2022; Pertz et al., 2023) and longer-term drops expected to be driven by improvements to operational efficiency, technology, and automation (Goyal et al., 2018). Therefore, understanding how travelers value in-vehicle travel time savings is important for gauging market potential and planning pricing for future UAM services.

Although the estimated UAM VTTS values shown in Figure 3 are higher than conventional appraisal benchmarks for personal travel, they should not be interpreted solely as reflecting the opportunity cost of time as measured by the wage rate. Jara-Díaz and Guevara (2003) illustrate, within a DeSerpa (1971) time-allocation framework, that the subjective VTTS estimated from travel choice models comprises two components: the value of reallocating travel time to alternative activities and the direct utility (or disutility) associated with the travel activity itself. Consequently, relatively high subjective VTTS estimates, as obtained from our SP experiment, may reflect not only the value of time as a scarce resource but also unfavorable perceptions of the travel experience. Jara-Díaz (2024) further demonstrates that the latter component may be related to considerations of discomfort, lack of safety, uncertainty, travel time unreliability, and the quality of the travel itself (such as being stuck in stop-and-go traffic versus smooth travel), which can increase the subjective VTTS beyond simply the opportunity cost of time itself.

Across travel contexts, VTTS is higher for UAM than for equivalent GB modes (GB VTTS values are not shown in Figure 3 for simplicity). This finding is consistent with the greater IVTT sensitivity observed for aerial modes and, in line with the Jara-Díaz decomposition of VTTS, suggests that the elevated values associated with UAM reflect both the value travelers place on travel time savings and the disutility associated with UAM travel itself. In particular, uncertainty regarding a relatively unfamiliar mode, together with concerns related to safety and other aspects of the travel experience, may increase the value travelers place on reductions in IVTT. Similar findings have been reported for conventional air travel, where VTTS estimates are often substantially higher than those observed for GB modes (Flügel, 2014; Wardman et al., 2016; Dekker et al., 2025). Flügel (2014) attributes this pattern to modal differences in the utility of the travel experience itself. In the context of UAM, these same modal effects may be amplified by the unfamiliar nature of UAM technology, further increasing VTTS. For example, VTTS estimates among the medium-income group for GB NENME trips are around \$56/hour, increasing to

\$70/hour for an equivalent NENME trip by UAM. This result implies that prospective users may be willing to pay a premium for aerial transportation, provided that UAM services deliver meaningful reductions in travel time. More broadly, the VTTS estimates indicate that both travel-time savings and improvements in the perceived quality of the UAM travel experience will be important determinants of long-term competitiveness with GB alternatives

VTTS also exhibits considerable variation across trip purposes, reflecting differences in the value placed on IVTT reductions across travel contexts. As discussed in Section 5.2.1, IVTT sensitivity is reduced for errand trips and elevated for aerial medical transport, leading to correspondingly low VTTS values for errands (\$29-\$42 per hour for intra-city trips) and high VTTS for medical trips (\$93-\$135 per hour for intra-city trips). This pattern reflects the varying levels of urgency associated with these trip purposes and suggests that emergency medical transportation may represent a promising early use case for UAM. High VTTS values for this trip purpose could help support initially elevated operational costs during early development.

Estimated VTTS values are also impacted by differing cost sensitivities across trip distances. VTTS increase dramatically in the inter-city trip (~120 mile one-way) context, reflecting the higher value travelers place on IVTT reductions as travel distances increase. Moreover, preferences are elevated for these inter-city travel contexts relative to short intra-city trips, suggesting that travelers recognize the substantial potential for long-distance travel time reductions offered by UAM modes. As a result, inter-city travel represents another promising early UAM market, as high willingness to pay for IVTT reductions coincides with long-distance travel contexts in which meaningful travel time savings are likely to be achieved.

Finally, higher income levels increase VTTS estimates across modes, corresponding to reduced cost sensitivity among higher-income groups. This variation has important implications for UAM adoption, as higher initial fare levels could limit accessibility and reduce the attractiveness of UAM modes for low-income groups, while broader adoption may depend on future reductions in cost. These income-based disparities are further amplified in travel contexts with elevated VTTS values. This pattern is illustrated in Figure 3, which shows the very high VTTS for emergency medical transport by UAM, an intuitive result given the time-sensitive nature of such trips. Importantly, the combination of income-based price sensitivity coupled with high VTTS results in large variation in the willingness to pay for time savings across income groups (resulting in a \$42/hour difference in VTTS between high- and low-income groups for intra-city trips, and a \$83/hour difference for inter-city trips). Notably, these disparities are amplified for aerial medical transportation relative to GB alternatives due to the elevated IVTT sensitivity observed in UAM contexts. Consequently, the rollout of medical UAM transport may disproportionately benefit high-income users. Although still present, VTTS differences between income groups are less pronounced among less time sensitive trip purposes such as work and leisure trips (the difference is \$27/hour for intra-city trips and \$55/hour for inter-city trips), while they are greatly reduced for errand trips (with a difference of \$13/hour for intra-city trips and \$26/hour for inter-city trips) due to a much lower VTTS overall. These findings suggest that the fairness of UAM pricing schemes may vary considerably across trip purposes, with time-sensitive applications providing both a promising application and an increased risk of perpetuating transportation inequalities within the aerial sphere. These results emphasize the need for policy regulating pricing schemes to promote fair access to UAM services, particularly within the context of medical transportation. Specific strategies to ensure that these services remain broadly accessible include tiered pricing or public-private partnerships to ensure equal access to rapid aerial medical transportation.

6.2 Implications for Vertiport Placement and Service Design

Beyond IVTT and pricing considerations, findings relating to waiting time and access/egress distance also have important implications for UAM network design. As shown in Table 8, increases in waiting time lead to a substantial reduction in the first-choice share for both aerial modes (corresponding to a 18.9% decrease in air taxi adoption and a 14.0% decrease in air metro adoption between the shortest and longest waiting times). Similarly, access distance has a large impact, with UAM adoption decreasing by 21.4% for air taxi and 10.7% for air metro in response to a shift from the shortest to longest access/egress distances. These findings emphasize the central role of convenience for prospective users making individual-level adoption decisions. Users place a high premium on minimizing waiting and access time, suggesting that UAM systems must compete not only with IVTT but also with first- and last-mile connectivity. Accordingly, vertiport placement strategies should prioritize locations that minimize access distance by focusing on activity hubs and connecting to existing transportation networks. Maintaining frequent service, whether through regularly scheduled or on-demand operations, should also be treated as a core requirement for users considering switching from GB alternatives. Further, these results suggest that individual-level preferences for convenient service outweigh any hesitance to have UAM operate in proximity to homes. This illustrates a potential divergence between individual and community-level perspectives, as community opposition to aerial operations in residential areas has been well documented (Cohen et al., 2021; Lin Tan et al., 2021).

A similar pattern emerges with respect to noise. Noise sensitive individuals are less likely to adopt UAM when they operate at high noise levels. The magnitude of this effect is substantial, corresponding to a 28.6% reduction in air taxi adoption and a 22.5% reduction in air metro adoption when UAM noise levels are high. This interaction effect reveals that individual-level UAM adoption is shaped by the joint influence of personal sensitivities and operational characteristics, rather than broader neighborhood disruptions which often lead to opposition at the community level (Connors, 2019; Eißfeldt, 2020; Çetin et al., 2022). From a planning perspective, these results suggest that reducing operational noise can play an important role in expanding the pool of potential UAM users, particularly among individuals who are sensitive to UAM-related noise disruptions. At the same time, noise concerns may be outweighed by the benefits of easy access when UAM vertiports offer short access/egress distances. This finding suggests that investments in first- and last-mile accessibility may produce larger increases in adoption than equivalent reductions in noise levels. Consequently, improving UAM accessibility through greater vertiport density and more convenient pick-up and drop-off options may be a more effective means of increasing adoption than noise mitigation alone. Importantly, these objectives are often at odds. Many of these accessibility improvements can also increase the exposure of nearby communities to UAM noise disruptions. Together, these patterns suggest that vertiport planning will require a careful balance between the accessibility benefits provided to individual users with efforts to minimize noise impacts on surrounding neighborhoods.

The ATE results also reveal that UAM availability, in-flight experience, environmental sustainability, and crash-related safety serve as key design levers for promoting UAM adoption. UAM vehicles should be designed to operate reliably across weather conditions, and to provide a spacious cabin and comfortable in-flight experience. These features are central to positioning UAM as a high-quality and attractive alternative to GB modes. Additionally, improvements in environmental performance and crash-related safety relative to existing GB modes should be prioritized within the vehicle and network design stage. Respondents exhibit sensitivity to these attributes, with low environmental impacts increasing air taxi adoption by 18.4%, while crash-

related safety concerns had an even stronger effect, decreasing adoption by 32.3% when UAM crash rates exceed those of GB alternatives on a per-mile basis. These findings suggest that any improvements in sustainability and crash-related safety levels should be clearly communicated through UAM positioning and marketing strategies. Overall, user preferences with respect to service attributes reflect an expectation that UAM will provide meaningful improvements over existing GB alternatives, with adoption contingent upon delivering a high-quality travel experience alongside advancements in environmental performance and crash-related safety.

6.3 Implications for Automation

Fully autonomous operations reduce utility across all modes (as discussed earlier in Section 5.2.1). These findings are reinforced through the ATEs for UAM full automation, indicating a reduction in the first-choice share of both the aerial modes on the order of 35% if the operation is fully autonomous rather than relying on an in-vehicle pilot (the ATEs for GB full automation are not shown in Table 8). At the same time, respondents evaluate full automation more favorably for aerial modes than in GB contexts, suggesting that resistance to automation stems from concerns regarding trust and familiarity. This result has important implications for UAM deployment strategies. In the near term, service providers should consider a phased approach to introducing automation, beginning with pilot-assisted operations during early roll out. The presence of a human pilot within the vehicle can help reduce the perceived risk, allowing users to build trust in and gain experience with UAM systems. During this stage, marketing strategies should emphasize the role of the pilot as providing vigilant oversight of a technology-assisted navigation system, rather than providing independent, manual control. By positioning technology as enabling safe and efficient UAM operations, these strategies can build on the relatively more favorable perceptions of automation in aerial vehicles compared to GB modes. Over time, the approach can support a gradual shift to higher levels of automation as the public gains trust. From a regulatory perspective, a phased deployment strategy could be facilitated through certification pathways that progressively increase the level of automation. Service providers could start with a license to operate pilot-assisted UAM vehicles and subsequently transition toward higher levels of automation. Policymakers will need to anticipate the rapid development of autonomous technology and take steps to proactively establish a clear pathway towards autonomous deployment that balances public acceptance, appropriate safety measures, and technological advancement.

6.4 Implications for Potential Market Segments

Diving further into heterogeneity, the results indicate clear patterns across use cases, trip contexts, and individuals that can inform directed and customized UAM deployment strategies. For instance, preferences for air metro differ between age groups and housing types. Relative to young adults (18-34 years of age), middle-aged (35-54 years of age) individuals exhibit a 14.2% lower probability of selecting air metro as their first-choice mode, while residents of single family housing exhibit a 6.1% lower probability relative to those living in other housing types. However, for both of these population sub-groups, the ATEs are higher for the air taxi mode. These findings suggest that air metro represents a distinct use case from the more commonly studied air taxi use case. Accordingly, air metro services should be designed to target younger users, with a focus on denser urban areas (with more non-single family residents) during early rollout, similar to existing GB public transportation services. By framing air metro as a novel alternative to existing transit services, providers can clearly distinguish it from the private, premium, technology-oriented air taxi use case, effectively tapping into two distinct market segments.

Turning to likely early adopters, the results highlight men, young adults, Black individuals, and high-income households. These groups therefore constitute attractive markets for early adoption. However, care must be taken to ensure that the benefits associated with UAM deployment are not distributed unevenly across population groups during initial deployment. For example, men exhibit a very strong preference for air taxi services (67.9%) and a slightly smaller but still positive preference for air metro services (28.6%). Therefore, early deployment strategies focused exclusively on maximizing ridership may unintentionally reinforce gender disparities in access to emerging transportation technologies. Expanding adoption beyond an initially predominately male base will require addressing concerns related to noise levels, crash-related safety, and other barriers that may disproportionately affect women. At the same time, the strong interest in UAM observed among Black respondents (corresponding to a 28.7% increase in air taxi adoption and a 20.9% increase in air metro adoption) suggests that emerging UAM services may have the potential to improve accessibility for groups that have historically experienced transportation disadvantages. Realizing this potential will require meaningful engagement with Black communities during the planning and deployment process to ensure that UAM services address local mobility needs, expand access, and distribute the benefits and burdens of UAM fairly across racial groups. Income-related disparities may represent an even greater challenge. High-income individuals are both more attitudinally predisposed toward UAM and less sensitive to costs, corresponding to a 52.2% increase in air taxi adoption and a 30.0% increase in air metro adoption relative to the low-income group. Together, these factors suggest that high-income individuals are especially likely to adopt early and bear the initially elevated costs associated with system development. However, the long-term success and scalability of UAM technology will depend on expanding adoption beyond these early adopter groups. Service providers should anticipate declining costs and proactively design systems that cater to a wider range of income groups over time, rather than focusing exclusively on high-income users.

7. CONCLUSION

In this study, we examine the impacts of both contextual and individual-level characteristics on stated preferences for air taxi and air metro. Using a blocked survey design, we incorporate a wide range of service attributes and trip contexts to examine individual-level preferences. A two-stage modeling framework is employed to jointly model individual attitudes alongside ranked modal preferences, while accounting for unobserved heterogeneity. The results provide insights into the priorities of prospective UAM users, documenting heterogeneous adoption patterns across service attributes, trip contexts, attitudes, and user groups. First, adoption depends heavily on service attributes, with convenience and travel experience emerging as central factors. Short waiting times, nearby vertiport locations, and consistent availability across weather conditions encourage UAM adoption, while users expect UAM services to offer meaningful improvements over existing GB alternatives. This involves spacious interiors, improved environmental sustainability, and enhanced crash-related safety. Although automation reduces preferences for all modes, it is perceived more positively in aerial contexts, providing an opportunity for a gradual shift towards autonomous UAM technology. Second, trip context plays a key role in determining UAM suitability and users' willingness to pay for in-vehicle travel time savings. Aerial modes are more attractive for long-distance inter-city trips and are well suited for time-sensitive medical transport, constituting promising applications of UAM technology. Third, we find that attitudes towards technology and travel time have a direct impact on stated UAM adoption preferences, while UAM noise sensitivity levels shape how individuals respond to operational noise levels. Finally, adoption

patterns vary across user groups. We identify substantial demand for the air metro use case specifically among young adults and older populations in urban contexts, suggesting that an aerial alternative to GB public transportation would be able to target a distinct market segment from the more commonly studied air taxi use case. Early UAM adoption is likely to be driven by men, young adults, Black individuals, high-income households, tech-savvy groups, and those are dissatisfied with their current travel. While these groups represent targets for initial deployment, the long-term growth of UAM will depend on extending adoption beyond these groups. Service providers and policymakers should ensure that system design and deployment fairly distribute benefits across population groups.

Our study points to the need for continuing research on UAM adoption as the technology progresses from development to deployment. Because human UAM vehicles are not yet widely operational, the current study relies on SP data. Future revealed preference investigations should be undertaken during early UAM rollout to more accurately capture how users respond to contextual characteristics outside of hypothetical SP scenarios. In addition, further research into pricing sensitivity is needed as UAM systems evolve, with a careful focus on potential disparate impacts. In particular, future research should examine how pricing structures affect accessibility across income groups, especially for time-sensitive trip purposes such as medical transportation. The current research focused on preferences at an individual level, but it is also important to examine how UAM preferences vary at a community-level, particularly in the context of vertiport placement priorities and noise/environmental considerations. Finally, additional research with a larger sample size and more expansive geographic coverage is needed to better understand regional or international differences in UAM adoption patterns.

AI STATEMENT

During the preparation of this work the authors used Microsoft Copilot to support the preparation of this manuscript, assisting with formatting content and refining language. After using this tool, the authors reviewed and edited the content as needed. AI tools were used only to improve communication, and the authors take full responsibility for the content of the published article.

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Table 1: Summary of Literature on UAM Adoption

Reference	Aerial Modes*	Ground-Based Modes*	Contextual Characteristics															Trip Context		Perceptions/Attitudes/Subjective Norms
			Service Attributes																	
			Traditional Attributes				UAM Salient Attributes													
			In-Vehicle Travel Time	Waiting Time	Distance to Pick-up/Drop-off Locations	Cost	UAM Flight Altitude	UAM Availability	Noise Level	UAM In-Flight Experience	Environmental Sustainability	UAM Crash-Related Safety Level	In-Vehicle Personal Safety Monitoring	UAM Pre-Boarding Security Screening	Level of Automation	Trip Purpose	Trip Distance			
General UAM Adoption Intentions																				
Johnson et al., 2022	AT									×			×		×	×		Tech-savviness, Safety perceptions		
Karami et al., 2024	AT					×					×							Tech-savviness, Green lifestyle propensity Safety perceptions		
Kim et al., 2023	AT		×			×		×		×				×				Safety perceptions		
Kim and Zhang, 2025	Airport Shuttle		×												×	×		Did not consider		
Lee et al., 2023	AT										×							Safety perceptions		
Lotz et al., 2023	AT				×	×				×	×				×			Tech-savviness		
Qu et al., 2024	AT		×		×	×				×						×	×	Did not consider		
Riza et al., 2024	AT, AM, Air Limousine					×				×						×		Did not consider		
Yavuz, 2024	AT														×			Tech-savviness, Safety perceptions		
UAM SP Experiments																				
Adamidis et al., 20205	Airport Suttle	PT, RH, PV	×	×		×										×		Travel satisfaction		
Al Haddad et al., 2020	AT	RH	×		×	×							×					Value of travel time savings, Affinity to automation, Data concerns, Safety perceptions		
Boddupalli et al., 2024	AT	PT, RH, PV	×		×	×		×										Did not consider		
Brunelli et al., 2023	Airport Shuttle	PT, RH, PV	×			×				×						×	×	Affinity to automation, Travel satisfaction		
Cho and Kim, 2022	AT	PT, PV	×			×										×		Safety perceptions		
Coppola et al., 2024	AT, Airport Shuttle	RH, PT, PV	×	×		×										×		Did not consider		
Fu et al., 2019	AT	PT, PV, Autonomous Taxi	×	×		×						×			×	×		Did not consider		
Hwang and Hong, 2023	AT, AM (combined for modeling)	RH, PT, PV	×	×	×	×				×					×	×	×	Did not consider		
Jang et al., 2025	Airport Shuttle	RH, PT, PV	×		×	×										×		Did not consider		
Karimi et al., 2024	AT	PV, RH	×		×	×												Green lifestyle propensity, Safety perceptions, Travel satisfaction		
Zaps and Chankov, 2022	AT	RH, PT	×			×					×					×		Did not consider		
This Study	AT, AM	RH, PT, PV	×	×	×	×	×	×	×	×	×	×	×	×	×	×	×	Tech-savviness, UAM noise sensitivity, Positive travel perceptions		
*Air Taxi (AT), Air Metro (AM), Ridehailing/Taxi (RH), Public Transportation (PT)																				

Table 2: Human Urban Air Mobility Experiment Design

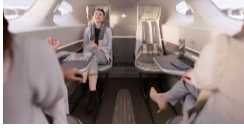
<i>Service Attributes</i>					
Attributes	Air Taxi (On-demand vehicles)	Air Metro (Shared vehicles, with fixed routes and departure times)	Ridehailing (Ground-based)	Public Transportation (Ground-based)	Private Vehicle (Ground-based)
Speed*	80 mph 120 mph 180 mph	50 mph 100 mph 120 mph	20 mph 30 mph 40 mph	15 mph 20 mph 30 mph	20 mph 30 mph 40 mph
Waiting Time	5 min 10 min 15 min	10 min 15 min 30 min	5 min 10 min 15 min	10 min 15 min 30 min	0 min
Distance to Pick-up/Drop-off Locations	Door-to-door Within 0.5 miles	Within 0.5 miles Within 1 mile More than 1 mile	Door-to-door	Within 0.5 miles Within 1 mile More than 1 mile	Door-to-door
Cost†	\$0.50 /mile \$1 / mile \$3 / mile \$8 / mile	\$0.25 / mile \$0.50 /mile \$1 / mile \$3 / mile	\$1 / mile \$2 / mile	\$3.50	\$5 (includes gas and parking)
UAM Flight Altitude‡	 (500 feet)	 (1,000 feet)	 (2,500 feet)	--	--
UAM Availability‡	Always available Available only in clear weather conditions	Always available Available only in clear weather conditions	Always available	Always available	Always available
Noise Level‡	Quiet outdoor environment Moderate car traffic A heavy truck or motorcycle	Quiet outdoor environment Moderate car traffic A heavy truck or motorcycle	Standard (moderate vehicle traffic)	Standard (moderate vehicle traffic)	Standard (moderate vehicle traffic)
UAM In-Flight Experience‡	 (Spacious interior with room for belongings)	 (Cramped interior space)	--	--	--
Environmental Sustainability‡	High impact Medium impact Low impact	High impact Medium impact Low impact	High impact	Medium impact	High impact
UAM Crash-Related Safety Level‡	More crashes per mile than ground vehicles Fewer crashes per mile than ground vehicles	More crashes per mile than ground vehicles Fewer crashes per mile than ground vehicles	--	--	--
In-Vehicle Personal Safety Monitoring§	No Monitoring Remotely monitored In-vehicle assistant	No Monitoring Remotely monitored In-vehicle assistant	No Monitoring Remotely monitored In-vehicle assistant	No Monitoring Remotely monitored In-vehicle assistant	No Monitoring

Table 2: Human Urban

<i>Service Attributes</i>					
Attributes	Air Taxi (On-demand vehicles)	Air Metro (Shared vehicles, with fixed routes and departure times)	Ridehailing (Ground-based)	Public Transportation (Ground-based)	Private Vehicle (Ground-based)
UAM Pre-Boarding Security Screening [‡]	Security screenings	Security screenings	No screenings	No screenings	No screenings
	No screenings	No screenings			
Level of Automation [§]	In-vehicle pilot Autonomous	In-vehicle pilot Autonomous	Driver Autonomous	Driver Autonomous	Driver (you) Autonomous
Trip Context:					
Trip Purpose	Work Errands Emergency medical transport Leisure				
Trip Distance	Short intra-city trip (~10 miles one-way) Long intra-city trip (~40 miles one-way) Inter-city trip (~120 miles one-way)				

* In-vehicle travel time is presented in the experiments rather than speed, calculated with the scenario-specific speeds and the scenario-specific trip length. Within scenarios, the speed level is kept consistent between the two UAM modes, and a different speed is specified for ridehailing and private vehicle alternatives, while public transportation speeds are set 25% lower than those of the other ground-based modes.

† Presented as a total cost based on the scenario trip length. In each scenario, per-mile cost values for air taxi and air metro are specified as paired levels, with the values in each row representing the combinations used in the experiments.

‡ In each scenario presented, the UAM flight altitude and UAM crash-related safety level were maintained at the same level across the two UAM alternatives.

§ Scenarios maintain a consistent level of automation between the two UAM alternatives, and a common level of automation across the three ground-based alternatives. In-vehicle personal safety monitoring is also kept consistent across all modes, except the private vehicle alternative, and is presented only when vehicles are autonomous.

Table 3: Descriptive Statistics of Exogenous Variables

Individual Demographic Characteristic	Observations	Share of Sample	ACS 2023 Percent	Household Demographic Characteristic	Observations	Share of Sample	ACS 2023 Percent
Gender				Household Income			
Male	577	54.6%	49.9%	Low income (less than \$35,000)	223	21.1%	21.9%
Female	474	44.8%	50.1%	Medium income (\$35,000-\$100,000)	361	34.2%	40.3%
Other gender*	6	0.6%	--	High income (more than \$100,000)	473	44.7%	37.8%
Age				Housing Type			
Age 18-24	157	14.8%	12.8%	Single family home	654	61.9%	67.1%
Age 25-34	261	24.7%	19.1%	Other housing type	403	38.1%	32.9%
Age 35-44	196	18.5%	18.9%	Housing Tenure			
Age 45-54	173	16.4%	16.4%	Homeowner	651	61.6%	62.6%
Age 55-64	115	10.9%	14.6%	Non-homeownership arrangement	406	38.4%	37.4%
Age 65+	155	14.7%	18.3%	Residential Location			
Level of Education				Low density (less than 6600 pop/sq mi)*	341	32.3%	--
Bachelor's degree or higher	741	70.1%	34.2%	Medium density (6600-15499 pop/sq mi)*	363	34.3%	--
Less than a bachelor's degree	316	29.9%	65.8%	High density (15500+ pop/sq mi)*	353	33.4%	--
Race				Household Composition			
White	680	64.3%	47.7%	Child(ren) under 13*	178	16.8%	--
Black	155	14.7%	12.3%	No child(ren) under 13*	879	83.2%	--
Asian	100	9.5%	5.7%	Household Size			
Other race	122	11.5%	34.3%	1 person	184	17.4%	26.5%
Ethnicity				2 people	330	31.2%	31.6%
Hispanic	251	23.7%	39.8%	3 people	208	19.7%	16.4%
Non-Hispanic	806	76.3%	60.2%	4+ people	335	31.7%	25.6%
Employment Status				Number of Motorized Vehicles in Household			
Full-time	595	56.3%	57.7%	0 vehicles	59	5.6%	5.5%
Part-time	115	10.9%	13.5%	1 vehicle	363	34.3%	33.3%
Student	111	10.5%	8.7%	2 vehicles	424	40.1%	38.7%
Retired	150	14.2%	15.5%	3+ vehicles	211	20.0%	22.5%
Other employment	86	8.1%	4.6%	State of Residence			
				Texan*	884	83.6%	--
				Non-Texan*	173	16.4%	--
*No ACS data available							

Table 4: Distribution of Modal Alternatives Rankings

Mode/Rank	First Rank	Second Rank	Third Rank	Fourth Rank	Fifth Rank
Air Taxi	469 (22.2%)	427 (20.2%)	326 (15.4%)	442 (20.9%)	450 (21.3%)
Air Metro	263 (12.4%)	530 (25.1%)	514 (24.3%)	520 (24.6%)	287 (13.6%)
Ridehailing	84 (4.0%)	451 (21.3%)	581 (27.5%)	642 (30.4%)	356 (16.8%)
Public Transportation	215 (10.2%)	339 (16.0%)	340 (16.1%)	417 (19.7%)	803 (38.0%)
Private Vehicle	1083 (51.2%)	367 (17.4%)	353 (16.7%)	93 (4.4%)	218 (10.3%)

Table 5: Determinants of Latent Variables

Latent Variable Measurement Equation Model	Tech-Savviness		UAM Noise Sensitivity		Positive Travel Perceptions	
	Loading	t-stat	Loading	t-stat	Loading	t-stat
If available to me today, I would feel comfortable riding in a self-driving vehicle.	1.480	17.954	--		--	
I like to be among the first to have the latest technology.	1.259	17.509	--		--	
I would be comfortable flying in a self-flying vehicle.	1.241	18.361	--		--	
I am concerned about UAM making too much noise in residential areas.	--		1.156	15.426	--	
I would not want to hear UAM noises near my home at night.	--		1.197	9.586	--	
The time I spend traveling to places provides a useful transition between activities.	--		--		0.944	10.401
I make good use of the time I spend traveling.	--		--		0.696	7.250
Correlations Between Latent Variables	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Tech-Savviness	1.000	--	-0.310	-3.314	0.379	6.027
UAM Noise Sensitivity	--	--	1.000	--	-0.011	-0.145
Positive Travel Perceptions	--	--	--	--	1.000	--
Variable (base category)	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Individual-level						
Gender (Women, Other gender)						
Men	0.752	6.918	-0.252	-2.042	--	
Age (18-44)						
Age 45-54	-0.405	-2.966	--		--	
Age 55-64	-0.787	-4.765	--		--	
Age 65+	-0.846	-5.656	-0.563	-2.986	--	
Education (less than a bachelor's degree)						
Bachelor's degree or higher	0.199	1.712	--		0.213	2.312
Race (White, Asian)						
Black	0.642	4.347	--		0.322	2.592
Other race	0.406	2.642	--		--	
Ethnicity (Non-Hispanic)						
Hispanic	--		--		0.287	2.801
Employment Status (Part-time, Student, Retired, Other employment)						
Full-time	--		-0.319	-2.314	--	
Household-level						
Household Income (High income, more than \$100,000)						
Medium income (\$35,000-\$100,000)	-0.331	-2.780	--		--	
Low income (less than \$35,000)	-0.727	-4.666	-0.356	-2.231	--	
Housing Tenure (Non-homeownership arrangements)						
Homeowner	--		--		0.219	2.446
Household Composition						
Child(ren) under 13	--		--		0.323	2.694
Household Size						
Household size	--		--		-0.066	-2.103

Table 6: Main Estimation Results

Variable	Air Taxi	Air Metro	Ridehailing	Public Transportation	Private Vehicle
	Estimate (t-score)	Estimate (t-score)	Estimate (t-score)	Estimate (t-score)	Estimate (t-score)
Constants	0.1163 (1.626)	0.2495 (3.214)	-0.1788 (-6.005)	0.1402 (2.071)	--
Service Attributes					
In-Vehicle Travel Time					
Travel time [hours]	-0.1449 (-4.793)			-0.0918 (-9.528)	
Travel time [hours] × Errands			0.0756 (7.034)		
Travel time [hours] × Emergency medical transport	-0.0771 (-2.589)		--	--	--
Waiting Time (0 minutes, 5 minutes)					
10 minutes			-0.0509 (-3.611)		
15 minutes			-0.0863 (-6.308)		
30 minutes			-0.1263 (-6.178)		
Distance to Pick-up/Drop-off Locations (More than 1 mile)					
Within 0.5-1 mile			0.0565 (3.264)		
Door-to-door service			0.1557 (6.101)		
Cost					
Cost [\$100s] × High income (more than \$100,000)			-0.1645 (-7.424)		
Cost [\$100s] × Medium income (\$35,000-\$100,000)			-0.2083 (-7.500)		
Cost [\$100s] × Low income (less than \$35,000)			-0.2383 (-7.486)		
Cost [\$100s] × High income (more than \$100,000) × Inter-city trip (~120 miles one-way)			0.0885 (4.044)		
Cost [\$100s] × Medium income (\$35,000-\$100,000) × Inter-city trip (~120 miles one-way)			0.1020 (3.736)		
Cost [\$100s] × Low income (less than \$35,000) × Inter-city trip (~120 miles one-way)			0.1320 (4.208)		
UAM Availability (Always available, Not shown)					
UAM available only in clear weather	-0.2015 (-5.633)		--	--	--
UAM In-Flight Experience (Spacious interior, Not shown)					
Cramped interior	-0.1689 (-4.454)		--	--	--
Environmental Sustainability (High environmental impact, Medium environmental impact, Not shown)					
Low environmental impact	0.0884 (1.936)		--	--	--
UAM Crash-Related Safety Level (Fewer crashes per mile than ground vehicles, Not shown)					
More crashes per mile than ground vehicles	-0.1294 (-2.960)		--	--	--
Level of Automation (In-vehicle pilot, Not shown)					
Fully autonomous	-0.2336 (-2.742)			-0.2670 (-3.162)	

Table 6: Main Estimation Results (cont.)

Variable	Air Taxi	Air Metro	Ridehailing	Public Transportation	Private Vehicle
	Estimate (t-score)	Estimate (t-score)	Estimate (t-score)	Estimate (t-score)	Estimate (t-score)
<i>Trip Context</i>					
Trip Purpose (Work commute)					
Errands	--	--	--	-0.1363 (-3.586)	--
Emergency medical transport	--	--	--	-0.1414 (-3.957)	--
Leisure trip	--	--	0.0821 (4.459)	--	--
Trip Distance (Long intra-city trip (~40 miles one-way), Inter-city trip (~120 miles one-way))					
Short intra-city trip (~10 miles one-way)	--	-0.1778 (-4.934)	--	--	--
<i>Latent Constructs</i>					
Tech-savviness	0.1668 (7.956)		--	-0.0876 (-5.198)	--
UAM Noise sensitivity × High UAM noise level (heavy truck or motorcycle)	-0.0749 (-1.355)		--	--	--
Positive travel perceptions	-0.0271 (-1.554)		--	--	--
<i>Demographic Characteristics</i>					
Gender (Woman)					
Man	0.0874 (3.988)	--	--	--	--
Age					
Age 35-64	--	-0.0904 (-4.202)	--	--	--
Age 35-64 × Fewer crashes per mile than ground modes	0.1425 (2.578)		--	--	--
Level of Education (less than a bachelor's degree)					
Bachelor's degree or higher	--	--	--	0.0666 (2.011)	--
Race (White, Asian, Other race)					
Black	--	--	--	-0.1186 (-2.548)	--
Household Income (Low income (less than \$35,000), Medium income (\$35,000-\$100,000))					
High income (more than \$100,000)	--	--	--	-0.108 (-3.128)	--
Housing Type (Other housing arrangement)					
Single family housing	--	-0.0731 (-3.185)	-0.0629 (-2.771)	-0.1361 (-3.618)	--
Number of Motorized Vehicles in Household					
Number of motorized vehicles within household	-0.0349 (-2.964)		--	-0.0495 (-3.618)	--
State of Residence					
Texan	-0.1558 (-4.941)		-0.0692 (-2.631)	-0.1366 (-2.923)	--
<i>Covariance Elements (differenced with private vehicle)</i>					
Scales	0.4360 (--)*	0.5454 (40.651)	0.3756 (20.651)	0.6094 (43.204)	--
Correlations					--
Air Taxi	1.0000 (--)	0.8501 (14.794)	0.4292 (8.984)	0.0891 (2.447)	--
Air Metro	--	1.0000 (--)	0.5673 (14.506)	0.2991 (8.601)	--
Ridehailing	--	--	1.0000 (--)	0.6303 (16.231)	--
Public Transportation	--	--	--	1.0000 (--)	--
Panel Correlations	0.2338 (4.046)	--	0.1090 (1.856)	--	--

*A t-statistic is not shown for this coefficient because this scale is determined from the other three scales, based on the normalization adopted as discussed in Section 3.2.2

Table 7: Disaggregate Data Fit Measures

Summary Statistics	Specification	
	Model with Correlations	Independent Model
Log-likelihood at convergence $L(\hat{\theta})$	-8243.82	-8594.89
Log-likelihood of constant-only model $L(c)$	-9454.21	
Number of parameters (including constants)	58	47
Bayesian Information Criterion (BIC)	8340.25	8673.03
Adjusted likelihood ratio index ($\bar{\rho}^2$)	0.122	0.086
Likelihood ratio test between model with correlations and independent model	$702.14 > \chi^2_{(11,0.00001)} = 54.39$	
Average probability of correct prediction	0.040	0.031

Table 8: Average Treatment Effects

Variable	Base	Treatment	Air Taxi	Air Metro	ATEs Ride- hailing	Public Transp.	Private Vehicle
<i>Service Attributes</i>							
Air Taxi Waiting Time	5 minutes	15 minutes	-18.9%	4.5%	1.8%	4.4%	6.9%
Air Metro Waiting Time	10 minutes	30 minutes	3.1%	-14.0%	3.4%	2.3%	1.8%
Air Taxi Distance to Pick-up/ Drop-off Locations	Door-to-door	Within 0.5 miles	-21.4%	5.2%	2.1%	5.0%	7.9%
Air Metro Distance to Pick-up/ Drop-off Locations	Within 0.5-1 miles	More than 1 mile	2.3%	-10.7%	2.5%	1.8%	1.4%
UAM Availability	Always available	UAM only available in clear weather	-36.0%	-27.9%	12.4%	15.9%	20.0%
UAM Noise	Quiet outdoor environment	A heavy truck or motorcycle	-28.6%	-22.5%	9.2%	11.8%	14.7%
UAM In-flight experience	Spacious interior	Cramped interior	-30.9%	-23.7%	10.5%	13.3%	16.8%
UAM Environmental Sustainability	High environmental impact	Low environmental impact	18.4%	13.6%	-5.9%	-7.2%	-9.0%
UAM Crash-Related Safety Level	Fewer crashes per mile than ground modes	More crashes per mile than ground modes	-32.3%	-24.0%	12.1%	14.8%	19.4%
UAM Level of Automation	In-vehicle pilot	Fully autonomous	-38.8%	-30.9%	14.2%	17.9%	22.6%
<i>Trip Context</i>							
Trip Purpose	Work commute	Errands	12.5%	13.9%	1.6%	-23.0%	-2.9%
	Work commute	Leisure	-2.0%	-5.3%	12.1%	-4.7%	-2.1%
	Work commute	Emergency medical transport	-1.4%	-5.0%	8.9%	-17.8%	6.1%
Trip Distance	Short intra-city trip (~10 miles one-way)	Inter-city trip (~120 miles one-way)	77.4%	41.5%	-13.4%	-17.3%	-21.5%
<i>Demographics</i>							
Gender	Woman, Other gender	Man	67.9%	18.6%	-7.1%	-22.4%	-17.1%
Age	Age 18-34	Age 35-54	7.6%	-14.2%	2.9%	1.4%	0.3%
	Age 18-35	Age 65+	-27.6%	-20.9%	6.1%	25.3%	13.5%
Education	Bachelor's degree or higher	Less than a bachelor's degree	-3.4%	-2.6%	3.7%	-5.6%	3.3%
Race	White	Black	28.7%	20.9%	-0.6%	-31.6%	-8.3%
	White	Other race	16.1%	11.8%	-3.0%	-10.6%	-6.3%
Household Income	Low income (less than \$35,000)	Medium income (\$35,000-\$100,000)	19.7%	12.8%	-2.5%	-9.8%	-5.8%
	Low income (less than \$35,000)	High income (more than \$100,000)	52.2%	30.0%	-2.6%	-33.1%	-12.8%
Housing Tenure	Homeowner	Non-homeownership arrangements	1.2%	0.9%	-0.4%	-0.5%	-0.6%
Housing Type	Other housing type	Single family home	10.8%	-6.1%	-0.3%	-14.8%	5.2%
Household Composition	Child(ren) under 13	No child(ren) under 13	-1.7%	-1.3%	0.6%	0.7%	0.9%
State of Residence	Non-Texan	Texan	-20.3%	-13.0%	6.3%	-4.9%	22.6%

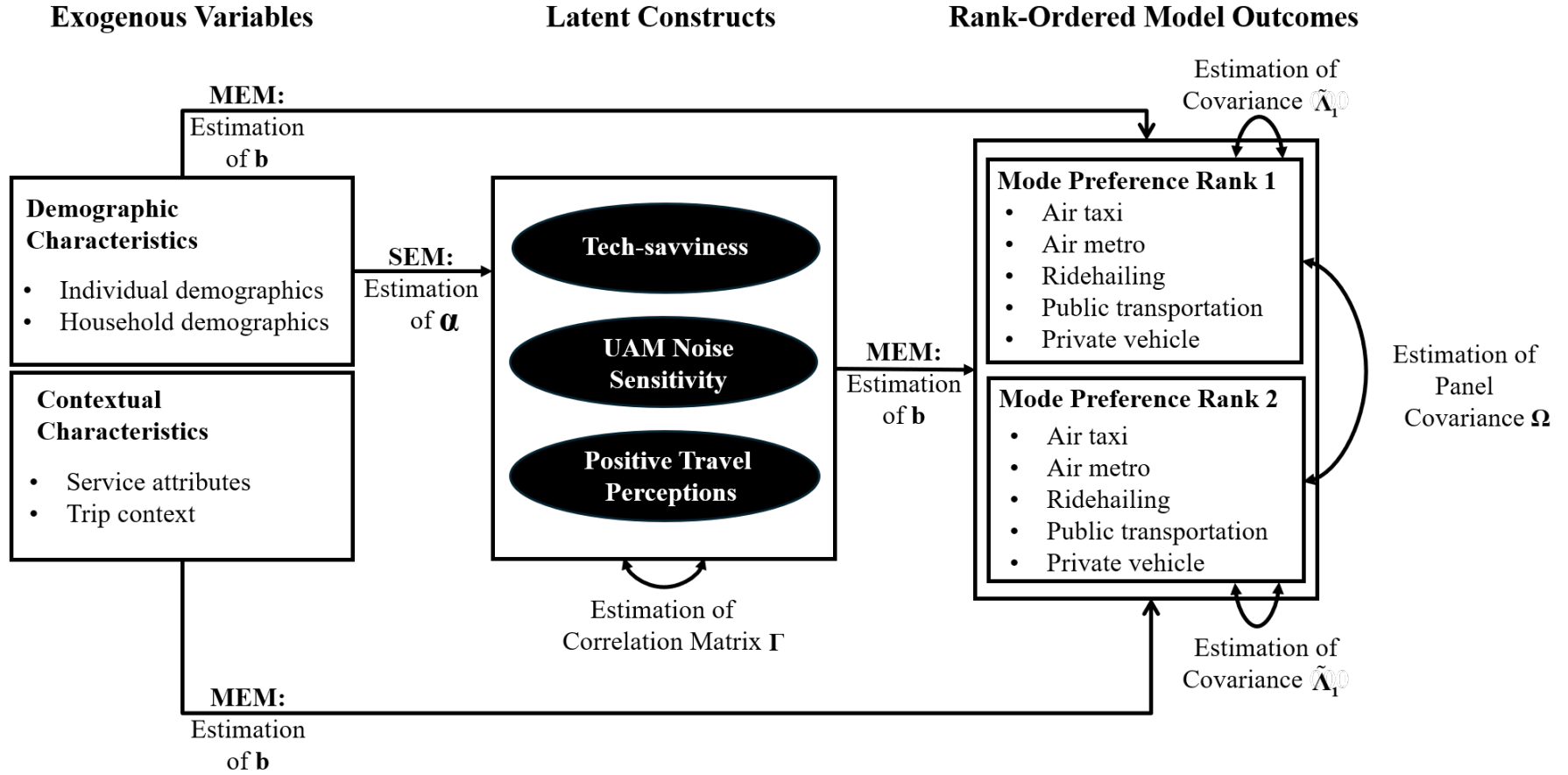


Figure 1: Analytic Framework

Please indicate the extent to which you agree or disagree with each of the following statements:

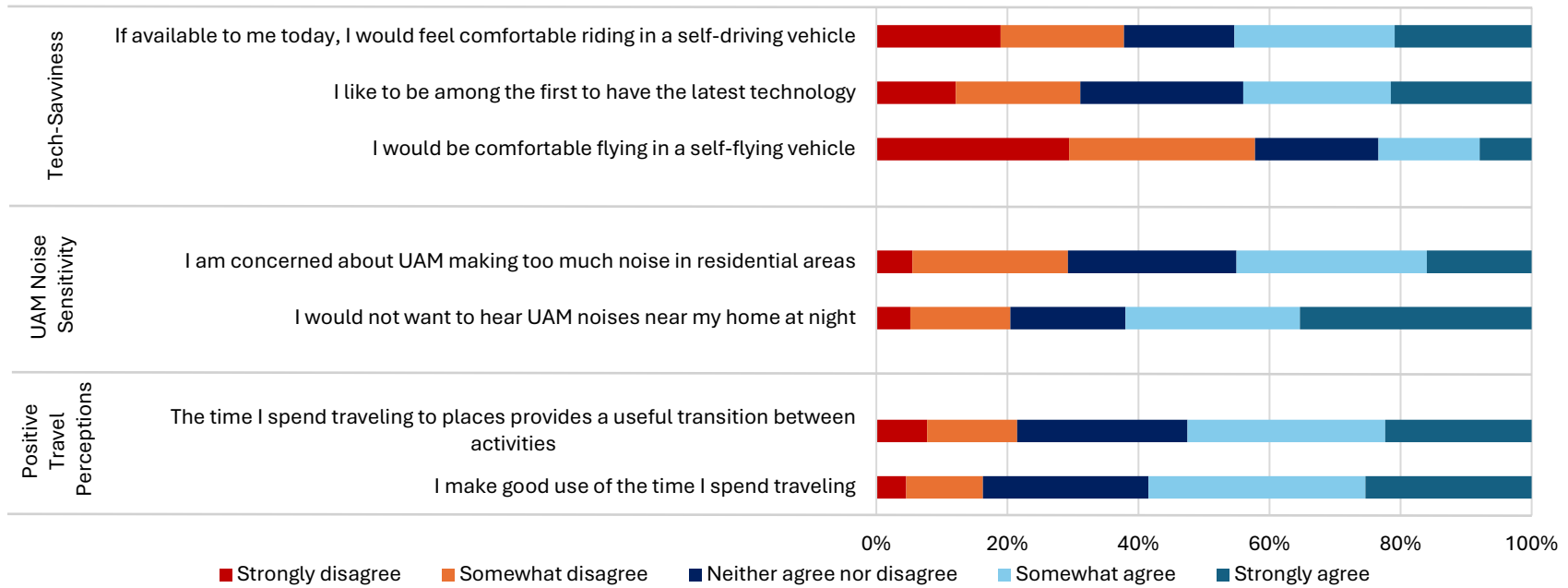


Figure 2: Distribution of Indicators of Latent Constructs

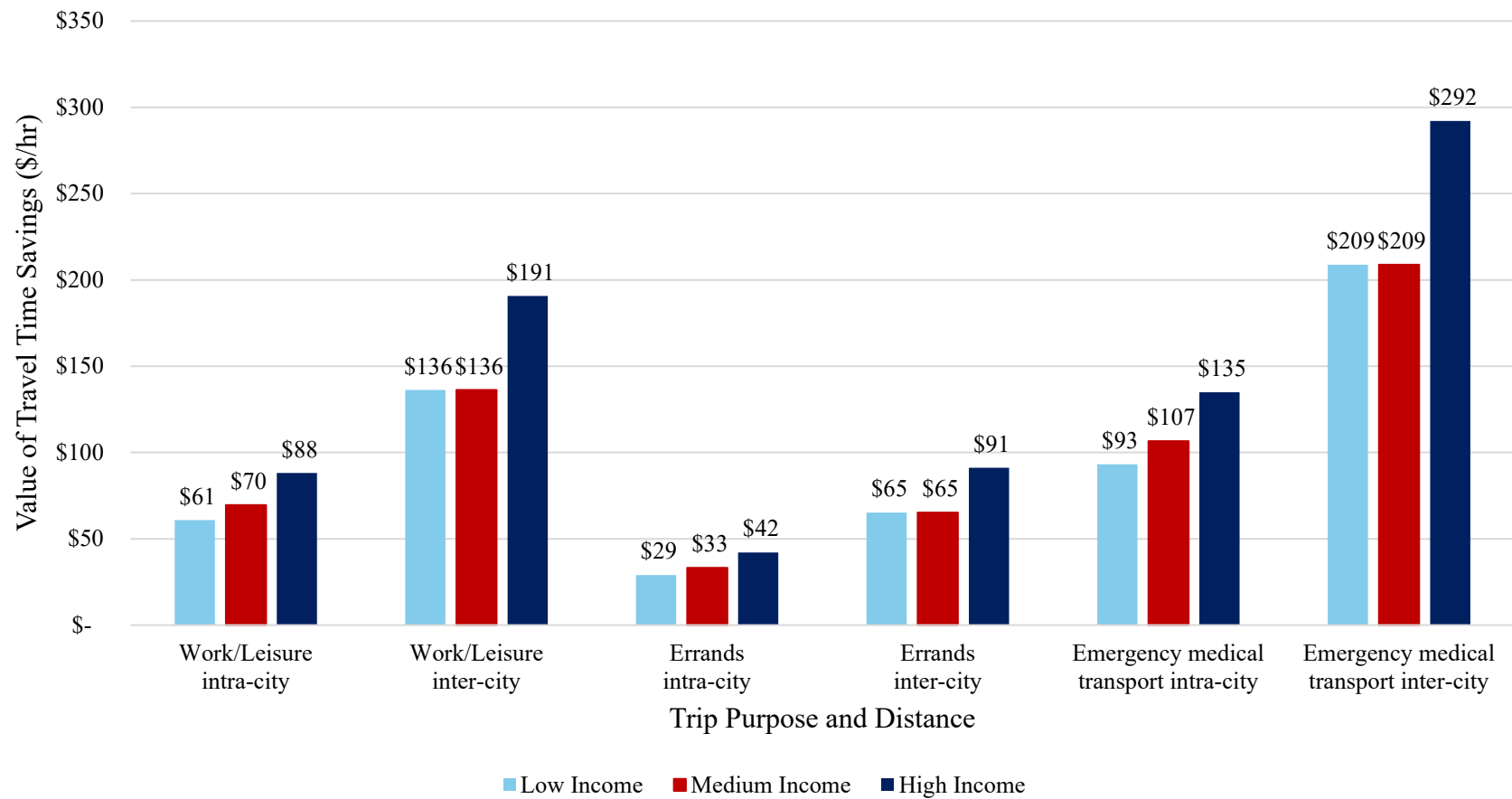


Figure 3: UAM In-Vehicle Value of Travel Time Savings