A Joint Framework for Drone Delivery Adoption, Delivery Frequency, and Demand Estimation

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ABSTRACT
Drone delivery services (DDS) are evolving rapidly, but a deeper understanding of who will use these services, and in what contexts, is necessary to anticipate future demand. Accordingly, this study develops a comprehensive framework for predicting DDS adoption intentions that incorporates service characteristics, delivery item attributes, demographics, individual attitudes, and current delivery frequency. A joint modeling approach accounts for potential endogeneity between current package and food delivery frequencies and DDS adoption, while latent constructs capture attitudes related to privacy, technology, and drone-related noise. In addition to delivery speed and cost, package accessibility, reliability, and safety emerge as central determinants of adoption. In addition, fully automated DDS is viewed favorably by respondents. Preferences also vary according to delivery item type, value, and weight, highlighting the importance of the delivery item itself. Current delivery behavior further influences adoption intentions, with frequent package and food delivery users exhibiting diverging adoption patterns. The findings provide new insights to guide potential service providers in designing DDS and offer a rigorous forecasting platform for planners, policymakers, and air traffic regulators.

Keywords: Drone delivery, Urban air mobility, Endogeneity effects, Delivery usage, Stated preference, Technology adoption

1. INTRODUCTION

Aerial drone delivery services are increasingly shifting from an experimental service to a mainstream last-mile delivery alternative. Recent advances in autonomous, battery-powered electric vertical take-off and landing (eVTOL) drone technology have made the deployment of these services increasingly feasible, drawing growing attention from commercial stakeholders and transportation researchers (Xiang et al., 2024; Kumar et al., 2025). For instance, Walmart and Wing's announcement of what they describe as the "world's largest drone delivery expansion" intends to grow service coverage to more than 40 million potential users and establish over 270 drone-enabled delivery locations by 2027 (Cunningham, 2026; *Wing and Walmart Expansion*, 2026). Such large-scale deployments situate drone delivery as a near-term possibility. Indeed, drone delivery services stand out as one of the most technologically mature use cases of urban air mobility technology, with the potential to add an efficient and environmentally friendly alternative to existing ground-based last-mile delivery systems (Cohen et al., 2021; Kumar et al., 2025).

At the same time, the rapid commercialization of drone delivery services raises questions that extend beyond technical feasibility, particularly regarding who will utilize such emerging services, and in what contexts. To address these questions, this study focuses exclusively on drone delivery applications involving the delivery of consumer goods to individuals and households, as opposed to deliveries to commercial establishments or for military purposes. Although drone delivery technologies may offer several operational advantages for last-mile logistics (see Engesser et al., 2023; Li et al., 2023), their success largely depends on consumer acceptance of such technologies, which is not yet fully understood. In particular, individual-level adoption decisions for emerging technologies are made through interactions between service realities and individual perceptions, shaped by both the operational context and personal attitudes. Especially as drone delivery services move closer to widespread deployment, there is a growing need for behavioral research that examines how individuals perceive, evaluate, and respond to such services.

Accordingly, the objective of the current research is to develop a comprehensive individual-level framework for understanding drone delivery adoption that accounts for service characteristics and attributes of the item being delivered, alongside subjective user perceptions. Further, from a consumer demand perspective, an important consideration is that the recent growth in use of ground-based delivery services is marked by significant heterogeneity in usage intensity across individuals. Existing delivery behaviors may therefore influence drone delivery adoption through a combination of unobserved individual characteristics (frequent ground-based delivery users, due to convenience and trust in delivery systems, may intrinsically be more likely to also choose drone delivery services) as well as the permeation of current behavioral outcomes (the propensity to have more items delivered in general) into the future (in econometric parlance, this situation represents a combination of unobserved heterogeneity and "true" state-dependence). To capture these relationships, we jointly model the frequency of current ground-based delivery service usage with adoption intentions for drone delivery services. In doing so, we also incorporate individual-level attitudinal latent constructs, capturing individuals' broader attitudes towards privacy, technology, and drone-related noise. Collectively, the results establish an empirical foundation for planners, policymakers, and service providers to better anticipate adoption patterns, identify prospective adopter segments, and guide system design.

The rest of this paper is organized as follows. Section 2 provides a brief overview of the relevant literature and positions the current research within this broader context. Section 3 reviews the data and presents the analytic framework. Section 4 presents the model estimation results. Section 5 discusses the implications of the research for drone delivery pricing and service design,

use cases, and adoption patterns. Finally, Section 6 concludes by summarizing the findings and identifying potential directions for future research.

2. LITERATURE REVIEW

In recent years, a growing body of research has examined drone delivery adoption, often using stated preference experiments to gain insight into future adoption trends. Collectively, this literature suggests that the factors shaping drone delivery adoption can be broadly grouped into three key dimensions: (1) drone delivery service (DDS) context, including delivery service characteristics and delivery item attributes, (2) individual-level factors including attitudes and demographics, and (3) current (ground-based) delivery usage. The following sections synthesize key findings relating to each of these dimensions from the extant literature, with discussion closely linked to Table 1, which summarizes the variables considered in prior stated preference studies.[1]

2.1 DDS Context

2.1.1 Service Characteristics

Within the category of general service considerations (see the column labeled "Service Context" in Table 1), prior studies have indicated that DDS are likely to be competitive when they offer an advantage over traditional ground-based delivery options such as faster delivery speeds or reduced delivery costs (Yoo et al., 2018; Merkert et al., 2022; Said et al., 2023). Specifically, services that are faster and more affordable encourage adoption, while longer delivery times and higher prices discourage use (Xie et al., 2022; Zhang et al., 2023b; Ardeshiri et al., 2024; Kyi et al., 2026). As indicated by Said et al., 2023, the delivery mode itself may shape user expectations, with prospective users generally expecting faster delivery from DDS than from conventional ground-based alternatives.

As may be observed in Table 1, almost all earlier studies consider both speed and cost as determinants of DDS adoption (see the first two columns under service context). In contrast, we identified only three studies that consider the locational convenience for consumers to retrieve goods after delivery (labeled as "Delivery Point" in Table 1). In this context, the delivery point refers to the location where a drone leaves a delivery for retrieval by the consumer, including locations such as the front door, an on-site delivery marker located on the property, or an off-site collection point such as a package locker. Previous studies have not identified a universally preferred delivery point for DDS. For example, in the context of residential preferences within urban air mobility-oriented neighborhoods, Zhao and Feng (2025) report a preference for direct drone delivery solutions such as home window docking (drones docking at window ports to deliver packages indoors) as a means to enhance package security. Conversely, Merkert et al. (2022) find on-site drone delivery to be less attractive than delivery to an off-site package locker when there is no secure delivery point at the residence. Beyond package security considerations, Bafounti-

[1] The studies summarized in Table 1 are limited to stated preference studies that directly examine individual-level DDS adoption indentions. Several related studies that focus on related aspects of drone delivery rather than adoption intentions are discussed in the text but excluded from Table 1. These include studies of residential choice of urban air mobility friendly neighborhoods (Zhao and Feng, 2025); general perceptions and acceptance of urban drone operations (as opposed to individual-level adoption intentions) (Yedavalli and Mooberry, 2019; Melo et al., 2023); perceptions of drone-related and general noise sensitivity (Miedema and Vos, 1999; Connors, 2019; Eißfeldt, 2020; Torija et al., 2020; Aalmoes et al., 2023a, 2023b; Zhang et al., 2023a); regulatory frameworks governing drone operations (Federal Aviation Administration, 2020; Saunders et al., 2024); and qualitative assessments of public reactions to delivery drones and autonomous operations (Oksman et al., 2024).

Kotta et al. (2023) highlight uncertainty around proximal drone delivery points in dense built environments such as multi-family residential locations. Reflecting these mixed preferences, Kyi et al. (2026) identify substantial heterogeneity in DDS delivery point preferences. Collectively, these findings suggest that consumers weigh risks such as delivery feasibility, theft, and convenience differently, leading to heterogeneous delivery point preferences.

In addition to these concerns relating to package retrieval, DDS reliability and safety also play a key role in DDS adoption decisions, particularly for high-priced items (Ardeshiri et al., 2024). Earlier studies have also found that perceived safety risks, such as the potential for property damage or injury of pedestrians, pose a barrier to DDS adoption, particularly in dense urban areas (Yoo et al., 2018; Serrano-Hernandez et al., 2021; Ardeshiri et al., 2024; Zhang et al., 2025). These concerns extend beyond risks to people and property to include the potential for damage to the delivery item itself, identifying package handling as an additional consideration in DDS adoption (Bafouni-Kotta et al., 2023; Said et al., 2023).

Beyond these performance considerations, the broader operational impacts of DDS, such as level of noise, raise concerns about localized externalities. Although noise is included as an adoption determinant in relatively few stated preference studies (see Table 1), it has received substantial attention in dedicated studies of drone noise perception. Collectively, this literature identifies drone noise as one of the most prominent barriers to public acceptance of drone operations (Eißfeldt, 2020; Aalmoes et al., 2023b), with annoyance increasing as noise levels become louder and more sustained over time (Connors, 2019; Yedavalli and Mooberry, 2019). Even individuals with favorable attitudes towards DDS often oppose drones flying over their own homes, coined the "not over my home" effect (Eißfeldt, 2020). Importantly, previous studies have shown that responses to drone noise vary systematically across individuals and operating contexts, suggesting that individual noise sensitivities play a central role alongside objective noise levels (Torija et al., 2020; Aalmoes et al., 2023a, 2023b).

Alongside noise impacts, environmental sustainability has emerged as an important factor shaping DDS adoption. Prior research suggests that reductions in last-mile emissions and energy use associated with electric drones can increase the attractiveness of DDS among environmentally conscious consumers (Yoo et al., 2018; Serrano-Hernandez et al., 2021; Xie et al., 2022). These benefits can play a meaningful role in service tradeoffs. For example, in a survey of public perceptions of drone delivery, Melo et al., (2023) find that respondents were willing to accept longer delivery times or pay higher prices in exchange for more environmentally sustainable drone delivery operations.

Interestingly, while numerous studies have examined how individuals' privacy concerns or perceived privacy risks impact DDS adoption intentions (as discussed further in Section 2.2.3), we are not aware of any published study that has considered the capability of drones to collect imagery of homes or surrounding neighborhoods as an actual operational characteristic influencing adoption intentions. As indicated in the last row of Table 1, our current research explicitly examines the influence of such operational privacy protections on adoption decisions, alongside subjective privacy concerns.

Finally, another unexplored DDS service characteristic is the level of automation, which shapes drone delivery safety perceptions and public trust. Most previous studies assume that drones will operate fully autonomously without any form of human intervention during regular operations (see, for example, Khan et al., 2019; Zhang et al., 2023b; Ardeshiri et al., 2024). However, in practice, current automation technologies and federal regulations require varying degrees of human oversight, with remote pilots monitoring and intervening in drone operations

(Federal Aviation Administration, 2020; Saunders et al., 2024). This creates a spectrum of operational models ranging from semi-human-controlled to fully autonomous systems. Despite these distinct possibilities, we are not aware of any previous studies which examine how adoption is impacted by differing levels of autonomy. Qualitatively, Oksman et al., (2024) find that the self-flying nature of delivery drones is seen in both positive and fearful lights by focus group members. While the potential operational benefits of autonomous delivery were recognized, respondents emphasized the need for regulation and clear communication to prevent security and privacy violations (Oksman et al., 2024). This mixed finding further emphasizes the need for systematic study of automation's impact on adoption.

2.1.2 Delivery Item Attributes

Together with service characteristics, the type, value, and weight of the item being delivered also play a role in driving last-mile delivery preferences, influencing perceived risk and suitability of DDS (see the column labeled "Delivery Item Attributes" in Table 1). Deliveries of non-medical and non-food items (referred to simply as package deliveries within this paper) are often viewed favorably by prospective DDS users (Kim, 2020; Said et al., 2023; Kyi et al., 2026). Acceptance is even stronger for medical supply deliveries, which constitute one of the most widely accepted applications of DDS, reflecting the importance of rapid delivery in the medical context (Kyi et al., 2026). In contrast, additional concerns for prepared food and grocery deliveries reflect tradeoffs between the operational strengths and constraints of drones. In the case of prepared food, delivery speed is critical, making time savings a dominant driver of adoption (Ardeshiri et al., 2024). On the other hand, grocery deliveries raise concerns related to package handling, with respondents exhibiting hesitancy to use DDS for fresh or bulky items such as produce (Said et al., 2023). Within these delivery item type groupings, item value further influences adoption decisions, with acceptance generally declining as the item value increases. For example, DDS is often viewed more favorably for lower-value items such as clothing or routine household goods than for higher-value products such as electronics (Kim, 2020; Merkert et al., 2022; Said et al., 2023; Kyi et al., 2026). Similarly, while DDS is generally viewed favorably for medical deliveries, adoption declines for high-value or scarce medical supplies (Zhang et al., 2025). These findings suggest that concerns regarding delivery reliability and potential damage are heightened as item values increase. Evidence on the role of delivery item weight is limited, with only Ardeshiri et al. (2024) explicitly considering its impact on DDS adoption. Their results suggest heterogeneous preferences, with some respondents favoring DDS only for lighter parcels while others do not adapt their preferences based on weight. Overall, these patterns indicate that DDS adoption rates vary not only by item type (such as package, medical supply, prepared food, or grocery delivery), but also according to item value and weight. Earlier studies, however, have generally examined these dimensions in isolation or through aggregate item categories (such as "household goods" or "electronics") which implicitly combine delivery item attributes such as type and value (see, for example, Said et al., 2023; Kyi et al., 2026). As shown in Table 1, the current study explicitly separates these attributes to identify their individual contributions to DDS adoption decisions.

2.2 Individual-Level Factors

2.2.1 Attitudes/Latent Constructs

Beyond service context, individual-level factors such as attitudes also play a central role in shaping DDS adoption intentions (see the column labeled "Attitudes/Latent Constructs" in Table 1). Previous research has often examined these relationships through behavioral frameworks such as

the Theory of Planned Behavior (TPB) and Technology Adoption Model (TAM), which consider how perceived usefulness, perceived ease of use, and subjective norms impact DDS adoption intentions (Khan et al., 2019; Kumar et al., 2023; Zhang et al., 2023b; Dabić et al., 2025). Within this literature, key attitudes such as privacy concerns and technological savviness consistently emerge as influential determinants of delivery mode choice (Yoo et al., 2018; Khan et al., 2019; Chen et al., 2022). Because drone operations may rely on imaging and data collection in residential environments (as discussed earlier in Section 2.1.1), prospective users may be concerned about surveillance, data misuse, and the sharing of personal information (Chen et al., 2022; Koh et al., 2023; Dabić et al., 2025). As a result, privacy concerns act as a consistent barrier to DDS adoption, and are commonly represented as negatively impacting attitudes towards DDS within the TPB framework. In contrast, technological savviness (or tech-savviness for short) is consistently associated with higher willingness to adopt DDS (Koh et al., 2023; Kumar et al., 2023; Mathew et al., 2021; Said et al., 2023; Sham et al., 2023; Yoo et al., 2018). Tech-savvy individuals are generally more inclined to adopt emerging technologies and exhibit greater confidence in their ability to engage with novel technologies. Accordingly, they tend have more positive perceptions of DDS and are more likely to express intentions to adopt such services. Within the literature, tech-savviness is often integrated into TAM and TPB through its positive influence on perceived ease of use, and positive attitudes toward technology (Yoo et al., 2018; Chen et al., 2022; Kumar et al., 2023).

Prior studies have also considered additional attitudinal factors such as green lifestyle propensity, drone experience, and safety concerns (Yoo et al., 2018; Zhu, 2019; Mathew et al., 2021; Zhang et al., 2023b), suggesting that DDS adoption reflects a broad range of perceptions, lifestyle preferences, and experiences. Finally, as discussed briefly in Section 2.1.1, general noise sensitivity is an individual-level characteristic that shapes how individuals perceive and respond to noise disruptions. Although studies of drone noise perceptions have largely been undertaken in isolation of broader DDS perceptions and adoption intentions, such studies have found that noise perceptions are influenced not only by objective noise levels, but also by individual sensitivity, prior drone perceptions, and the operational context (Connors, 2019; Eißfeldt, 2020; Torija et al., 2020; Aalmoes et al., 2023a; Zhang et al., 2023b). Consequently, individuals with greater sensitivity to drone-related noise may be less likely to adopt DDS than other prospective users, even when objective noise levels are similar.

2.2.2 Demographics

In addition to attitudinal influences, previous research indicates substantial heterogeneity in DDS adoption intentions based on demographic characteristics such as gender, age, and household context. To maintain concise presentation, we have not identified the specific demographic variables used in each earlier study in Table 1. But, across studies, men and younger individuals tend to report higher preferences for DDS, a pattern that may be attributed to greater risk acceptance and technology inclination (see, for example Sham et al., 2022; Kumar et al., 2023; Ardeshiri et al., 2024; Kyi et al., 2026). At the household level, higher income households, larger households, and those located in rural areas often exhibit elevated DDS adoption preferences, potentially reflecting a greater demand for delivery convenience or a greater reliance on delivery services (Ardeshiri et al., 2024; Tamakloe et al., 2024; Kyi et al., 2026). Findings relating to residential context support this pattern, as households located in higher-density urban and multi-family environments may exhibit heightened concerns related to package security and delivery logistics, discouraging DDS adoption (Bafouni-Kotta et al., 2023; Kyi et al., 2026).

Collectively, these demographic patterns suggest that adoption preferences are shaped by an interplay of individual, household, and residential characteristics.

2.3 Current Delivery Frequency

Some earlier DDS-related studies have found that familiarity with alternative delivery services (e.g. package lockers, in-store pick-up, delivery robots, or contactless delivery) contributes to elevated stated preferences for DDS (Koh et al., 2023; Tamakloe et al., 2024). These findings indicate that prior experience with emerging delivery technologies may shape openness to DDS. However, investigations of the role of traditional last-mile delivery usage (that is, the current frequency of ground-based deliveries) on DDS adoption remain relatively limited. We identified only two studies that incorporate current ground-based delivery usage into analyses of DDS adoption. Specifically, Bafouni-Kotta et al. (2023) include online shopping frequency as an explanatory variable when segmenting respondents into clusters reflecting different levels of support for DDS. Their results highlight heterogeneity, with frequent delivery service users being more likely to belong to supporter groups, while infrequent users are split between likely supporter and non-supporter clusters. However, beyond this clustering approach their analysis does not directly quantify the impact of current delivery frequency on adoption outcomes. This relationship is examined more directly by Tamakloe et al. (2024), who incorporate aggregate delivery frequency into models of DDS adoption. Their results indicate that that a higher frequency of home deliveries is associated with a reduced tendency to adopt DDS, while the opposite is true for delivery to the workplace. Both of these studies suggest that current delivery frequency may influence adoption preferences, even if the reported effects differ. Neither analysis explicitly employs disaggregate measures of delivery frequency by item type (such as package or food delivery), instead relying on aggregate measures of overall delivery usage. Furthermore, both studies consider current delivery frequency as exogenous to the DDS adoption decision, without considering the possibility that common unobserved individual effects may simultaneously elevate or depress both current ground-based delivery frequency and stated future DDS adoption intentions. Thus, a deeper investigation of the relationship between current delivery frequency and DDS adoption is needed, particularly given the central role of delivery frequency in driving overall demand.

2.4 The Current Paper

The current study is motivated by the need for a comprehensive examination of individual-level DDS adoption decisions, advancing the literature in five key ways. First, the study estimates the effects of nine distinct service characteristics, expanding on previous works that have examined only a subset of these attributes (See the final row of Table 1 for a comparison between the characteristics considered in our study in comparison to those considered in other related literature). Importantly, we examine the impact of privacy protection and level of automation on DDS adoption, service characteristics that, to our knowledge, have not yet been analyzed quantitatively. Second, the study advances our understanding of DDS adoption by explicitly accounting for delivery item attributes, not only based on delivery item type (package, medical supply, prepared food, or grocery delivery), but also based on the value and the weight of the item. By independently including all three of these item attributes, and designing our experiments to provide sufficient variation in their levels, we are able to capture DSS adoption tendencies across all possible combinations of the delivery item attributes. Third, the analysis incorporates current package and food delivery usage as an endogenous component of drone delivery adoption, jointly

modeling ordinal current delivery frequencies alongside future binary adoption outcomes. To our knowledge, this is the first study to consider the possibility that current delivery frequency is endogenous to future DDS adoption. In particular, the relationship between current (ground-based) delivery frequency and future stated DDS adoption may reflect either common unobserved individual-level factors (such as a desire for convenience or intrinsic high consumption level of goods), rather than a "true" structural causal effect of current delivery frequency on DDS adoption. If the former association pathway is ignored when actually present, it would inappropriately overestimate the structural causal pathway effect, leading to higher projected returns (than would be in actuality) from DDS promotion policies directed toward individuals with frequent ground-based delivery usage. It would also result in inaccurate projections of DSS adoption, especially given the substantial heterogeneity in current delivery usage across individuals. More broadly, the model structure explicitly accommodates multiple sources of unobserved heterogeneity through correlations across individual attitudes, choice occasions, delivery usage patterns, and adoption decisions. By capturing these unobserved factors, the model provides a more realistic representation of how individual preferences and behaviors shape DDS adoption. Fourth, the modeling approach integrates service context, demographic characteristics, existing delivery usage, and latent attitudes into a single framework. This integrated modeling approach provides a more holistic view of DDS adoption, building on previous works that have examined these elements more in isolation (see, for example, Zhang et al., 2023b; Ardeshiri et al., 2024; Kyi et al., 2026). Specifically, individuals' privacy concerns, tech-savviness, and drone noise sensitivity are captured through latent constructs, representing underlying attitudes that play an important role in shaping adoption decisions (Yoo et al., 2018; Khan et al., 2019; Chen et al., 2022). Within the joint framework, these attitudes influence both current delivery usage and DDS adoption outcomes, while interactions with service context and demographic characteristics capture heterogeneity in their effects across delivery contexts and individuals. By including these attitudinal interactions, we provide new insight into how individual perceptions shape DDS adoption. Finally, the analysis results are translated to average treatment effects (ATEs) that support interpretation and inform policy. The ATE estimates quantify the overall impacts of service characteristics, delivery item attributes, and demographic variables, allowing the relative importances of these factors to be directly compared. In addition, by combining predicted DDS adoption probabilities with current (ground-based) delivery frequencies, the ATEs move beyond binary adoption measures to provide estimates of expected DDS demand.

3. METHOLDOGY

3.1 Data Description

The data used in this analysis were obtained from an online survey conducted between March and October 2025, with recruitment efforts concentrated primarily in Texas. Participants were recruited using a convenience sampling approach that relied on social media outreach, flyer distribution, and outreach by community and neighborhood organizations located in Austin, Dallas, Houston, San Antonio, Lancaster, and Waco. This effort resulted in 890 responses from Texas residents. Additional recruitment outside Texas was supported through collaborations with researchers at the University of California, Irvine and Iowa State University, yielding 173 respondents from other states. To incentivize participation, the first 150 respondents received a $10 electronic gift card, while subsequent participants were entered into a drawing for one of 100 additional $10 e-gift cards. After data collection, geographic data from the 2023 American Community Survey (ACS) County Business Patterns (CBP) database (United States Census Bureau, 2023) were appended

based on each respondent's zip code. The resulting dataset was then cleaned to remove six respondents with substantial item non-responses, resulting in a final sample of 1,057 respondents.

The development of the survey instrument was informed by collaboration with local stakeholders from industry, 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. Discussions and feedback from these partners provided insight into how aerial transportation technology is being developed and considered by policymakers in Texas, guiding the selection of issues and attributes most relevant for empirical investigation. The final survey collected information on individual and household demographics, frequency of package and food delivery, general attitudinal measures, and drone-specific attitudes alongside responses to stated preference experiments for delivery preferences between aerial DDS and traditional ground-based delivery.

3.1.1 Exogenous Variables

Service Context: Attributes corresponding to DSS and ground-based delivery service characteristics are experimentally assigned in the stated preference scenarios, serving as exogenous attributes. The stated preference portion of the survey consisted of a pair of hypothetical choice scenarios in which respondents were asked to indicate their preferred option between drone delivery and ground-based delivery based on the service context presented.[2] To effectively examine a comprehensive set of service characteristics, a blocked survey structure was employed. For each choice scenario, three core service characteristics: (1) speed, (2) cost, and (3) delivery point were always specified for both the DSS and ground delivery modes. In addition to these core characteristics, each scenario included a rotating subset of three additional service characteristics, selected from the following set: (4) reliability, (5) safety, (6) noise, (7) environmental sustainability, (8) privacy protection, and (9) level of automation.

Each scenario was further contextualized by delivery item attributes (presented in all scenarios), including item (a) type, (b) value, and (c) weight. Levels for all contextual variables were varied across scenarios according to a predefined experimental design, summarized in Table 2. As many respondents are likely to be unfamiliar with delivery drones, DDS characteristics such as noise and environmental sustainability were presented relative to conventional ground-based

[2] Because drone delivery remains an emerging technology, revealed preference data on consumer adoption decisions are necessarily unavailable. Consequently, stated preference experiments provide one of the few practical means of examining prospective behavioral responses prior to widespread deployment. Although respondents are asked to evaluate hypothetical scenarios, a substantial literature in social psychology, information systems, and consumer behavior has demonstrated that behavioral intentions elicited in such settings are systematically related to actual behavior through underlying attitudes, subjective norms, perceived behavioral control, perceived usefulness, and perceived ease of use. These concepts form the foundation of the Theory of Planned Behavior (Ajzen, 1991) and the Technology Acceptance Model (Davis, 1989; Venkatesh and Davis, 2000). Numerous empirical studies have further shown that demographic characteristics, attitudes, lifestyle preferences, and technology-related perceptions successfully explain adoption behavior for emerging technologies, including smartphones, voice-controlled virtual assistants, advanced driver assistance systems, and other automated technologies (see, for example, Astroza et al., 2017; Marikyan et al., 2019; Asmussen et al., 2020; Dannemiller et al., 2021; Asmussen et al., 2022). Thus, eliciting stated behavioral responses to carefully designed drone delivery scenarios, together with rich information on individual characteristics and attitudes, provides a scientifically grounded framework for anticipating adoption patterns in a future operating environment. Indeed, for technologies that are not yet widely available, such an approach is considerably more defensible than relying on unsubstantiated assumptions regarding future behavior (see also Ge et al., 2019; Chee et al., 2020).

delivery services to provide a familiar benchmark for comparison. For example, drone noise levels are described as "quieter than a standard delivery vehicle," "same as a standard delivery vehicle," or "louder than a standard delivery vehicle."

Given the large number of possible attribute-level combinations, an orthogonal design was used to select 48 scenarios reflecting realistic delivery conditions while providing sufficient variation, prioritizing the ability to identify main effects and two-way interaction effects. These scenarios were then grouped into 24 blocks, each consisting of two scenarios with the same set of contextual variables but differing levels. A single two-scenario block was randomly assigned to each survey participant. Drone delivery speeds were constrained to be equal to or faster than ground-based delivery in all scenarios, reflecting the expected speed gains associated with DDS (Turgut and Şeker, 2023). An overview of the resulting distribution of attribute levels in the final sample is provided in Table 3.

Demographic Characteristics: The analysis also incorporates a set of individual and household demographic characteristics as exogenous factors. Descriptive statistics for the demographic characteristics of the sample are provided in Table 4, alongside 2023 ACS one-year estimates for the state of Texas. Although the sample is not directly comparable to the population of Texas due to the inclusion of non-Texas residents, the ACS data provides an appropriate benchmark as Texas residents make up 83.6% of the sample. Relative to the state-level estimates, the sample overrepresents men, young adults (18-23 and 25-34 age groups), those with a bachelor's degree or higher, White individuals, and students. On the other hand, older individuals (55-64 and 65+ age groups), Hispanics, those within the other race category (including multiracial respondents and those not represented by other categories) are underrepresented. At the household level, higher-income households (income greater than $100,000) are overrepresented, while residents of single-family (detached) housing, medium-income households ($35,000-$100,000), and single person households are underrepresented. In addition, appended ACS CBP data (at the zip code level) were used to classify households according to surrounding geographic conditions. The population density, measured in persons per square mile, was used to classify households into high (15500+), medium (6600-15499), and low (less than 6600) density areas, dividing the sample roughly into thirds, as shown in Table 4. The same data were used to characterize the number of nearby transportation facilities, including commercial transportation and warehousing establishments (North American Industry Classification Sectors (NAICS) 48-49) as a representation of local last-mile logistics infrastructure. Counties were categorized as having either a high (17 or more) or low number (fewer than 17) of transportation and warehousing establishments, based on the median in the sample.[3] Finally, state residence was determined from respondent zip codes, allowing respondents to be classified as either Texas or non-Texas residents.

The observed skews in the sample data relative to the ACS data are expected given the convenience-based sampling approach. In particular, the use of community groups in survey distribution may have contributed to the overrepresentation of high-income and highly educated individuals (Dutta-Bergman, 2003; Sandstrom and Alper, 2019). Although the resulting sample differs from the population distribution of Texas, these limitations do not prevent the estimation of

[3] Alternative continuous and categorical specifications were explored for both geographic variables. In each case, the categorical thresholds described here (based on the sample tertiles for population density and median for transportation establishments) produced the best statistical fit while retaining behaviorally meaningful results, as discussed in more detail in Section 4.

individual-level adoption trends. Importantly, the sampling approach was exogenous to the modeled outcomes, as sampling occurred independently of respondents' delivery preferences and adoption intentions. Under exogenous sampling conditions, an unweighted approach provides consistent and more efficient parameter estimates (Solon et al., 2015; Robbennolt et al., 2026). Consequently, we employ an unweighted estimation approach in this case. Together, the exogenous sampling approach and the adequate variation across exogenous variables support the identification of systematic relationships in DDS adoption trends, even if exact population shares may differ from Texas' composition.

3.1.2 Endogenous Outcomes

Current Delivery Frequency: The first set of endogenous outcomes correspond to respondents' current ground-based delivery frequency of package items and the current ground-based delivery frequency of food items (the latter including both prepared foods and groceries). Delivery frequency is modeled as an ordinal outcome for both package and food delivery item types, with the ordinal categories defined as 0, 1-2, 3-5, 6-10, and more than 10 deliveries per month. Respondents were asked to classify their delivery frequency for the preceding month by selecting the category that best described their usage for each item type.[4] The top panel of Table 5 summarizes the observed distribution of delivery frequencies within the sample by item type.

The reported delivery frequencies suggest that package deliveries are quite prevalent. The largest share of the sample (35.3%) reports receiving package deliveries on a weekly basis (3-5 deliveries per month), and 210 respondents (19.9% of the sample) report receiving more than 10 package deliveries per month. Food delivery is less frequent overall, with 40.7% of respondents reporting no food deliveries within the preceding month. However, a distinct subset of the sample, 106 respondents, or 10.0%, report very frequent food delivery, receiving more than 10 food deliveries per month.

Stated Delivery Mode Preference: The other endogenous outcome examined in this study is the binary delivery mode preference dimension for the choice between delivery drones and traditional ground-based delivery. Respondents were presented with two stated preference choice scenarios with varying attributes, as described in detail in Section 3.1.1. For each scenario, the binary outcome indicates whether the respondent preferred DDS over a conventional ground-based

[4] One may question whether respondents can accurately report their delivery activity over a one-month period. In the current study, however, respondents were asked to report their delivery behavior during the preceding month, thereby limiting the recall task to a recent period and reducing concerns associated with long-term memory retrieval. In addition, respondents were not asked to recall the exact number or timing of individual deliveries. Instead, they classified their package and food delivery activity into broad monthly frequency categories (0, 1–2, 3–5, 6–10, and more than 10 deliveries), substantially reducing the cognitive burden associated with recall. More generally, survey methodology research indicates that aggregate or summative measures of past behavior are recalled considerably more reliably than detailed event-level information (see, for example, Bell et al., 2019; te Braak et al., 2023). Further, Palm et al. (2024) argue that recall periods between approximately one week and one month provide a reasonable balance between recall accuracy and the ability to capture behaviors that occur only intermittently. This consideration is particularly relevant in the present context because package and food delivery usage varies substantially across individuals, and many households do not use such services on a daily or even weekly basis. Indeed, the activity-based travel behavior literature has long recognized that many discretionary activities occur infrequently, implying that very short recall periods may systematically underrepresent typical behavioral patterns (see Spissu et al., 2009; Haghighi and Miller, 2025). Thus, the one-month recall period adopted in this study represents a reasonable compromise between minimizing recall error and capturing representative delivery behavior.

delivery in the specified context. As shown in the bottom panel of Table 5, preferences are nearly evenly split, with 47.9% of observations across all respondents indicating a preference for DDS within the context of the presented scenarios. Disaggregating responses at the individual level reveals additional distinct behavioral patterns. Just over a quarter (25.4%) of the sample consistently selected DDS across both scenarios, while a slightly larger share (29.6%) consistently preferred ground-based delivery. The remaining 45.0% of respondents altered their choice between scenarios, selecting each delivery mode once (these disaggregated statistics are not shown in Table 5). These patterns indicate that stated preferences reflect both individuals' underlying modal preferences and sensitivity to changes in the DDS context. While a substantial portion of the sample exhibits consistent preferences for a single delivery mode, nearly half of respondents adjust their choices in response to variation in service characteristics. Overall, these descriptive statistics suggest substantial interest in DDS within the sample and provide evidence of individual-level variation in delivery mode selection. However, moving beyond univariate trends is necessary to analyze how preferences vary across service contexts and individual-level factors.

3.1.3 Attitudes/Latent Constructs

The modeling framework incorporates three stochastic latent constructs representing individuals' attitudes related to privacy, technology, and drone-related noise. As discussed in Section 2.2.1, the inclusion of latent attitudes is consistent with prior work grounded in the Theory of Planned Behavior (TPB) and Technology Acceptance Model (TAM) that underscore the central role of attitudinal perceptions and lifestyle preferences in driving adoption decisions for emerging technologies (Davis, 1989; Ajzen, 1991; Venkatesh and Davis, 2000).

In addition to the final set of three constructs identified above, preliminary specifications explored additional latent constructs representing green lifestyle propensity, drone experience, adventurousness, and safety concerns, consistent with theoretical relationships identified in the literature. The final specification was reduced to three latent constructs based on analysis of internal consistency and explanatory power. Constructs related to green lifestyle propensity and drone experience did not demonstrate adequate internal consistency, with loadings differing by a factor greater than two across associated indicators, suggesting that they did not reliably capture a common underlying attitude. In contrast, the adventurousness and safety concerns constructs exhibited more consistent measurement properties but did not significantly impact DDS adoption outcomes. The lack of an independent effect for the adventurousness construct is likely attributable to its strong correlation (0.787) with tech-savviness, as both constructs capture closely related dimensions of inclination towards innovation and experimentation. Similarly, the limited explanatory power of the safety concerns latent construct may reflect the explicit inclusion of DDS safety within the stated preference scenarios. These relationships led to the determination of the set of three latent constructs included in the final specification, each of which is discussed briefly below.

The privacy concerns latent construct represents the degree to which individuals perceive drone delivery operations as intrusive or violating personal privacy. The indicators for this construct center around perceived intrusion onto private residential property through in-person home visits by delivery providers, the collection of imagery, and drone operations near the home. Within the TBP framework, attitudes toward privacy are often modeled as having a negative impact on DDS attitudes, indirectly reducing adoption (Yoo et al., 2018; Mathew et al., 2021; Koh et al., 2023). Consistent with previous drone delivery studies, heightened privacy concerns are expected to diminish DSS preferences.

Next, the tech-savviness latent construct captures an individual's inclination toward engaging with emerging technologies and automation. Within the TAM framework, this attitude is closely related to perceived ease of use, as individuals who are more familiar with technology are more comfortable when interacting with technological systems (Chen et al., 2022; Kumar et al., 2023). From a TPB perspective, tech-savviness contributes to more favorable attitudes toward DDS and an increased propensity to adopt emerging technologies (Yoo et al., 2018). Accordingly, individuals with higher levels of tech-savviness are expected to exhibit a greater likelihood of DDS adoption (Yoo et al., 2018; Chen et al., 2022; Said et al., 2023; Sham et al., 2023).

Finally, the drone noise sensitivity latent construct represents an individual's sensitivity to drone-related noise and aversion to drone operations near their residence. In contrast to the noise service characteristic, which captures objective noise levels of delivery drone operations relative to ground-based delivery vehicles, the indicators for this construct reflect personal annoyance with drone-related noise in residential environments. Because prior research suggests that noise perceptions are shaped not only by acoustics but also by individual predispositions (Miedema and Vos, 1999; Shepherd et al., 2010; Zhang et al., 2023a), this construct allows the effects of individual noise sensitivity to be distinguished from the effects of operational noise levels. Consistent with previous findings relating to noise perceptions and DDS adoption (discussed in Section 2.2.1), higher levels of drone noise sensitivity are expected to decrease respondents' drone delivery preferences.

The distributions of responses to the attitudinal indicators associated with each of these latent constructs are shown in Figure 1. Responses to the privacy concerns indicators suggest a generally balanced perception of privacy risk, with the sample overall expressing a slight wariness of drone-related privacy violations. As for the indicators of the tech-savviness latent construct, responses suggest that the sample overall is inclined toward emerging technologies. Drone noise sensitivity-related responses are also fairly evenly spread, with a more negative response to the second statement relating to nighttime noise impacts.

3.2 Analytic Framework

The modeling approach employed in this study follows a two-stage estimation framework to jointly analyze current delivery behavior and DDS adoption decisions while incorporating attitudinal latent constructs, as illustrated in Figure 2 (the mathematical notation in Figure 2 refers to the notations used in the following section). This sequential estimation procedure mimics the generalized heterogenous data model (GHDM) framework developed by Bhat (2015), but separates the identification and estimation of the latent constructs from the estimation of the main endogenous outcomes. The two-stage procedure used produces consistent estimates while reducing computational complexity, even if it is somewhat less efficient than a full joint estimation approach (Newey and McFadden, 1994; White, 1996; Murphy and Topel, 2002). The first stage consists of the structural equation modeling (SEM) portion of the GHDM framework as well as the portion of the measurement equation modeling (MEM) component relating to the indicators of the latent constructs (Bhat, 2015). In this first stage, the three latent constructs representing privacy concern, tech-savviness, and drone noise sensitivity are estimated based on their loadings onto the ordered indicators (individual indicators are omitted from Figure 2 for simplicity). Demographic factors are regressed onto each of these latent constructs using a multivariate regression, which is then estimated and used to develop the latent construct values for each individual. During this stage, the correlation matrix among the latent constructs is estimated ($\mathbf{\Gamma}$ in Figure 2). This correlation matrix quantifies the role of unobserved factors which may jointly shape multiple

constructs. For example, an individual who frequently uses outdoor spaces such as a backyard pool may place a greater value on maintaining privacy and a quiet residential environment, leading to both heightened privacy concerns and increased sensitivity to drone-related noise disruptions.

The second stage follows the MEM portion of the GHDM relating to the main endogenous outcomes (Bhat, 2015). This stage consists of a multivariate ordered-response probit (MORP) model representing current delivery behavior and binary probit model of DSS adoption (labeled "Endogenous Outcomes" on the right side of Figure 2). The estimated values of the continuous latent constructs from the first stage are treated as exogenous variables in this second stage. The correlation matrix across the two current delivery frequency outcomes (for package and food deliveries) is also estimated ($\tilde{\mathbf{\Lambda}}$ in Figure 2), capturing unobserved factors that may simultaneously affect both delivery behaviors. For instance, individuals residing in locations with elevated delivery security risks may exhibit infrequent use of both package and food delivery services. The formulation also incorporates a correlation matrix among the current delivery frequencies (of package and food deliveries) and stated DDS adoption ($\mathbf{\Omega}$ in Figure 2). Further, to accommodate the panel structure of the data in which each respondent evaluates two choice scenarios, a correlation across choice scenarios for each individual is estimated ($\mathbf{\Lambda}$ in Figure 2). This correlation matrix captures the influence of unobserved individual-level factors that may affect the choice in both the stated preference scenarios. For example, if an individual perceives delivery drones as visually obtrusive in their residential environment, they may be less likely to select drone delivery across both scenarios. The following section describes the mathematical formulation of the model.

3.3 Model Formulation

3.3.1 First Stage Estimation of Latent Constructs

For the formulation of the first stage portion of the model, pertaining to the estimation of the latent constructs, let l be the index for the latent constructs $(l = 1, 2, \ldots, L)$ and label each latent construct as z_l^*. Then, the $(L \times 1)$ vector of latent constructs may be written as $\mathbf{z}^* = (z_1^*, z_2^*, ..., z_L^*)'$. In the current context $L = 3$, corresponding to the three latent constructs shown in the central portion of Figure 2. Each of these latent constructs is identified using a series of ordinal indicators (not shown in Figure 2 for parsimony). Denote these indicators as n $(n = 1, 2, ..., N)$. 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 $(j_n = 1, 2, ..., J_n)$. Then, each indicator may be written based on an underlying latent variable $\tilde{\tau}_n^*$ whose horizontal partitioning leads to the observed ordinal category selection. Using the usual ordered response formulation, we may write these as a function of the latent constructs as:

$$\tilde{\tau}_n^* = \tilde{\mathbf{d}}_n' \mathbf{z}^* + \tilde{\varepsilon}_n \tag{1}$$

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 each indicator, the thresholds are ordered $\tilde{\psi}_{n,0} < \tilde{\psi}_{n,1} < \tilde{\psi}_{n,2} \ldots < \tilde{\psi}_{n,J_n-1} < \tilde{\psi}_{n,J_n}$, with $\tilde{\psi}_{n,0} = -\infty$, $\tilde{\psi}_{n,1} = 0$, and $\tilde{\psi}_{n,J_n} = +\infty$. Stack these thresholds into the vectors $\tilde{\mathbf{\psi}}_n = (\tilde{\psi}_{n,2}, \tilde{\psi}_{n,3}, ..., \tilde{\psi}_{n,J_n-1})'$ and matrix

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

$$\tilde{\boldsymbol{\tau}}^* = \tilde{\mathbf{d}}\mathbf{z}^* + \tilde{\boldsymbol{\varepsilon}}, \quad \tilde{\boldsymbol{\psi}}_{low} < \tilde{\boldsymbol{\tau}}^* < \tilde{\boldsymbol{\psi}}_{up}. \tag{2}$$

Finally, each latent construct may be written as a function of covariates as:

$$z_l^* = \boldsymbol{\alpha}_l'\mathbf{w} + \eta_l \tag{3}$$

where $\mathbf{w}$ is a $(D \times 1)$ vector of observed variables, $\boldsymbol{\alpha}_l$ is a corresponding $(D \times 1)$ vector of coefficients, and η_l is a random error term that is assumed to be standard normally distributed. Also, stack these components into the $(L \times D)$ matrix $\boldsymbol{\alpha} = (\boldsymbol{\alpha}_1, \boldsymbol{\alpha}_2, ..., \boldsymbol{\alpha}_L)'$ and the $(L \times 1)$ vector $\boldsymbol{\eta} = (\eta_1, \eta_2, \ldots, \eta_L)'$. In order to accommodate unobserved factors that may also jointly influence multiple latent variables, we allow a multivariate normal correlation structure for $\boldsymbol{\eta}$. $\boldsymbol{\eta} \sim MVN_L[\mathbf{0}_L, \boldsymbol{\Gamma}]$, where $\mathbf{0}_L$ is an $(L \times 1)$ column vector of zeros and $\boldsymbol{\Gamma}$ is an $(L \times L)$ correlation matrix (see the two-headed arrow in the central portion of Figure 2). Then, the equation for the latent constructs may be written in matrix form as:

$$\mathbf{z}^* = \boldsymbol{\alpha}\mathbf{w} + \boldsymbol{\eta}. \tag{4}$$

The complete system may then be written in a reduced form by replacing $\mathbf{z}^*$ in equation (2) with the right side of equation (4):

$$\tilde{\boldsymbol{\tau}}^* = \tilde{\mathbf{d}}\mathbf{z}^* + \tilde{\boldsymbol{\varepsilon}} = \tilde{\mathbf{d}}(\boldsymbol{\alpha}\mathbf{w} + \boldsymbol{\eta}) + \tilde{\boldsymbol{\varepsilon}} = \tilde{\mathbf{d}}\boldsymbol{\alpha}\mathbf{w} + \tilde{\mathbf{d}}\boldsymbol{\eta} + \tilde{\boldsymbol{\varepsilon}}, \tag{5}$$

with the multivariate joint distribution of the vector of indicators written as $\tilde{\boldsymbol{\tau}}^* \sim MVN_N(\tilde{\mathbf{d}}\boldsymbol{\alpha}\mathbf{w}, \tilde{\mathbf{d}}\boldsymbol{\Gamma}\tilde{\mathbf{d}}' + \boldsymbol{IDEN}_N)$. The parameters $\boldsymbol{\alpha}$ and $\tilde{\mathbf{d}}$ are then estimated simultaneously using a maximum likelihood approach. For additional discussion of the necessary identification conditions for this first stage of the model, see Bhat (2015). Essentially, for the current model specification with $L \geq 2$, it is sufficient that there are at least two factor complexity one indicator variables for each latent construct. This sufficiency condition is satisfied in our analysis because each latent construct loads exclusively on at least two indicators. Then, estimated values of the continuous latent constructs are constructed for each individual as $\hat{\mathbf{z}}^* = \hat{\boldsymbol{\alpha}}\mathbf{w}$ where $\hat{\boldsymbol{\alpha}}$ are the estimated coefficients. These estimated values are then used in second stage of the model, as discussed next.

3.3.2 Second Stage Estimation of Main Outcomes

For the formulation of the second stage portion of the model, pertaining to the estimation of the endogenous outcomes, we first consider the two current delivery frequency outcomes (relating to the frequency of package deliveries and food deliveries). Denote the index for the ordinal outcomes as m $(m = 1, 2, ..., M)$, with $M = 2$ in our current context. Further, mirroring the above formulation, let J_m be the number of ordinal categories for the m^{th} outcome, denote the corresponding index as j_m $(j_m = 1, 2, ..., J_m)$, and let the actual outcome level selected by the

individual of interest be b_m. Then, the ordinal outcomes may be denoted with an underlying latent variable $\tilde{y}_m^*$, whose horizontal partitioning leads to the observed outcome:

$$\tilde{y}_m^* = \boldsymbol{\gamma}_m' \mathbf{x} + \tilde{\varsigma}_m, \text{ with } \tilde{\varphi}_{m,b_m-1} < \tilde{y}_m^* < \tilde{\varphi}_{m,b_m} \quad (6)$$

where $\mathbf{x}$ is an $(A \times 1)$ vector of exogenous variables, including the estimated values of the latent constructs from the first stage ($\hat{\mathbf{z}}^*$) and interactions between the latent constructs and other exogenous variables (but not including a constant). $\tilde{\boldsymbol{\gamma}}_m$ is a corresponding vector of coefficients, and the error term ς_m is again assumed to be standard normally distributed across individuals. Also, the $\tilde{\varphi}$ terms represent thresholds partitioning the underlying latent variable based on the ordinal category chosen by the individual under consideration. These thresholds must again be ordered $\tilde{\varphi}_{m,0} < \tilde{\varphi}_{m,1} < \tilde{\varphi}_{m,2} ... < \tilde{\varphi}_{m,J_m-1} < \tilde{\varphi}_{m,J_m}$, and we fix the values of $\tilde{\varphi}_{m,0} = -\infty$ and $\tilde{\varphi}_{m,J_m} = +\infty$. Let $\tilde{\boldsymbol{\varphi}}_m = (\tilde{\varphi}_{m,1}, \tilde{\varphi}_{m,2}, ..., \tilde{\varphi}_{m,J_m-1})'$ and $\tilde{\boldsymbol{\varphi}} = (\tilde{\boldsymbol{\varphi}}_1', \tilde{\boldsymbol{\varphi}}_2', ..., \tilde{\boldsymbol{\varphi}}_{\mathrm{M}}')'$. Stack the underlying continuous variables $\tilde{y}_m^*$ into an $(M \times 1)$ vector $\tilde{\mathbf{y}}^*$, and the M error terms $\tilde{\varsigma}_m$ into an $(M \times 1)$ vector $\tilde{\boldsymbol{\varsigma}}$. Also, to account for correlations among the ordinal outcomes, we allow a general correlation structure for $\tilde{\boldsymbol{\varsigma}}$ such that $\tilde{\boldsymbol{\varsigma}} \sim MVN_M(\mathbf{0}_M, \tilde{\boldsymbol{\Lambda}})$, where $\mathbf{0}_M$ is an $(M \times 1)$ column vector of zeros, and $\tilde{\boldsymbol{\Lambda}}$ is an $(M \times M)$ correlation matrix (depicted with a two headed arrow between the delivery frequency outcomes in Figure 2). Finally, define the $(M \times A)$ matrix $\boldsymbol{\gamma} = (\boldsymbol{\gamma}_1, \boldsymbol{\gamma}_2, ..., \boldsymbol{\gamma}_M)'$ and stack the M lower thresholds for the decision maker $\tilde{\varphi}_{m,b_m-1}$ into an $(M \times 1)$ vector $\tilde{\boldsymbol{\varphi}}_{low}$ and the M upper thresholds $\tilde{\varphi}_{m,b_m}$ into a vector $\tilde{\boldsymbol{\varphi}}_{up}$. Then, in matrix form, the ordinal outcomes may be written as:

$$\tilde{\mathbf{y}}^* = \boldsymbol{\gamma}\mathbf{x} + \tilde{\boldsymbol{\varsigma}}, \quad \tilde{\boldsymbol{\varphi}}_{low} < \tilde{\mathbf{y}}^* < \tilde{\boldsymbol{\varphi}}_{up}. \quad (7)$$

Next, consider the binary outcome pertaining to the choice between drone delivery and traditional ground-based delivery. Let i $(i = 1, 2, ..., I)$ index the choice instance each respondent. In our empirical case, each respondent was asked to respond to two separate stated preference questions for their delivery mode preferences, so $I = 2$. At each choice instance, the latent propensity (y_i^*) referring to the propensity to choose the DDS mode relative to a ground-based delivery mode may be written as:

$$y_i^* = \boldsymbol{\beta}'\tilde{\mathbf{x}} + \varsigma_i \quad (8)$$

where, $\tilde{\mathbf{x}}$ is a $(B \times 1)$ vector of exogenous variables, including a constant as well as (a) the estimated values of the latent constructs from the first stage ($\hat{\mathbf{z}}^*$), (b) interactions between the latent constructs and other exogenous variables, and (c) the current service frequency of package deliveries and food deliveries. $\boldsymbol{\beta}$ is the corresponding $(B \times 1)$ coefficient vector (some of whose elements have an entry of zero) and ς_i is a standard-normal error term assumed to be independent and identically distributed across respondents. As with the ordered-response formulation, if m_i is the actually realized alternative for outcome i, each respondent's response may be expressed as $y_i = m_i$ if $\theta^{m_i-1} < y_i^* < \theta^{m_i}$. In the case of the binary response outcomes, however, all of the thresholds are fixed as $\theta^0 = -\infty$, $\theta^1 = 0$, and $\theta^2 = \infty$. Stack the underlying continuous variables into the $(I \times 1)$ vector $\mathbf{y}^* = (y_1^*, y_2^*, ..., y_I^*)'$, and the error terms into the $(I \times 1)$ vector $\boldsymbol{\varsigma}$. Also, to

account for correlations among the binary outcomes, we allow a general correlation structure for $\boldsymbol{\varsigma}$ such that $\boldsymbol{\varsigma} \sim MVN_I(\mathbf{0}_I, \boldsymbol{\Lambda})$, where $\mathbf{0}_I$ is an $(I \times 1)$ column vector of zeros, and $\boldsymbol{\Lambda}$ is an $(I \times I)$ correlation matrix (depicted with a two headed arrow connecting the binary delivery mode box to itself in Figure 2). The correlation matrix $\boldsymbol{\Lambda}$ accounts for panel effects between the two choice occasions from the same individual. Also, stack the I lower thresholds θ^{m_i-1} for each respondent into a vector $\boldsymbol{\theta}_{low}$, the corresponding I upper thresholds θ^{m_i} into a vector $\boldsymbol{\theta}_{up}$, and define the $(M \times B)$ matrix $\tilde{\boldsymbol{\beta}} = (\boldsymbol{\beta}, \boldsymbol{\beta}, ..., \boldsymbol{\beta})'$. Then, in matrix form, the binary outcomes may be written as:

$$\mathbf{y}^* = \tilde{\boldsymbol{\beta}}\mathbf{x} + \boldsymbol{\varsigma}, \ \boldsymbol{\theta}_{low} < \mathbf{y}^* < \boldsymbol{\theta}_{up}. \tag{9}$$

Finally, consider the $((M+I)\times 1)$ vector of outcomes $\mathbf{Y} = \begin{bmatrix} \tilde{\mathbf{y}}^* \\ \mathbf{y}^* \end{bmatrix}$. Define $\mathbf{B} = \begin{bmatrix} \boldsymbol{\gamma}\mathbf{x} \\ \tilde{\boldsymbol{\beta}}\tilde{\mathbf{x}} \end{bmatrix}$ and $\boldsymbol{\Sigma} = \begin{bmatrix} \tilde{\boldsymbol{\Lambda}} & \boldsymbol{\Omega} * \mathbf{1}_I' \\ \mathbf{1}_I * \boldsymbol{\Omega}' & \boldsymbol{\Lambda} \end{bmatrix}$, where $\boldsymbol{\Omega}$ is an $(M \times 1)$ column vector with correlations between each of the ordered outcomes and the binary outcomes (depicted with a two headed arrow between the delivery frequency outcomes and the delivery mode choice outcomes in Figure 2). This structure ensures that there is a consistent correlation between the ordinal frequencies and the delivery mode preference at each choice occasion. Then the multivariate joint distribution of the main outcome is given by $\mathbf{Y} \sim MVN_{M+I}(\mathbf{B}, \boldsymbol{\Sigma})$, denoting the $(M+I)$-dimensional multivariate normal distribution with mean $\mathbf{B}$ and correlation matrix $\boldsymbol{\Sigma}$. Let the set of parameters to be estimated be $\boldsymbol{\delta} = \{\boldsymbol{\gamma}, \boldsymbol{\beta}, \tilde{\boldsymbol{\varphi}}, \text{Vechup}(\tilde{\boldsymbol{\Lambda}}), \text{Vechup}(\boldsymbol{\Lambda}), \boldsymbol{\Omega}\}$ where Vechup(.) row-vectorizes all non-zero upper diagonal elements of a matrix. Also define the two $\left((M+I)\times 1\right)$ threshold vectors $\ddot{\boldsymbol{\psi}}_{low} = \begin{pmatrix} \tilde{\boldsymbol{\varphi}}_{low} \\ \boldsymbol{\theta}_{low} \end{pmatrix}$ and $\ddot{\boldsymbol{\psi}}_{up} = \begin{pmatrix} \tilde{\boldsymbol{\varphi}}_{up} \\ \boldsymbol{\theta}_{up} \end{pmatrix}$. Then, the likelihood function for the individual may be written as:

$$L(\boldsymbol{\delta}) = \Pr\left[\ddot{\boldsymbol{\psi}}_{low} \le \mathbf{Y} \le \ddot{\boldsymbol{\psi}}_{up}\right] = \int_{D_r} f_{M+I}(\mathbf{r} \mid \mathbf{B}, \boldsymbol{\Sigma}) d\mathbf{r} \tag{10}$$

where the integration domain $D_r = \{\mathbf{r} : \ddot{\boldsymbol{\psi}}_{low} \le \mathbf{r} \le \ddot{\boldsymbol{\psi}}_{up}\}$ is the multivariate region of the elements of the $\mathbf{Y}$ vector determined by the observed outcomes. 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) for the computation of standard errors using a two-stage optimization estimator.

4. RESULTS

The final model specification was developed through an iterative process of testing alternate combinations of explanatory variables based on statistical fit. Household size and the number of vehicles were tested both in a dummy variable form (to allow for non-linearities) as well as in a linear form. For both these ordinal variables, the linear form was found to be adequate. For the remaining demographic variables (including income, which was collected in grouped categories,

and other naturally occurring categorical variables such as race and ethnicity), variable effects were tested in their most disaggregate categorical form collected in the survey and progressively aggregated as appropriate based on statistical tests to support parsimonious behavioral representations. During both stages of the modeling process, a t-statistic threshold of 1.645 (corresponding to a 90% confidence level) was used to retain variables.[5] The final estimation results are presented in Table 6 for the first stage component of the model and Table 7 for the second stage component of the model. A "--" entry in the results tables indicates that the variable in that row was not found to have a statistically significant impact on the outcome variable for a given column.

Before discussing the estimation results, a note is in order regarding the blocked stated preference design employed in this study. As described in Section 3, only a rotating subset of the drone service characteristics were presented to each respondent to reduce survey burden while enabling the estimation of preferences across a broad set of service characteristics. For each service characteristic subject to this rotating presentation scheme, we initially specified a separate "not shown" category to test whether the absence of that attribute from a choice scenario had an independent effect on respondents' choices. We also tested interactions between the "not shown" indicators and other explanatory variables to examine whether omitted attributes indirectly influenced sensitivities to the attributes that were presented. In all cases, the "not shown" category was statistically indistinguishable from one of the explicitly presented attribute levels, and the interaction effects involving the "not shown" indicators were not statistically significant. Accordingly, in the final specification reported in Table 7, the attribute level that was empirically indistinguishable from the corresponding "not shown" category is used alongside "not shown" as the base category for that service characteristic. This presentation allows the substantive effects of the remaining attribute levels to be interpreted relative to the behavioral baseline empirically revealed by the blocked experimental design. For example, in the case of reliability, the "not shown" category was statistically indistinguishable from the "always available" category. This result suggests that, when delivery reliability is not explicitly presented, respondents implicitly evaluate the choice scenarios as though DDS were available under all weather conditions.

With that important note, we now proceed to a discussion of the results. First, Section 4.1 presents the first stage estimation results describing the impacts of demographic characteristics on the three latent constructs. Next, Section 4.2 presents the estimation results for the delivery frequency and DDS adoption outcomes, with subsections detailing findings relating to DDS context, individual-level characteristics, current delivery frequency, and estimated correlations. Finally, model fit and average treatment effects are discussed in Sections 4.4 and 4.5, respectively.

[5] The use of a 90% confidence level reflects a deliberate balance between the risks of Type I errors (falsely attributing significance to unrelated variables) and Type II errors (incorrectly rejecting meaningful variables). Consistent with guidance from the American Statistical Association (Wasserstein and Lazar, 2016; Wasserstein et al., 2019), the selection of statistical thresholds should be determined by researcher judgement as informed by the context of the study rather than relying uniformly on the commonly used 95% confidence level (0.05 level of significance). In this analysis, we prioritize reducing the probability of Type II errors compared with this commonly used threshold due to the modest sample size and selective availability of certain service context variables. This allows us to identify relationships with a reasonable significance in the current dataset, which may inform future investigations benefiting from larger sample sizes, even if this leads to a slightly higher probability of Type I error.

4.1 Attitudes/Latent Constructs

Table 6 presents the demographic determinants of the three latent constructs. Gender plays a role for all latent constructs, with men exhibiting lower levels of privacy concern, higher tech-savviness, and reduced sensitivity to noise. The finding of lower privacy concerns among men is consistent with prior work documenting gender differences in perceived online privacy risks (Fogel and Nehmad, 2009; Rowan and Dehlinger, 2014). In the specific context of drone operations in residential environments, variation in privacy concern may also reflect differences in vulnerability to privacy violations. Prior work suggests that misuse of drone imagery may pose an elevated risk for women, as visual surveillance raises concerns related to bodily privacy, modesty violations, and exposure under the male gaze (Waltorp and Bruun, 2022; Sun and Moon, 2025). Higher levels of tech-savviness among men are also consistent with established evidence linking gender to openness toward emerging technologies (Galyani Moghaddam, 2010; Asmussen et al., 2020; Mushtaq and Riyaz, 2020; Asmussen et al., 2022). Turning to drone noise sensitivity, prior research generally does not identify gender-based differences in general noise perceptions (Miedema and Vos, 1999; Schutte et al., 2007; Shepherd et al., 2010; Zhang et al., 2023a), although women have been found to exhibit greater sensitivity to noise disruptions near the home (Michaud et al., 2022). Given that the noise sensitivity indicators in this study focus explicitly on drone-related noise in residential settings, the result suggests that gender differences may be specific to the residential environment.

Age also plays an important role in attitudes, with privacy concerns decreasing for middle-aged (35-54) and older (65+) individuals. One possible explication is that younger individuals may exhibit greater awareness of data-related risks (Gallistl et al., 2026), leading to elevated privacy concerns. Conversely, older individuals may weigh privacy concerns against functional tradeoffs such as increased autonomy and convenience, reducing the relative importance of privacy considerations (Beach et al., 2009). Tech-savviness is found to decrease with age, consistent with a large body of previous work (Lee and Coughlin, 2015; Lavieri and Bhat, 2019; Asmussen et al., 2020; Gomez et al., 2021). This decline is often attributed to lower exposure to emerging technologies and greater difficulty of adapting to new systems among older populations (Correa et al., 2010; Helsper and Eynon, 2010; Kim et al., 2023). Drone noise sensitivity is also found to vary across age groups, with lower sensitivity among individuals aged 65 and above. This mirrors previous findings of reduced sensitivity to noise among older adults (Miedema and Vos, 1999; Ni and Huang, 2022), potentially due to lifecycle differences and less acute hearing among seniors.

Beyond age and gender, educational attainment also influences attitudes towards technology and drone-related noise. Results indicate that college-educated individuals exhibit higher levels of tech-savviness, consistent with prior findings linking education to greater exposure to emerging technologies in both educational and workplace settings (van Laar et al., 2017; Nair and Bhat, 2021). At the same time, this group demonstrates lower sensitivity to drone-related noise, although previous research has produced mixed evidence regarding the relationship between education and noise sensitivity (Miedema and Vos, 1999; Zhang et al., 2023a).

Turning to racial and ethnic differences, Black and Hispanic individuals are found to be less concerned with privacy, while individuals in the "Other" race category exhibit heightened concerns. These findings contrast with prior literature, which has often documented elevated privacy concerns among racial minority groups in online and emerging technology contexts (Lee and Hess, 2022; Wang and Metzger, 2024). One possible explanation for this difference is the property-centric representation of privacy concerns captured by the specific indicators employed in this study. American notions of privacy and private property have long been associated with

ideas of Whiteness (Harris, 1993; Reichel, 2017; Grigoleit-Richter and Krämer, 2026), potentially leading White respondents to be more sensitive than Black and Hispanic individuals to perceived incursions onto their property. Further, the results indicate that Black and Hispanic individuals are more technologically inclined. One possible explanation is that these groups may be more likely to view technology as providing pathways to new opportunities, increasing receptiveness towards emerging technologies (Ning and Essien, 2026). Finally, individuals in the "Other" race category are more sensitive to drone-related noise disruptions.

At the household level, housing type, ownership, income, and household composition further shape attitudes. Individuals residing in detached single-family homes and homeowners exhibit elevated privacy concerns, reflecting stronger expectations of residential privacy relative to those in muti-family or other shared housing environments. This pattern aligns with the property-related indicators underlying the privacy construct, suggesting that perceived intrusions into private residential property are more salient for homeowners and single-family home residents, where expectations of environmental control are higher. Housing type also influences noise perceptions, with residents of single-family housing displaying greater sensitivity to drone-related noise. This pattern may reflect differences in perceived disruption due to background noise levels, with drone noise appearing less disruptive in higher-noise environments such as mixed-use areas (King et al., 2012; Torija et al., 2020; Aalmoes et al., 2023a). Higher-income households are found to be more tech-savvy, consistent with previous findings linking income to greater access to and familiarity with emerging technologies (Kalba, 2008; Lavieri et al., 2017; Dannemiller et al., 2021; Nair and Bhat, 2021). Finally, larger households exhibit lower levels of privacy concern and drone noise sensitivity. While prior work has linked household size to a small increase in noise sensitivity (Miedema and Vos, 1999), these results may indicate patterns specific to residential areas, where living with more individuals reduces baseline privacy expectations, while increasing in-home noise levels.

The "Latent Variable Measurement Equation Model" section of Table 6 reports the loadings of each latent construct on the corresponding indicators, which exhibit the expected directions as discussed in Section 3.1.3. The bottom panel of Table 6 presents the estimated correlations among the latent constructs. These results indicate that unobserved factors which increase privacy concerns also lead to increased drone noise sensitivity, while both of these constructs are negatively correlated with tech-savviness. These patterns suggest that individuals who are more sensitive to the privacy risks associated with drone operations also tend to exhibit heightened sensitivity to noise disruptions. In contrast, individuals with higher levels of tech-savviness appear to be less concerned with both privacy and noise-related aspects of drone operation due to a greater general acceptance of, and interest in, emerging technologies.

Overall, the resulting first-stage component of the model relating to the estimation of the latent constructs achieved a root mean square error of approximation (RMSEA) of 0.044 and a standardized root mean square residual (SRMR) of 0.033. These low RMSEA and SRMR values indicate a good fit between the retained measurement structure and the observed covariance relationships among the indicators. Together with the strong and statistically significant factor loadings (shown in the central panel of Table 6) and the clear theoretical interpretation of the retained constructs (as discussed in Section 4.2.1), these results suggest that latent constructs provide reliable representations of the underlying attitudinal dimensions influencing DSS adoption preferences.

4.2 Main Estimation

The results for the current delivery frequency and DSS adoption outcomes are presented in Table 7. The threshold parameters and constant reported in the top panel of Table 7 do not have a meaningful interpretation and are simply estimated to adjust baseline frequencies to match those observed within the sample.

4.2.1 DDS Context Effects

Service Characteristics: The estimation results indicate that improvements in speed and reductions in cost lead to more widespread adoption, consistent with previous stated preference studies (Yoo et al., 2018; Merkert et al., 2022; Xie et al., 2022; Ardeshiri et al., 2024), although the magnitude of these effects varies across delivery item types. A one-day reduction in delivery time is valued most strongly for prepared food deliveries, which is intuitive because the utility of prepared food is highly time-sensitive. Delays directly affect freshness, temperature, and overall meal quality, making even modest improvements in delivery time behaviorally meaningful. This result positions prepared food as a particularly promising use case for rapid DDS, consistent with Ardeshiri et al. (2024). By contrast, longer delivery windows may be more acceptable for packages, groceries, and medical supplies because their value to the consumer is often less immediately tied to consumption at the time of arrival. However, larger time savings, such as a two-day reduction relative to ground-based delivery, substantially increase DDS adoption for packages and medical supplies. This pattern suggests that while small delivery speed improvements are most consequential for prepared food, more substantial time savings can make DDS attractive for other delivery item types, particularly when faster receipt reduces inconvenience, uncertainty, or addresses time-sensitive needs.

Responses to cost are generally consistent across delivery item types, exhibiting the expected decline in DDS adoption as the cost premium relative to ground-based delivery increases. An exception is grocery deliveries, for which the relative cost effect is almost entirely offset by the grocery interaction term (with an effective cost coefficient for grocery deliveries of -0.033 + 0.027 = -0.006), indicating that the delivery cost differences examined in this study ($5-$20) have little influence on delivery mode choice for this delivery item type. One possible explanation is that grocery delivery decisions are driven primarily by the convenience of avoiding a shopping trip, rendering relatively modest differences in delivery charges of secondary importance. Further, grocery deliveries entail additional considerations, including the handling of perishable items and the need for recipients to be available to receive the delivery (Said et al., 2023), which may cause respondents to place greater emphasis on service quality and convenience than on cost differentials.

Together, the estimated coefficients for delivery speed and cost allow the imputation of the willingness to pay (WTP) for DDS time reductions, revealing variation across delivery item types. Because the effective cost coefficient for groceries is close to zero, the corresponding WTP estimates are not behaviorally meaningful; therefore WTP values are reported only for package, prepared food, and medical supply deliveries. For a single day reduction in DDS delivery time, WTP is highest for prepared food deliveries ($14.67), followed by package deliveries ($10.39) and medical supply deliveries ($8.18). Larger time savings result in higher WTP, with delivery time reductions of two days more than doubling single day values for package ($25.30) and medical supply deliveries ($43.52). Overall, these findings paint a picture of the variation in consumer preferences across delivery contexts, with general desires for faster and lower-cost delivery options playing an important role in last-mile mode selection. The corresponding WTP estimates quantify

the magnitude of these preferences, providing insight into the tradeoffs prospective users are willing to make.

Turning to delivery point, respondents exhibit reduced preferences for deliveries to off-site collection points relative to on-site alternatives. No significant difference is observed between front door delivery and delivery to an on-site marker, indicating that preferences are driven by the ease of access of on-site delivery as opposed to the specific delivery point. Moreover, this suggests that respondents do not exhibit elevated concerns relating to delivery drone operations near homes, with preferences instead driven by the convenience of on-site delivery. Beyond location, reliability of DDS also plays a critical role in the last-mile mode choice decisions. Adoption decreases when drones are only available in clear weather conditions, reflecting the importance of reliability and predictability of delivery timelines (Ardeshiri et al., 2024). This reduction in adoption is exacerbated for medical deliveries, with reliable service across weather conditions being especially highly valued when shipping medical supplies, as delays may carry greater consequences.

Another important determinant of DDS adoption is the safety of operations. The results indicate that respondents are less likely to adopt DDS when drone operations are characterized as having a higher risk of malfunction or crash than comparable ground-based delivery services, relative to scenarios in which the two modes offer similar levels of safety. Conversely, describing DDS as having a lower risk of malfunction or crash than ground-based delivery results in a comparable increase in adoption. These findings are broadly consistent with earlier studies that identify operational safety as a central determinant of DDS acceptance (Yoo et al., 2018; Serrano-Hernandez et al., 2021; Zhang et al., 2023b; Ardeshiri et al., 2024). They further suggest that prospective users do not simply expect DDS to achieve safety performance comparable to that of tradition ground-based delivery services, but place additional value on improvements in safety beyond this threshold.

A more asymmetric pattern emerges from the findings on noise and environmental sustainability. The attractiveness of DSS is reduced when DSS is characterized as being louder than ground-based delivery vehicles, consistent with prior work linking higher noise levels to increased annoyance (Connors, 2019; Yedavalli and Mooberry, 2019). However, no corresponding increase is observed when drones operate at lower noise levels than ground-based delivery services. This result suggests that noise disruptions associated with ground-based delivery have come to be accepted as a part of the residential soundscape, and reductions in noise below this level will not necessarily result in increased adoption. In a similar fashion, DSS adoption decreases when drones are described as producing more emissions than ground-based delivery options, while more environmentally sustainable operations do not yield a comparable increase in adoption. Although previous studies have documented a positive impact of environmental sustainability on drone adoption (Yoo et al., 2018; Sham et al., 2022; Xie et al., 2022), we identify a reverse effect where negative environmental impacts decrease DDS preferences. Together, these results suggest an uneven response to changes in DDS noise and environmental sustainability, where deteriorations relative to existing conditions have a stronger effect than improvements. This pattern indicates that the noise and environmental impacts associated with ground-based delivery are treated as baseline expectations within the residential environment.

The final service characteristic shaping stated preferences relates to the level of automation. The results indicate that fully autonomous operations increase drone adoption intentions relative to scenarios in which a remote pilot is available to take control during drop-off and emergencies. Additionally, we did not identify significant differences in responses to level of automation associated with individuals' tech-savviness. Interestingly, this finding contrasts with evidence from

urban air mobility applications for passenger transportation, where fully autonomous operations have been shown to reduce adoption likelihood relative to operations involving a human pilot (Beliveau et al., 2026). One possible explanation is the different role played by perceived risk across applications. While passengers may view a human pilot as a reassuring safeguard of their own safety in a high-risk context, DDS users are exposed to substantially less personal risk. As a result, autonomous DDS operations may be perceived as more efficient or technologically mature than human-controlled alternatives. Conversely, the presence of a remote pilot may raise concerns about potential surveillance or privacy intrusion during delivery.

Delivery Item Attributes: All of the three delivery item attributes (type, value, and weight) impact last-mile delivery mode selection. First, relative to other delivery item types, respondents are more likely to select DDS for medical supplies. This aligns with previous findings indicating that medical shipping is one of the most widely accepted uses for DDS (Zhang et al., 2025; Kyi et al., 2026). This increased preference persists even after controlling for the delivery item type-specific sensitivities to speed and cost discussed above, suggesting that DDS are perceived as offering unique advantages in medical contexts. One possible explanation is that users may be more willing to adopt novel technologies when the perceived benefits, such as access to critical medical supplies, outweigh uncertainty. Delivery item value also plays an important role, with heightened preferences for drone adoption when the value of the delivery item is less than $50. This is finding is consistent with previous research indicating that lower-value items are associated with lower perceived risk under unfamiliar DDS conditions (Kim, 2020; Ardeshiri et al., 2024; Kyi et al., 2026). Finally, DDS adoption decreases for heavy delivery items (those weighing more than 30 pounds), suggesting user concern regarding the operational capabilities of drone systems and their suitability for heavier loads (Ardeshiri et al., 2024).

4.2.2 Effects of Individual-Level Characteristics

Attitudes/Latent Constructs: The effects of the three latent constructs on current delivery frequency and DDS adoption are all in the expected directions. We find that elevated privacy concerns both reduce current food delivery frequency and lower DDS adoption. This pattern reflects a heightened sensitivity to residential privacy violations, which discourages both in-person delivery interactions (such as direct hand-offs of prepared food or groceries), and drone operations near the home. The negative impact of privacy concerns on DDS adoption is consistent with a large body of prior research (Yoo et al., 2018; Mathew et al., 2021; Chen et al., 2022; Koh et al., 2023; Dabić et al., 2025). Notably, this effect arises from individuals' perceptions of privacy risks rather than operational privacy protections such as the drone's ability to collect images or video of homes, which is not found to significantly impact adoption decisions. In contrast, greater tech-savviness is associated with higher current frequencies of both package and food deliveries, as well as greater DSS adoption. This pattern likely reflects an overall affinity for technology that encourages the use of online shopping, food delivery services, and the adoption of emerging delivery technologies such as drones (Yoo et al., 2018; Chen et al., 2022; Said et al., 2023; Sham et al., 2023). Lastly, drone noise sensitivity influences adoption through its interaction with home ownership. Homeowners with higher drone noise sensitivity are less likely to adopt DDS, while no corresponding relationship is observed for renters. This finding suggests that a greater perceived control over neighborhood noise conditions among homeowners increases sensitivity to drone-related noise disruptions, therefore discouraging adoption. Thus, while renters and homeowners may both experience high levels of drone noise sensitivity, its impact on DDS adoption is limited

to homeowners. These findings emphasize the importance of considering how attitudes and contextual factors jointly influence adoption decisions beyond their individual effects.

Demographics: Demographic characteristics play an important role in shaping current delivery frequency but have little direct impact on DDS adoption after accounting for service characteristics, latent construct effects, and the endogenous effects of existing delivery frequencies. At the individual level, delivery frequency varies across age, level of education, race, and employment status. Food delivery frequency decreases with age, consistent with prior findings of reduced usage of prepared food and grocery delivery among older individuals (Van Droogenbroeck and Van Hove, 2017; Keeble et al., 2020; Haddad et al., 2023; Lanfranchi et al., 2025). College-educated individuals more frequently utilize package delivery services, reflecting greater engagement with online shopping (Mishra et al., 2023). At the same time, higher educational attainment is associated with reduced food delivery frequency, although prior work indicates mixed findings (Van Droogenbroeck and Van Hove, 2017; Keeble et al., 2020; Lanfranchi et al., 2025). With respect to race, the only significant relationship identified is a reduced frequency of both delivery item types among individuals in the "Other" race category, consistent with previous findings (Kim and Wang, 2021; Mishra et al., 2023). Employment status also plays a role, with students exhibiting lower food delivery frequency and unemployed individuals showing reduced frequencies across both delivery types. These patterns are consistent with prior findings of greater delivery usage among employed individuals (Unnikrishnan and Figliozzi, 2021), reflecting differences in disposable income and time constraints.

At the household level, housing type, ownership, number of vehicles, and household composition further shape delivery usage. Residents of single-family homes as well as homeowners use package delivery services more frequently, reflecting a greater sense of delivery security relative to those with less control over their residential environment (Cheng et al., 2021; Bafouni-Kotta et al., 2023). Similarly, a high number of vehicles within the household is associated with an increased propensity for package deliveries (see also, Cheng et al., 2021; Unnikrishnan and Figliozzi, 2021). In addition, the presence of children under the age of 13 is found to increase frequency of food delivery services. This finding aligns with prior studies (Keeble et al., 2020; Shen et al., 2022; Haddad et al., 2023), reflecting the time constraints associated with childcare which make prepared food and grocery delivery services convenient alternatives to out-of-home dining or shopping. Geographic context further shapes delivery frequencies. Residents of high-density areas tend to use package delivery services more frequently, an unsurprising result given the relatively lower costs, improved delivery speeds, and increased options in urban areas. In contrast, those who live in areas with a low number of transportation warehousing locations tend use package and food delivery services less frequently, mirroring the previous result and suggesting that reduced availability or efficiency of delivery services in areas with limited last-mile logistics infrastructure is associated with lower levels of usage of these services.

Only two demographic effects are found to directly impact DDS adoption, the first being state of residence.[6] The results indicate that Texas residents are less inclined towards DDS than non-Texas residents within the sample. This suggests that unobserved regional influences such as

[6] Additional specifications including interactions between state of residence and service context variables were explored, however these interaction effects were not statistically significant. This limited statistical power may be due, in part, to the limited number of non-Texas residents within the sample (173 individuals, 16.4% of the overall sample). As discussed in Section 6, future studies with larger and more geographically balanced samples may offer additional insight into the specific factors driving potential regional heterogeneity in DDS adoption patterns.

social norms or differences in local experience with drone technology may shape geographic adoption trends beyond the factors included in the model. The second direct demographic effect is captured by an interaction effect indicating that high-income (more than $100,000) men exhibit elevated drone delivery preferences. This effect persists even after accounting for the impacts of gender and income-level on individual attitudes, suggesting that differences in adoption extend beyond perceptions of privacy, technology, and drone-related noise. One possible explanation is that emerging technologies may serve as a form of status signaling, with high-income individuals deriving utility not only from functional performance but also from the association with innovation and technological advancement (Bagwell and Bernheim, 1996). In addition, prior work suggests that men are more likely to associate technologies, particularly vehicles, with identity and status (Sovacool and Axsen, 2018; Robbennolt et al., 2025), contributing to stronger preferences for novel delivery modes. Together, these factors suggest that adoption preferences among high-income men may reflect specific patterns of consumption, identity expression, and engagement with emerging technologies.

4.2.3 Current Delivery Frequency Effects

The results relating current package and food delivery frequencies to DDS adoption reveal important differences across delivery item types. For package delivery, individuals who currently use receive packages infrequently (0-2 times/month) are more likely to adopt DDS for package deliveries than more frequent users. This aligns with some preliminary findings in the literature that indicate that higher-frequency package delivery users may be satisfied with their current delivery experience, and therefore less inclined to adopt to a new last-mile delivery mode (Tamakloe et al., 2024). We expand on these findings to establish that this tendency persists even when service characteristics, accessibility to transportation infrastructure, and possible endogeneity effects are accounted for. In contrast, the opposite relationship is observed for food delivery. Individuals who currently use food delivery services infrequently (0-2 deliveries per month) are less likely to adopt DDS for grocery deliveries than more frequent users. This pattern suggests that delivery frequency plays a different role in the context of food deliveries, capturing differences in familiarity and expectations. More frequent food delivery users may be more familiar with app-based ordering and delivery interactions, making them more comfortable with the logistics and expectations of the service. Conversely, less frequent users of food delivery services may face greater uncertainty when it comes to food delivery, and prefer familiar, ground-based delivery services. Additionally, the time-sensitive nature of food delivery may reinforce this relationship. Frequent users experience ground-based delivery performance more regularly, including unexpected delays or inefficiencies, which may lead them to be more receptive to delivery alternatives that offer potential improvements. This contrasts with package delivery, where frequent users exhibit satisfaction with existing options.

4.2.4 Correlations

The model results reveal three statistically significant correlations among the outcomes. The first is a positive correlation between the two current delivery frequencies of package and food deliveries. That is, unobserved factors influencing delivery usage tend to operate across both the package and food delivery item types. This could relate, for instance, to unobserved travel or mobility constraints that make physical access to both stores and restaurants more challenging, leading to elevated delivery frequencies of both types. The second is a small (but statistically significant) positive correlation between delivery frequency of package items and drone delivery

service adoption. This positive correlation suggests that unobserved factors (such as a desire for convenience in accessing non-food items) contributes to both an elevated delivery frequency and elevated adoption intention for DDS. The immediate implication is that if this correlation were ignored, the direct effect estimated from delivery frequency of package items to DDS adoption would be overestimated. Notably while a corresponding correlation was estimated between delivery frequency of food items and DDS adoption, it was found to be insignificant. The final significant correlation is a positive panel correlation between the two stated preference choice occasions of each individual. This result suggests that individual-level unobserved factors contribute to a uniformly elevated or depressed preference for DSS across the two scenarios, an unsurprising result.

4.3 Model Fit

To evaluate the fit of the second stage MORP model, we compare the performance of the final model specification with that of an independent model that does not account for correlations across package and food item delivery frequencies or across choice occasions. To compare these specifications, we use several disaggregate measures reported in Table 8. These measures are assessed using 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 drone adoption constant and the delivery frequency thresholds. The Bayesian Information Criterion (BIC) statistic is calculated as:

$$BIC = -L(\hat{\theta}) + 0.5 \text{ (\# of model parameters) } \log(\text{sample size}) \tag{11}$$

and the adjusted likelihood ratio index is calculated as:

$$\bar{\rho}^2 = 1 - \frac{L(\hat{\theta}) - M}{L(c)} \tag{12}$$

where M is the number of parameters (excluding constants) estimated in the model. As shown in Table 8, the model with correlations corresponds to lower BIC and higher adjusted likelihood ratio index values, indicating improved fit relative to the independent model. Given that the independent model is nested within the final specification, we also conduct a log-likelihood ratio test, computed as:

$$-2[L(\hat{\theta}_{Independent}) - L(\hat{\theta}_{With\ Correlations})]. \tag{13}$$

The resulting test statistic of 172.50 exceeds the critical chi-squared threshold corresponding to 2 degrees of freedom at the 99.9999% confidence level, providing strong statistical support for the inclusion of correlations. Finally, to provide an intuitive representation of the predictive power of both models, we calculate the average probability of correct prediction for each specification. Although the magnitude of these probabilities may seem small due to the large number of possible joint outcomes, both model specifications provide a substantial improvement over the most naïve joint model for a binary outcome and two ordered outcomes with five categories each, which has an average probability of correct prediction of 0.0250. The model with correlations provides a 7.2% increase in the probability of correct prediction over the independent model, again suggesting that accounting for unobserved effects enhances predictive power. Overall, the disaggregate fit statistics consistently support the inclusion of correlations within the final specification. These results suggest that while endogeneity between current delivery usage and DDS adoption is

limited, accounting for unobserved heterogeneity between package and food item delivery frequencies and across choice occasions substantially improves model fit.

4.4 Average Treatment Effects

To gain a better understanding of the magnitude of the effects discussed in Section 4.2, both in terms of the likelihood of adopting DDS and the actual projected delivery volumes expected for DDS, we compute average treatment effects (ATEs). These values characterize the change in the outcome variables resulting from shifting an exogenous variable from a base to treatment level, using counterfactual simulations to isolate its effect. For example, to evaluate the effect of gender, all individuals in the sample are assigned to the category of "Woman" without changing any of the other variables. For each individual, joint probability predictions are then computed for all combinations of delivery frequency and drone adoption outcomes. By marginalizing over these combinations, we obtain the overall probability of adopting DDS for each individual. We also directly obtain the probabilities associated with each ordinal level of package and food delivery frequency, conditional on choosing DDS. For ease of presentation, we then assign a cardinal value to each frequency bin (0 deliveries per month = 0 deliveries, 1-2 deliveries per month = 1.5 deliveries, 3-5 deliveries per month = 4 deliveries, 6-10 deliveries per month = 8 deliveries, and 10+ deliveries = 12 deliveries), allowing us to compute the expected number of deliveries of each type by DDS per month. The same procedure is then repeated for the treatment scenario in which the gender of all respondents is set to "Man." The resulting change in the adoption probability and the expected frequencies of package deliveries and food deliveries using DDS are the ATE values reported in Table 9. Note that by using the joint estimation results, this procedure explicitly identifies the frequency of deliveries (of each type) using DDS, an important quantity for overall demand, rather than solely the individual-level adoption decision.

In the top two panels of Table 9, which present the ATEs for service characteristics and delivery item attributes, we report delivery item type-specific effects as well as selected aggregate measures to highlight sensitivity differences across delivery item types. The bottom panel of Table 9 provides ATEs for demographic characteristics, presenting impacts on both the expected delivery volumes and the overall drone adoption outcome. These results provide insight into the combined influence of demographics on DDS demand through existing delivery behavior, individual attitudes, and direct effects on adoption decisions. For example, the gender effect shows that, on average, men are expected to order 0.700 more package deliveries and 0.562 more food deliveries by drone per month than women, along with a 0.100 increase in DDS adoption probability. This indicates that, in a pool of 100 men, we would expect approximately 70 additional package deliveries by drone (0.700 × 100), 56 additional prepared food deliveries by drone (0.562 × 100), and about 10 additional individuals adopting DDS relative to a pool of 100 women (0.100 × 100). These ATEs complement the main model results by providing clear, interpretable relationships between exogenous variables and projected trends in drone adoption and demand, constituting the empirical foundation for the service design, planning, and policy implications discussed in the following section.

5. IMPLICATIONS

5.1 Implications for Pricing and Service Design

The results highlight the importance of service enhancements relative to ground-based delivery. Delivery speed improvements and cost reductions particularly emerge as important levers for service providers to encourage adoption, although their effects vary by delivery item type. For

time-sensitive deliveries items, such as prepared food and medical supplies, reductions in delivery timeframes are especially impactful and should be prioritized in service design. For example, a one-day reduction in delivery time increases the expected monthly number of drone-based prepared food deliveries by 0.499 and increases the probability of choosing DDS for groceries and medical supply deliveries by 0.086, while a two-day reduction increases the probability of choosing DDS for medical supply deliveries by 0.385. WTP estimates suggest that users may accept reasonable price increases required by investments to increase delivery efficiency. Further, these delivery time reductions will require careful coordination with the entire supply chain, as DDS currently provides only last-mile shipping solutions. Within aerial delivery systems, medical goods may need to be positioned closer to end users at local fulfillment centers, or pharmacy-based distribution networks to facilitate rapid dleivery. Consequently, infrastructure investments supporting decentralized fulfillment may be as important as investments in drone technology itself. In contrast, the results relating to more constrained delivery contexts, such as groceries, indicate that adoption decisions are less responsive to cost differences, instead shaped by feasibility constraints such as perishability and convenient delivery. Accordingly, service providers should invest in flexible infrastructure solutions (e.g. temperature-controlled drop-off options, or flexible delivery windows) to lessen these practical burdens (Said et al., 2023), even if these improvements correspond to increased service costs.

In terms of broader service design, accessible and reliable delivery within residential environments emerges as an important prerequisite for adoption. Providing delivery directly to the home, whether that be to the door or to an on-site delivery marker, emerges as an important factor for adoption, increasing the expected number of drone package deliveries per month by 0.263. This effect makes safe operations in proximity to residences a top priority. Similarly, service reliability across weather conditions is critical, especially for applications such as medical supply deliveries where consistent service is highly valued. Limiting DDS availability only to clear conditions reduces adoption probability by 0.061 for non-medical deliveries, but by nearly six times as much (-0.324) for medical supply deliveries, making service reliability especially important in medical applications. These results suggest that early deployment strategies should prioritize robust and predictable operating capabilities, while clearly communicating any service limitations to users. For time-sensitive deliveries, investments in redundant infrastructure and weather-resilient operations may provide adoption benefits comparable to those associated with faster delivery times.

When it comes to acceptable safety, noise, and environmental sustainability, the results indicate that user evaluations are largely shaped by comparisons to existing ground-based delivery services. Ensuring that operations meet, or even better, exceed, safety standards set by familiar ground alternatives is a necessary condition for adoption. Moving from the lowest to highest safety levels increases DDS adoption probability by 0.401, translating to an additional 2.248 drone package deliveries and 1.239 drone food deliveries monthly, the largest demand effect reported in Table 9. Findings relating to noise and environmental sustainability reveal a similar trend, but with an asymmetric nature. While performance comparable to that of ground-based delivery services substantially improves adoption, increasing probability of choosing DDS by 0.158 and 0.146, respectively. In terms of demand, these effects correspond to approximately 0.892 and 0.815 additional package deliveries by drone per month, with increases of 0.508 and 0.478 estimated for food deliveries. Beyond this threshold, however, further improvements do not have a significant impact. This pattern suggests that during initial rollout service providers should ensure drone operations are at least as quiet and environmentally sustainable as ground-based delivery, with

long term plans to further improve these characteristics as services are developed and operating costs are reduced (Goyal et al., 2018).

Additionally, the results provide new insight into perceptions of automation in the context of drone delivery, an aspect that has received limited attention in prior work. The analysis indicates that prospective users respond positively to fully autonomous drone operations, increasing adoption probabilities by 0.120 relative to remotely piloted alternatives. Consistent with this increase in adoption, expected demand for autonomous DDS rises by approximately 0.672 package deliveries and 0.396 food deliveries per month. This finding suggests that automation may facilitate, rather than hinder, early DDS adoption. In line with this, service providers should position DDS in a way that emphasizes their autonomous capabilities, highlighting efficiency, technological maturity, and the evolution of logistics beyond traditional ground-based systems. However, the early roll-out period will play a critical role in shaping longer-term perceptions of automation. As users gain first- and second-hand experience with autonomous drones, attitudes toward automation may evolve in response to system performance. This makes robust oversight, fail-safe design, and high levels of operational safety particularly important during early deployment. From a policy perspective, these findings suggest a need for a balance between enabling higher levels of drone automation and maintaining appropriate safety standards. Regulators should work with service providers to establish and enforce safeguards, allowing greater levels of automation where safe and reliable performance can be demonstrated.

5.2 Implications for Use Cases

Beyond the variation in evaluation of service characteristics, delivery item attributes have important implications for identifying likely DDS use cases. The results indicate a need for intentional positioning across delivery contexts to align with user expectations and perceived risks. For example, medical supply deliveries are more widely accepted (Kyi et al., 2026), making them well suited for early rollout. While the baseline effect of delivery type alone is relatively modest, our results suggest that the greatest potential for DDS adoption occurs when medical supply deliveries are paired with substantial reductions in delivery time and highly reliable operations., as discussed in Section 5.1. Overall, results suggest that early adoption is more likely in low-risk, low-value delivery contexts. Prospective users are more hesitant to adopt DDS for higher-value items and heavier deliveries. Relative to items valued under $50, adoption probability decreases by 0.093 for items valued at $50 or more, translating to approximately 0.518 fewer drone package deliveries monthly. Similarly, adoption probability decreases by 0.089 for large deliveries weighing more than 30 pounds relative to those weighing less than 5 pounds, corresponding to approximately 0.492 fewer drone package deliveries monthly. These findings suggest that initial deployment strategies should focus on smaller, lower-value deliveries to build familiarity and trust. Marketing strategies such as offering a free first delivery or offering reduced introductory pricing may help lower initial adoption barriers, while clear communication about the limitations of drone capacity can inform user expectations and reduce perceived risk. By initially targeting these lower-risk contexts, service providers can implement a phased approach to drone deployment, building user confidence while moving towards broader applications.

5.3 Implications for Adoption Patterns

Finally, a key contribution of the analysis is the ability to distinguish between adoption propensity and expected delivery volumes, identifying not only who is more likely to adopt drone delivery, but also which groups are likely to generate the highest DDS volumes. In terms of adoption, the

results indicate that men, younger people, Black individuals, those living in multifamily residences, and high-income households exhibit higher adoption propensities. As shown in Table 9, the largest increases in adoption probability are observed for men (0.100), Black individuals (0.065), and high-income households (0.051). These patterns suggest that early deployment strategies should target tech-savvy and higher resource groups who are more receptive to DDS.

Expected DDS demand largely mirrors these adoption trends, with the addition of full-time workers and individuals under 45 years of age whose frequent delivery usage leads to greater projected drone delivery volumes, despite exhibiting adoption propensities similar to those of their respective base groups. For package deliveries, higher expected demand is observed among individuals with higher levels of formal education, full-time workers, and homeowners (corresponding to increases of approximately 0.631, 0.948, and 0.406 drone package deliveries per month, respectively). For food deliveries, households with children are expected to order approximately 0.586 additional drone deliveries monthly. In contrast, individuals aged 65 or older are expected to generate 1.645 fewer monthly drone food deliveries than those under age 45, suggesting that drone food delivery demand may be concentrated among younger households and families with children. These findings highlight the need to target not only early adopters, but also those whose existing behavior suggests a higher likelihood of frequent use. While adoption determines who is willing to use DDS, demand determines which user groups are likely to generate the delivery volumes necessary to support efficient and sustained service deployment.

Furthermore, current behaviors may lead distinct user groups to adopt for different reasons. Frequent package delivery users may require incentives or clear service improvements to encourage switching to aerial alternatives, while frequent food delivery users appear more likely to adopt due to familiarity with delivery systems. These findings suggest that positioning strategies would benefit from differentiation across current delivery usage patterns, recognizing that adoption is driven by different underlying mechanisms. Importantly, the greater willingness of frequent food delivery users to adopt DDS may also provide an operational advantage during early deployment by generating a stable base of demand among high-frequency users. Such users can support both short-term adoption and recurring delivery demand, providing the delivery volumes needed to sustain operations while DDS networks are established and expanded.

The findings also demonstrate the importance of individual attitudes in shaping adoption decisions beyond what is explained by service characteristics alone. Tech-savviness boosts adoption, suggesting that early deployment strategies should target digitally engaged groups. To attract less tech-savvy users, DDS service providers should integrate DDS shipping options into familiar online ordering platforms and promote firsthand experience with the technology using free-trial deliveries or targeted pilot programs. As familiarity increases and successful deliveries are demonstrated within communities, perceptions of DDS may become less dependent on technological attitudes and more strongly tied to service context. In contrast, privacy concerns and drone noise sensitivity limit adoption, particularly among those with more control over their residential environment. To mitigate the impacts of these negative perceptions, successful deployment will require more than just meeting operational benchmarks. Implementation strategies should be developed specifically to address these persistent barriers, providing transparent communication of residential privacy safeguards, and implementing volume reduction measures in residential areas. Additionally, policymakers should proactively address such privacy and noise related concerns, working with their constituents to develop regulations that protect prospective DDS users against privacy violations and undue noise burdens.

6. CONCLUSION

This paper examines drone delivery adoption by jointly modeling individuals' adoption decisions alongside current delivery frequency outcomes. The results highlight the central role of service improvements relative to traditional ground-based delivery options in driving adoption, particularly with respect to delivery time, cost, and safety. However, when it comes to noise and environmental sustainability, users expect services to match the performance of existing ground-based delivery services, with diminishing returns beyond that threshold. Additionally, we reveal a favorable perception of autonomous delivery drones among prospective users, suggesting that autonomy may support adoption if effective operations are demonstrated and regulated. With respect to likely use cases, the results suggest that adoption is highest in low-risk contexts when delivery item types are viewed positively, delivery item values are low, and delivery contents are lightweight. Accordingly, a phased roll out approach, where users have the opportunity to test out DDS as service providers gradually scale services to encompass more challenging delivery contexts is recommended. DDS adoption is likely to be driven by early adopter, high-volume population segments such as men, Black individuals, full-time workers, and high-income households. At the same time, marketing strategies must consider the disparate adoption motivations associated with current delivery usage, emphasizing benefits over existing services for package delivery while leveraging familiarity among experienced food delivery users. The analysis also demonstrates that individual attitudes including privacy concerns, tech-savviness, and drone noise sensitivity play an important role in shaping adoption decisions beyond objective service characteristics. Planners and policymakers must directly address perception-driven barriers through transparent communication, and context-sensitive operational strategies. Overall, the successful deployment and growth of drone delivery technology will rely on carefully tailored services which align with user needs, expectations, and perceptions.

The current work suggests a continued need for research on DDS adoption patterns, both during the development phase and throughout service deployment. First, this study relies on stated preferences, as DDS are not yet widely available. However, as these services are deployed and individuals gain experience with the technology outside of controlled stated preference scenarios, preferences and perceptions will continue to evolve. When possible, revealed preference investigations into DDS usage could provide additional insight into evolving patterns. Second, a deeper exploration of how drones will interact with the built environment is warranted. While this study explores the impacts of delivery point on adoption, it raises further questions about secure delivery drop-off solutions, specialized infrastructure such as distributed logistics infrastructure, connection to existing shipping networks, temperature-controlled package lockers, and drone access to multifamily residences. Third, while we examine individual-level adoption trends, future work should consider broader community-level opposition to privacy violations and noise disruptions associated with drone delivery, considering reactions of both users and non-users. Finally, a broader geographical scope and expanded sample size would be beneficial to provide a more comprehensive representation of regional or international differences in DDS preferences.

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 Adoption of Drone Delivery Services (DDS)

Reference	Service Context												Individual-Level Factors	Current Delivery Frequency	
	DDS Service Characteristics									Delivery Item Attributes			Attitudes/Latent Constructs		
	Speed	Cost	Delivery Point	Reliability	Safety	Noise	Environmental Sustainability	Privacy Protection	Level of Automation	Type*	Value*	Weight		Package Items	Food Items
Yoo et al., 2018	×				×		×						Privacy concerns, Tech-savviness, Green lifestyle propensity		
Khan et al., 2019							×						Privacy concerns, Safety concerns		
Zhu, 2019													Privacy concerns, Safety concerns		
Kim, 2020	×	×								×	×		Did not consider		
Mathew et al., 2021													Privacy concerns, Green lifestyle propensity, Safety concerns		
Serrano-Hernandez et al., 2021	×	×			×	×	×						Did not consider		
Chen et al., 2022													Privacy concerns, Tech-savviness		
Merkert et al., 2022	×	×	×								×		Did not consider		
Sham et al., 2022							×			×			Tech-savviness, Safety concerns		
Xie et al., 2022	×						×						Privacy concerns, Tech-savviness		
Bafouni-Kotta et al., 2023	×	×	×		×		×						Privacy concerns		×
Koh et al., 2023													Privacy concerns, Tech-savviness, Drone experience, Alternative delivery experience		
Kumar et al., 2023													Tech-savviness		
Said et al., 2023	×	×			×						×		Tech-savviness, Green lifestyle propensity		
Sham et al., 2023													Tech-savviness		
Zhang et al., 2023b	×	×					×						Drone noise sensitivity, Drone experience, Safety concerns		
Ardeshiri et al., 2024	×	×		×	×					×		×	Drone experience		
Tamakloe et al., 2024													Alternative delivery experience		×
Dabić et al., 2025													Privacy concerns		
Zhang et al., 2025	×	×			×					×	×		Drone experience		
Kyi et al., 2026	×	×	×								×		Did not consider		
This Study	×	×	×	×	×	×	×	×	×	×	×	×	Privacy concerns, Tech-savviness, Drone noise sensitivity	×	×

*Previous studies have often evaluated specific item categories (e.g. household goods, electronics), implicitly combining delivery item type and value, while the current study distinguishes these dimensions.

Table 2. Delivery Mode Preference Experiment Design

Attribute	DDS	Ground-Based Delivery
DDS Service Characteristics:		
Speed	2-hour delivery Same-day delivery 2-day delivery	2-hour delivery Same-day delivery 2-day delivery
Cost	$0 $5 $10 $20	$0 $5 $10 $20
Delivery Point	Front door delivery On-site delivery marker Off-site collection point	Front door delivery Off-site collection point
Reliability	Always available Available only in clear conditions	--
Safety	Low danger of malfunction or crash High danger of malfunction or crash	Low danger of malfunction or crash High danger of malfunction or crash
Noise	Quieter than a standard delivery vehicle Same as a standard delivery vehicle Louder than a standard delivery vehicle	--
Environmental Sustainability	Less emissions than a ground-based delivery The same emissions as a ground-based delivery More emissions than a ground-based delivery	--
Privacy Protection	Drones can collect imagery of home or neighborhood Drones cannot collect imagery of home or neighborhood	--
Level of Automation	Fully autonomous drone Remote drone pilot- can assist with drop-off and take control in case of emergency	--
Delivery Item Attributes:		
Type	Package delivery Medical supply delivery Prepared food delivery Grocery delivery	
Value	Less than $25 $25-$50 $50-$100 More than $100	
Weight	Light (less than 5 lbs) Medium (5-30 lbs) Heavy (more than 30 lbs)	

Table 3. Descriptive Statistics of Service Context Variables Across Both SP Experiments

Variable	Observations	Share of Sample
DDS Service Characteristics:		
Speed		
Same speed	1098	52.0%
DDS 1 day faster	836	39.5%
DDS 2 days faster	180	8.5%
Cost		
DDS $15 more expensive	257	12.2%
DDS $10 more expensive	175	8.3%
DDS $5 more expensive	257	12.2%
Same price	665	31.4%
DDS $5 less expensive	229	10.8%
DDS $10 less expensive	274	12.9%
DDS $20 less expensive	257	12.2%
Delivery Point		
Front door delivery	795	37.6%
On-site delivery marker	711	33.6%
Off-site collection point	608	28.8%
Reliability		
Not shown	1058	50.1%
DDS always available	436	20.6%
DDS available only in clear conditions	620	29.3%
Safety		
Not shown	1056	50.0%
DDS less safe	265	12.5%
Same safety	539	25.5%
DDS safer	254	12.0%
Noise		
Not shown		
DDS quieter	1068	50.5%
Same noise	346	16.4%
DDS louder	346	16.4%

Variable	Observations	Share of Sample
DDS Service Characteristics:		
Environmental Sustainability		
Not shown	1068	50.5%
DDS less emissions	387	18.3%
Same emissions	270	12.8%
DDS more emissions	389	18.4%
Privacy Protection		
Not shown	1048	49.6%
Drones can collect imagery	581	27.5%
Drones cannot collect imagery	485	22.9%
Level of Automation		
Not shown	1044	49.4%
Fully autonomous drone	624	29.5%
Remote drone pilot	446	21.1%
Delivery Item Attributes:		
Type		
Package delivery	585	27.7%
Medical supply delivery	477	22.6%
Prepared food delivery	531	25.1%
Grocery delivery	521	24.6%
Value		
Less than $25	430	20.3%
$25-$50	489	23.1%
$50-$100	479	22.7%
More than $100	716	33.9%
Weight		
Small (less than 5 lbs)	886	41.9%
Medium (5-30 lbs)	612	29.0%
Large (more than 30 lbs)	616	29.1%

Table 4. Descriptive Statistics of Demographic Characteristics

Demographic Characteristic	Observations	Share of Sample	ACS 2023 Percent
Gender			
Man	577	54.6%	49.9%
Woman	474	44.8%	50.1%
Other gender*	6	0.6%	--
Age			
Age 18-24	157	14.8%	12.8%
Age 25-34	261	24.7%	19.1%
Age 35-44	196	18.5%	18.9%
Age 45-54	173	16.4%	16.4%
Age 55-64	115	10.9%	14.5%
Age 65+	155	14.7%	18.3%
Level of Education			
Bachelor's degree or higher	741	70.1%	34.2%
Less than a bachelor's degree	316	29.9%	65.8%
Race			
White	680	64.3%	47.7%
Black	155	14.7%	12.3%
Asian	100	9.5%	5.7%
Other race	122	11.5%	34.3%
Ethnicity			
Non-Hispanic	806	76.3%	60.2%
Hispanic	251	23.7%	39.8%
Employment Status			
Full-time	595	56.3%	57.7%
Part-time	115	10.9%	13.5%
Student	111	10.5%	8.7%
Retired	150	14.2%	15.5%
Other employment	86	8.1%	4.6%
Housing Type			
Single-family home	654	61.9%	67.1%
Other housing type	403	38.1%	32.9%
Home Ownership			
Homeowner	651	61.6%	62.6%
Other housing arrangement	406	38.4%	37.4%
Household Income			
Low income (less than $35,000)	223	21.1%	21.9%
Medium income ($35,000-$100,000)	361	34.2%	40.3%
High income (more than $100,000)	473	44.7%	37.8%
Household Size			
1 person	184	17.4%	26.5%
2 people	330	31.2%	31.6%
3 people	208	19.7%	16.3%
4+ people	335	31.7%	25.6%
Number of Vehicles in Household			
0 vehicles	59	5.6%	5.5%
1 vehicle	363	34.3%	33.3%
2 vehicles	424	40.1%	38.7%
3+ vehicles	211	20.0%	22.5%
Household Composition			
Child(ren) under 13*	178	16.8%	--
No child(ren) under 13*	879	83.2%	--
Population Density			
Low density (less than 6600 pop/sq mi)*	341	32.3%	--
Medium density (6600-15499 pop/sq mi)*	363	34.3%	--
High density (15500+ pop/sq mi)*	353	33.4%	--
Transportation Establishments			
Low count (fewer than 17 establishments)*	529	50.0%	--
High count (17 establishments or more)*	528	50.0%	--
State Residence			
Texas resident*	884	83.6%	--
Non-Texas resident*	173	16.4%	--

* No ACS data available

Table 5. Main Outcome Distributions

Current Ground-Based Delivery Frequency	Package Deliveries	Food Deliveries
0 deliveries per month	86 (8.1%)	430 (40.7%)
1-2 deliveries per month	186 (17.6%)	182 (17.2%)
3-5 deliveries per month	373 (35.3%)	204 (19.3%)
6-10 deliveries per month	202 (19.1%)	135 (12.8%)
More than 10 deliveries per month	210 (19.9%)	106 (10.0%)
Drone Delivery Service (DDS) Adoption	**DDS**	**Ground-Based Delivery**
Stated Delivery Mode Preference	1012 (47.9%)	1102 (52.1%)

Table 6. Determinants of Latent Constructs

Latent Variable Structural Equation Model (Estimates of the elements of the α matrix)						
Variable (base category)	**Privacy Concerns**		**Tech-Savviness**		**Drone Noise Sensitivity**	
	Coeff.	**t-stat**	**Coeff.**	**t-stat**	**Coeff.**	**t-stat**
Gender (Woman, Other gender)						
Man	-0.281	-3.087	0.755	5.195	-0.378	-3.835
Age (Age 18-34)						
Age 35-54	-0.203	-2.036	-0.328	-2.275	--	
Age 55-64	--		-1200	-5.081	--	
Age 65+	-0.685	-4.588	-1.142	-5.215	-0.425	-2.988
Level of Education (Less than a bachelor's degree)						
Bachelor's degree or higher	--		0.358	2.425	-0.223	-2.344
Race and Ethnicity (White, Asian)						
Black	-0.333	-2.593	0.707	3.703	--	
Other race	0.251	1.716	0.513	2.551		
Ethnicity (Non-Hispanic)						
Hispanic	-0.351	-3.244	0.314	2.071	--	
Housing Type (Other housing type)						
Single-family home	0.407	3.896	--		0.283	2.844
Housing Ownership (Other housing arrangement)						
Homeowner	0.260	2.396	--		--	
Household Income (Low income, less than $35,000)						
Medium income ($35,000-$100,000)	--		0.410	2.358	--	
High income (more than $100,000)	--		0.706	3.553	--	
Household Size						
Number of household residents	-0.089	-2.704	--		-0.079	-2.308
Latent Variable Measurement Equation Model (Estimates of the elements of the $\tilde{\alpha}$ matrix)						
Attitudinal Statements	**Privacy Concerns**		**Tech-Savviness**		**Drone noise Sensitivity**	
	Coeff.	**t-stat**	**Coeff.**	**t-stat**	**Coeff.**	**t-stat**
I would not be willing to let a delivery company (such as FedEx or Amazon) conduct a site visit of my home's exterior if it were needed for drone package delivery.	0.662	13.484	--		--	
I would not be comfortable with drones collecting images of my property.	0.589	11.729	--		--	
I believe that having drones near my property is an invasion of my privacy.	0.555	12.141	--		--	
If available to me today, I would feel comfortable riding in a self-driving vehicle.	--		0.571	8.569	--	
I like to be among the first to have the latest technology.	--		0.459	8.451	--	
I think delivery drones would be disruptive in my neighborhood.	--		--		0.760	9.349
I would not want to hear urban air mobility (UAM) noises near my home at night.	--		--		0.417	8.245
Correlation Between Latent Constructs (Estimates of the correlation matrix Γ)	**Param.**	**t-stat**	**Param.**	**t-stat**	**Param.**	**t-stat**
Privacy Concerns	1.000	--	-0.524	-5.861	0.559	7.626
Tech-Savviness	--	--	1.000	--	-0.235	-2.597
Drone Noise Sensitivity	--	--	--	--	1.000	--

Table 7. Main Estimation Results

Variable (base)	Delivery Frequency of Package Items		Delivery Frequency of Food Items		Drone Delivery Service Adoption	
	Est.	**t-score**	**Est.**	**t-score**	**Est.**	**t-score**
Thresholds *(Estimates of the elements of* $\tilde{\varphi}$ *)*						
0 deliveries/ month | 1-2 deliveries/ month	-0.905	-8.608	-0.741	-7.531	--	
1-2 deliveries/ month | 3-5 deliveries/ month	-0.099	-1.005	-0.209	-2.171	--	
3-5 deliveries/ month | 6-10 deliveries/ month	0.891	8.750	0.464	4.874	--	
6-10 deliveries/ month | 10+ deliveries/ month	1.498	14.231	1.105	10.801	--	
Constant	--		--		-0.052	-0.365
DDS Service Characteristics						
Speed (Same speed)						
DDS 1 day faster × Package delivery	--		--		0.343	2.817
DDS 1 day faster × Prepared food delivery	--		--		0.484	4.304
DDS 1 day faster × (Grocery or medical supply delivery)	--		--		0.270	2.358
DDS 2 days faster × Package delivery	--		--		0.835	5.319
DDS 2 days faster × Medical supply delivery	--		--		1.436	4.193
Cost						
Drone cost - Ground cost	--		--		-0.033	-6.815
(Drone cost - Ground cost) × Grocery delivery	--		--		0.027	2.959
Delivery Point (Front door delivery, On-site delivery marker)						
Off-site collection point	--		--		-0.152	-1.693
Reliability (DDS always available, Not shown)						
DDS only available in clear conditions	--		--		-0.197	-2.106
DDS only available in clear conditions * Medical supply delivery	--		--		-0.911	-3.488
Safety (Same safety, Not shown)						
DDS less safe	--		--		-0.664	-5.188
DDS safer	--		--		0.682	4.686
Noise (DDS quieter, Same noise, Not shown)						
DDS louder	--		--		-0.518	-5.250
Environmental Sustainability (DDS less emissions, Same emissions, Not shown)						
DDS more emissions	--		--		-0.479	-4.617
Level of Automation (Remote drone pilot)						
Fully autonomous drone	--		--		0.383	4.240
Delivery Item Attributes						
Type (Package delivery, Prepared food delivery, Grocery delivery)						
Medical supply delivery	--		--		0.410	3.351
Value (Less than $50)						
Delivery value $50+	--		--		-0.295	-4.033
Weight (Small (less than 5 lbs), Medium (5-30 lbs))						
Large (more than 30 lbs)	--		--		-0.283	-3.103

Table 7. Main Estimation Results cont.

Variable (base)	Delivery Frequency of Package Items		Delivery Frequency of Food Items		Drone Delivery Service Adoption	
	Est.	**t-score**	**Est.**	**t-score**	**Est.**	**t-score**
Latent Constructs *(Estimates of the elements of* γ *and a subset of* β*)*						
Privacy concerns	--		-0.091	-1.852	-0.130	-2.289
Tech-savviness	0.106	2.960	0.207	4.250	0.233	5.446
Drone noise sensitivity × Homeowner	--		--		-0.110	-1.867
Demographic Characteristics						
Age (Under 45)						
Age 45-54	--		-0.347	-3.838	--	
Age 55-64	--		-0.490	-3.688	--	
Age 65+	--		-1.154	-8.491	--	
Level of Education (Less than a bachelor's degree)						
Bachelor's degree or higher	0.260	3.423	-0.363	-4.343	--	
Race (White, Black, Asian)						
Other race	-0.264	-2.548	-0.342	-2.720	--	
Employment (Full-time, Part-time, Retired, Other employment)						
Student	--		-0.542	-4.526	--	
Unemployed	-0.620	-3.774	-0.802	-4.217	--	
Housing Type (Other housing type)						
Single-family home	0.192	2.564	--		--	
Home Ownership (Other arrangement)						
Homeowner	0.244	2.992	--		--	
Number of Vehicles in Household						
Number of vehicles in household	0.146	4.750	--		--	
Household Composition (No child(ren) under 13)						
Child(ren) under 13	--		0.416	4.714	--	
Population Density (Medium density (6600-15499 pop/sq mi), Low density (less than 6600 pop/sq mi))						
High density (15500+ pop/sq mi)	-0.168	-2.409	--		--	
Transportation Establishments (High transportation establishment count (17+))						
Low transportation establishment count (less than 17)	-0.183	-2.639	-0.207	-2.842	--	
State Residence (Non-Texas resident)						
Texas resident	--		--		-0.293	-3.229
Gender/ Income Interaction						
Income high (more than $100,000) × Man	--		--		0.180	2.167
Current Delivery Frequency *(Estimates of a subset of elements of* β*)*						
0-2 package deliveries/ month × Package delivery	--		--		0.341	2.451
0-2 food deliveries/ month × Grocery delivery	--		--		-0.226	-1.763
Correlations *(Estimates of the elements of* $\tilde{\Lambda}$ *and* Ω*)*						
Delivery frequency of package items	1.000	--	0.172	2.752	0.063	1.648
Delivery frequency of food items			1.000	--	--	
Drone delivery service adoption					1.000	--
Panel Correlation *(Estimate of Correlation* Λ*)*	--		--		0.445	14.551

Table 8. Disaggregate Data Fit Measures

Summary Statistics	Specification	
	Model with Correlations	**Independent Model**
Log-likelihood at convergence $L(\hat{\theta})$	-4010.19	-4096.45
Log-likelihood of constant-only model $L(c)$	-4628.61	
Number of parameters (including constants)	57	54
Bayesian Information Criterion (BIC)	4096.38	4178.10
Adjusted likelihood ratio index ($\overline{\rho}^2$)	0.1232	0.1053
Likelihood ratio test between model with correlations and independent model	$172.50 > \chi^2_{3,0.00001} = 35.41$	
Average probability of correct prediction	0.0370	0.0345

Table 9. Average Treatment Effects

Base	Treatment	Delivery item type	Change in average probability of choosing drone	Change in number of package deliveries/ month by drone	Change in number of food deliveries/ month by drone
DDS Service Characteristics					
Same speed	DDS 1 day faster	Package	0.107	0.601	--
Same speed	DDS 1 day faster	Medical supply, Grocery	0.086	--	0.285
Same speed	DDS 1 day faster	Prepared food	0.152	--	0.499
Same speed	DDS 2 days faster	Package	0.260	1.451	--
Same speed	DDS 2 days faster	Medical	0.385	--	--
Same cost	DDS $15 more expensive	Package, Medical supply, Prepared food	-0.150	-0.840	-0.492
Same cost	DDS $20 less expensive	Package, Medical supply, Prepared food	0.203	1.146	0.658
Off-site collection point	Front door delivery	All	0.047	0.263	0.147
Always available	DDS available only in clear conditions	Package, Prepared food, Grocery	-0.061	-0.340	-0.190
Always available	DDS available only in clear conditions	Medical supply	-0.324	--	--
DDS less safe	DDS safer	All	0.401	2.248	1.239
DDS louder	Same noise	All	0.158	0.892	0.508
DDS more emissions	Same emissions	All	0.146	0.815	0.478
Remote drone pilot	Fully autonomous drone	All	0.120	0.672	0.369
Delivery Item Attributes					
Package delivery	Medical supply delivery	--	0.019	--	--
Less than $50	More than $50	All	-0.093	-0.518	-0.287
Small (less than 5 lbs)	Large (more than 30 lbs)	All	-0.089	-0.492	-0.276
Demographic Characteristics					
Woman	Man	All	0.100	0.700	0.562
Age under 45	Age 65+	All	-0.046	-0.435	-1.645
Less than a bachelor's degree	Bachelor's degree or higher	All	0.031	0.631	-0.284
White	Black	All	0.065	0.496	0.485
White	Other race	All	0.016	-0.242	-0.272
Non-Hispanic	Hispanic	All	0.037	0.260	0.257
Unemployed	Full-time employment	All	0.000	0.948	0.935
Single-family home	Other housing type	All	0.022	-0.176	0.122
Other ownership arrangement	Homeowner	All	0.003	0.406	-0.020
Low income	High income	All	0.051	0.397	0.356
0 vehicles	1 vehicle	All	0.000	0.223	0.000
No child(ren) under 13	Child(ren) under 13	All	0.000	0.000	0.586
Low population density	High population density	All	0.000	-0.253	0.000
High transportation establishment count	Low transportation establishment count	All	0.000	-0.286	-0.299
Non-Texas resident	Texas resident	All	-0.091	-0.511	-0.282

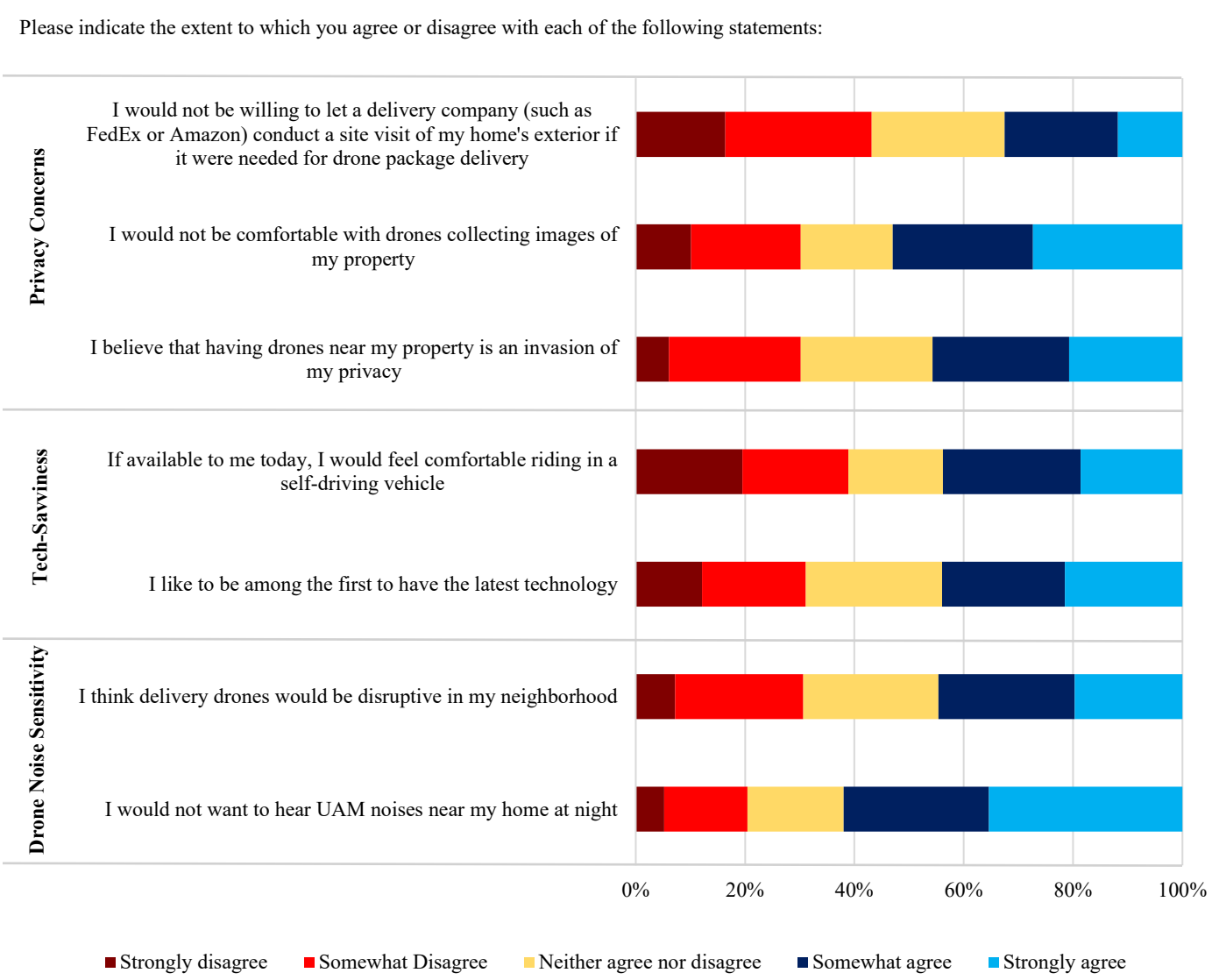


Figure 1. Distribution of Indicators of Latent Constructs

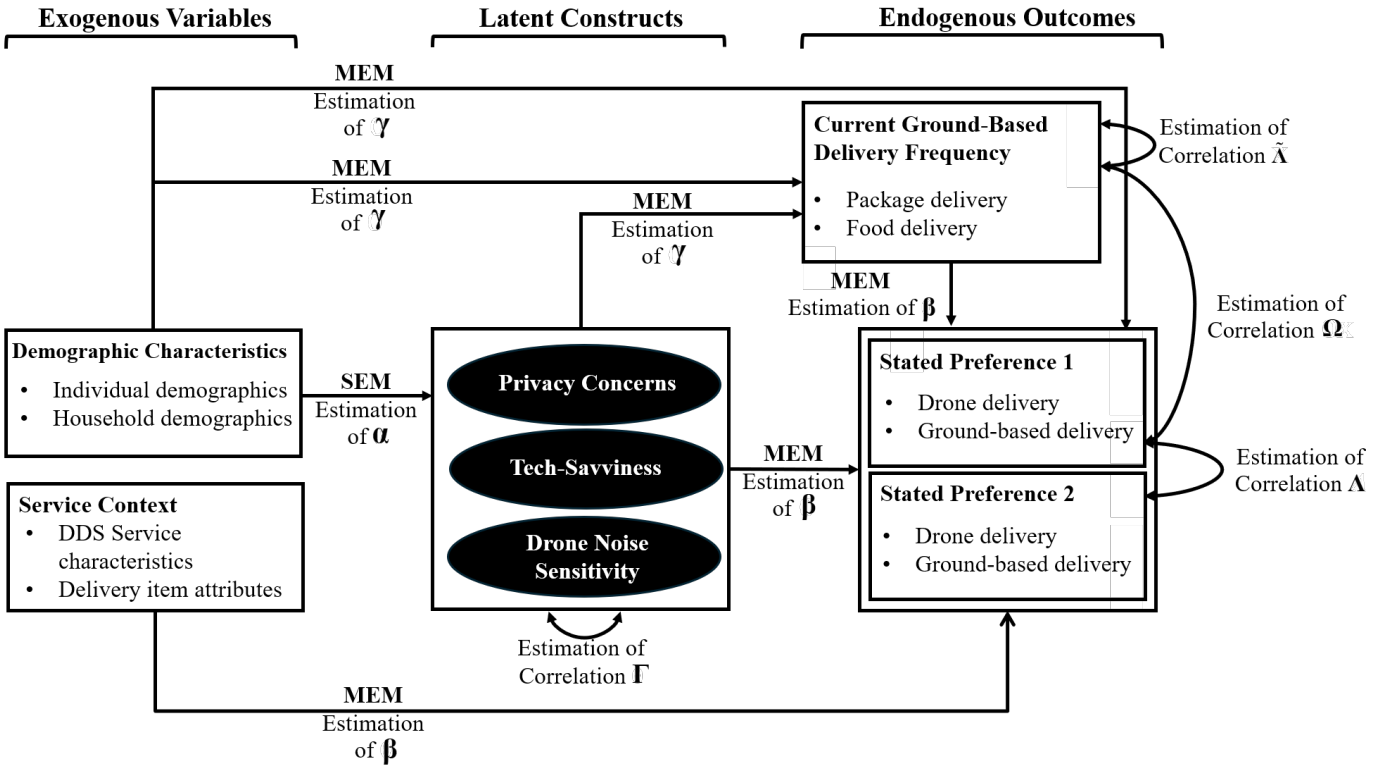


Figure 2. Analytic Framework