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Drone delivery and the value of customer privacy: A discrete choice experiment with U.S. consumers☆

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A R T I C L E I N F O

Dataset link: https://github.com/aberke/drones-consumer-privacy.

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A B S T R A C T

Drone delivery services are becoming increasingly available, but they introduce new consumer privacy risks. As a result of safety regulations that require drones to broadcast their locations, third-party observers may link customers to their purchases by following a delivery from vendor to customer. These privacy risks can be reduced with routing strategies that aggregate customer orders, at the potential cost of additional delivery wait times or fees. This study measures the importance of these privacy risks to delivery service customers, their willingness to pay for privacy, and how this differs across consumer groups and product types. We developed a discrete choice experiment and mode choice logit models using data from over 3700 U.S. consumers who chose between ground vehicle versus drone delivery across a range of privacy, delivery fee, and wait time options. Preferences were tested for various product types: take-out food, liquor store items, groceries, and prescription medications. Results show offering privacy enhancements significantly increased consumers' likelihood of choosing drone delivery. Without privacy enhancements, when fees and wait times were the same, consumers chose ground vehicle 4 times more often than drone. Offering privacy for the drone option closed this gap. Yet preferences differ by demographic group. Males and frequent e-commerce users were more likely to prefer drone regardless of privacy, while privacy improvements had a significantly larger impact on females and younger consumers. We measured consumers' value of privacy in both money and time. The value of privacy for medications delivery was about twice that for other product types. The value of privacy was then highest for liquor store items, then groceries, then take-out food. Our results can inform delivery service planning as well as contribute to a broader understanding of how consumers value privacy and methods to measure that valuation.

1. Introduction

Door-to-door delivery services that use drones instead of ground vehicles are becoming increasingly available, particularly in the U.S., where this study takes place. Here, drone delivery presents a new and specific consumer privacy risk, which can be mitigated

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with strategies that may incur additional delivery costs or wait times. This work studies the extent to which delivery customers are willing to pay for privacy enhancements, and under what circumstances.

1.1. Background

In 2013, the company Amazon, which has one of the largest and fastest growing delivery services (Pitney Bowes, 2021), announced they were experimenting with drones as an alternative delivery method. Amazon's CEO predicted that someday the skies would be filled with flying machines delivering packages to people's homes (CBS News, 2013). Early reports estimated drones can reduce delivery costs by around 4–5× and allow profitability for small packages (Bain & Company, 2016). Now as drone delivery enters the market, many experts expect drones to change the landscape of the commercial delivery industry (O'Brien, 2021).

In the U.S, the first commercial drone delivery took place in Virginia in 2019 (Levin, 2019) and many more companies are now operating drone delivery services across the U.S. However, whether these services take off depends on both their economic feasibility and public acceptance (Rifan et al., 2022), which may depend on public perception of the associated privacy risks.

For example, a 2016 survey by the United States Postal Service (USPS) concluded that although most respondents (75%) expected drone delivery within the next 5 years, launching drone delivery services at that time would negatively impact brand perception for the larger players in the logistics and technology fields (U.S. Postal Service Office of Inspector General, 2016). The USPS survey uncovered concerns with drone delivery that varied across socio-demographic groups, including that drones would not respect privacy.

Other studies have explored the relationship between privacy and drones through a regulatory or techno-ethical lens (Thompson and Richard, 2015; Lee et al., 2022; Luppicini and So, 2016) and a prior analysis suggested that as perceived privacy risk increases, the intention to adopt drone delivery service decreases (Leon et al., 2021). However, "privacy" is often ambiguous; these works have focused on aerial surveillance and more general privacy concerns without being specific about how the privacy infringement may come about.

1.2. A new privacy risk

Rather than privacy risks related to aerial surveillance, we consider new privacy risks, with more specific impacts on individual drone delivery customers. These risks have emerged due to new safety regulations which require drones to publicly broadcast their in-flight locations (e.g., Remote ID regulations in the U.S. (Federal Aviation Administration, 2021a,b)). Third parties can collect the broadcasted location information and deduce the routes of delivery drones, from a vendor where a drone picked up a product to the address where the drone delivered the product to a customer. This can allow third parties to link customers with their purchases, even when the third parties may be unrelated to both the business that a customer ordered delivery from and the drone delivery service. This can lead to possible invasions of customer privacy ranging from targeted advertisement to inference of personal health information.

These privacy risks are particularly salient for an emerging business model where services operate fleets of drones in order to make door-to-door deliveries between smaller vendors and customers.[1] Drone service operators have also partnered with pharmacies, hospitals, and other healthcare providers to deliver prescription medications directly to patients' homes.[2] This work focuses on these use cases.

While knowledge that someone received prescription medications clearly risks revealing personal health information, even delivery of more mundane products can present privacy risks. Smaller vendors may offer more specific products, and knowledge that a customer ordered from the vendor might reveal information about their preferences or behaviors (e.g. a specific cuisine for take-out food or items from a liquor store). Furthermore, the real and perceived privacy risks can vary by vendor type. However, these privacy risks can be mitigated with alternative routing strategies for the delivery drone. For example, if a drone aggregates delivery orders by stopping at multiple vendors before customer addresses, then the link between a specific vendor and customer can be obfuscated.

Consider a case where two customers, A and B, each order products for delivery to their homes: Customer A orders take-out food from a restaurant and customer B orders prescription medications from a pharmacy. If a delivery drone goes to the restaurant and then directly to customer A's address, and then goes to a pharmacy and then to customer B's address, then a third-party observer collecting the drone's location information can deduce that customer A ordered take-out food from that specific restaurant and customer B received medications. However, if the drone instead visits both the restaurant and the pharmacy before delivering to either customer, then the third-party observer would not know for certain which order was delivered to which customer. Although the more privacy-preserving route may be preferred by some customers (especially those ordering medications), it may incur additional delivery fees or wait times (which might particularly impact take-out food customers). While we only provide a simple example with two customer orders, previous work has explored expanded examples of routing strategies for more private drone deliveries, and quantified their impact on both privacy and efficiency (Ding et al., 2022). However, questions remain

[1] Examples of such drone delivery services in operation at the time of writing include Wing (https://wing.com), Flytrex (https://www.flytrex.com), and Manna (https://www.manna.aero).

[2] At the time of writing, partnerships have been proposed or started in the U.S. by companies UPS with CVS in Florida (Hawkins, 2020), Prime Air with Amazon Pharmacy in Texas (College Station Texas Tast Force, 2023), and Zipline with multiple hospitals and healthcare companies, including in Utah (Bellan, 2022) and Michigan (Shamus, 2023).

regarding the extent to which potential drone delivery customers value privacy, and whether delivery services should invest in more privacy-preserving routing strategies and capabilities.

We measure how privacy for drone delivery, and differences in delivery costs and wait times, impact potential customers' likelihood to choose drone delivery over standard ground vehicle delivery options. Given that privacy considerations vary across vendor types and consumer groups, we also evaluate how preferences differ across these categories. We do this by developing a discrete choice experiment (DCE) and use survey data from more than 3700 U.S. consumers to estimate mode choice models and customers' willingness to pay (WTP) for privacy in drone delivery. The findings can inform how businesses offering delivery services handle customer privacy, as well as contribute to a more general understanding of how consumers value privacy and methods to measure that valuation.

The remainder of this paper is structured as follows: Section 2 reviews related work with attention towards how previous studies have used DCEs or other survey methods to evaluate consumer perceptions of air taxis and drones, along with their findings. Section 3 describes the DCE and methodology, including the survey design and data collection, and the development of the mode choice models. Section 4 then presents the results, with a discussion of their implications, limitations, and future work in Section 5. We conclude in Section 6 with a summary and directions for future work.

2. Related work

Similar to this work, previous studies have used stated preference (SP) surveys and DCEs to calibrate mode choice models in order to estimate demand for urban air mobility (UAM) as an alternative to ground vehicle transport, as well as estimate individuals' value of time (VOT) for these alternatives (Garrow et al., 2019; Haan et al., 2021; Cho and Kim, 2022; Fu et al., 2019). However, in these prior works, UAM is a mode of transportation for people rather than a mode of transporting purchased goods. We borrow from their methodology and build on their findings. The U.S. study by Haan et al. (2021) and German study by Fu et al. (2019) both found that UAM was overall not preferred relative to standard ground transport when travel times and costs were the same. Furthermore, age was a significant factor in the German study, with older respondents less likely to favor UAM. However, a similar study in Korea yielded different results, where respondents, including older respondents, favored UAM. Noting results may differ by country or culture, our study reports on U.S. consumers.

Other related studies have used survey-based experiments to measure privacy preferences and the value of privacy, sometimes with explicit dollar values. For example, an early study of online privacy reported that among U.S. subjects, protection against secondary use of personal information is worth \$30.49–\$44.62 (USD) (Hann et al., 2007). A following experiment found U.S. consumers may be willing to pay a premium for privacy when shopping online, suggesting businesses may be able to leverage privacy protection as a selling point (Tsai et al., 2011). A growing body of work uses DCEs to evaluate the value of consumer privacy, including in domains related to this work that range from online services (Glasgow and Butler, 2017) and e-commerce (Potoglou et al., 2015) to services using location data (Paliński, 2022; Goad et al., 2021). In the latter case, studies report that users are willing to share the locations of their smartphones (Paliński, 2022) or IoT devices (Goad et al., 2021) for a small discount or benefit.

Online surveys have also been used to assess consumer intention to adopt drone delivery services (Leon et al., 2021; Merkert et al., 2022; U.S. Postal Service Office of Inspector General, 2016). A study in Australia using a DCE found that traditional postal delivery was preferred to drone delivery, unless drone delivery was cheaper or faster (Merkert et al., 2022). In the U.S., the USPS found that while more than half of the participants expected drone delivery to be fast, less than half expected it to cost less, and about a third of the participants were concerned drone delivery would not be safe or respect privacy (U.S. Postal Service Office of Inspector General, 2016). Furthermore, the survey revealed differences between U.S. consumer groups: Frequent e-commerce users, younger participants, and male participants were more favorable towards drone delivery than the overall sample. In addition, female participants were more likely to have privacy concerns for drone delivery and were more skeptical of the potential benefits. Finally, a more recent study of U.S. consumers found that increasing perceived usefulness of drone delivery services decreased perceived risk, and that increasing perceived privacy risk decreased intention to adopt drone delivery services (Leon et al., 2021).

While these prior works provide theoretical groundwork and initial data points, none of them use quantitative methods to assess the value of privacy in the context of drone delivery. Furthermore, the specific privacy risk we address in this work has not yet been examined.

This study fills these gaps and builds upon the above works, borrowing methods from both the UAM mode choice models, as well as studies using DCEs to evaluate the value of privacy. Noting salient differences between socio-demographic groups identified in prior works, we similarly incorporate consumer level variables in our study design. The design of our DCE and mode choice models allow us to measure consumers' value of privacy, along with value of time, for drone delivery relative to ground vehicle delivery, across a variety of product types. The resulting analysis both contributes to this growing body of literature and can be used to inform business decisions.

3. Materials and methods

We conducted a DCE by designing a SP survey to collect data used to then calibrate a set of mode choice logit models (Train, 2009).

Here, mode is the type of vehicle used for delivery, where the options are drone and ground vehicle. We examine how different consumer groups value privacy for drone delivery and make trade-offs between privacy, delivery cost, and wait times for each of

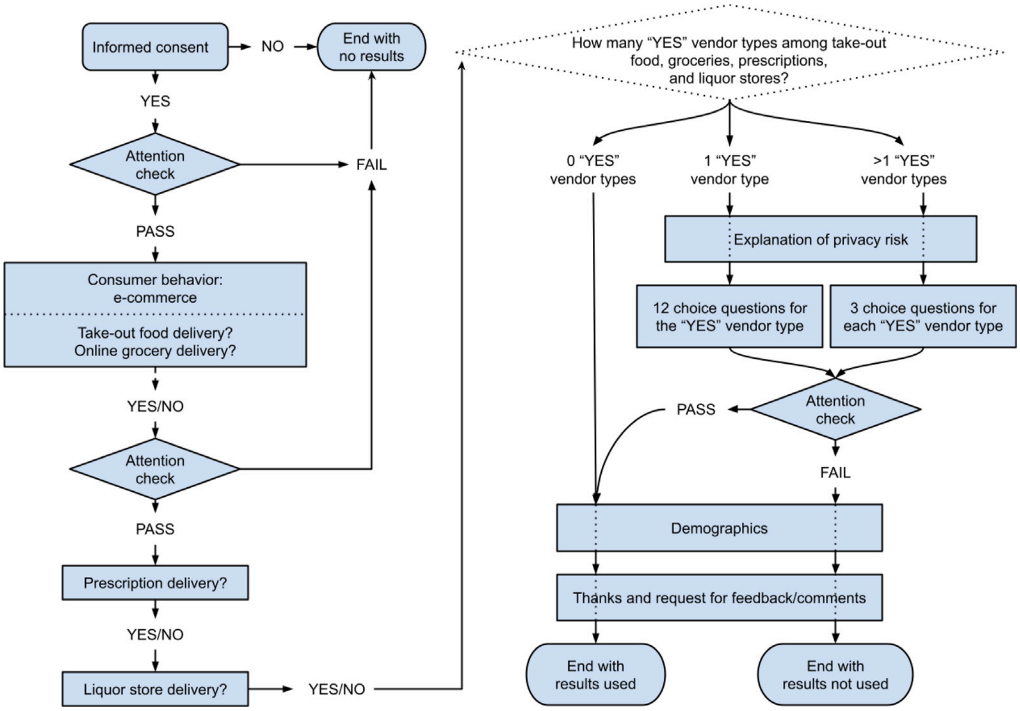

Fig. 1. Flowchart summarizing survey design.

the modes, and how preferences vary by product type. To do this, we developed choice sets and collected data for four different products/vendor types: take-out food, items from a liquor store, last-minute groceries, and prescription medications.

We chose these product types to meet the following criteria. First, there are examples of drones delivering each of these product types. Second, the product is commonly ordered for delivery (take-out food), or delivery options are becoming increasingly available (groceries, liquor store products, medications).[3] Furthermore, together they represent a range of products that might appeal differently across consumer groups and might attract varying levels of privacy concerns. Prescription medications are included in the study because health information is commonly protected as private. Take-out food is included because of the assumed importance of fast delivery, where the value of time may well supersede the value of privacy. Liquor store products are included as a group of products where knowledge of their delivery is sensitive for some consumer groups. Groceries are included because they may provide a baseline, least sensitive to time and privacy.

The following sections describe the survey, the data collected, and the analysis methods. The Appendix contains further details about how the survey was created along with a copy of the survey instrument. This experiment was approved by the Massachusetts Institute of Technology institutional review board (evaluation E-3924). All code and analysis data used in this work are available in an open source repository.[4]

3.1. Study design and survey instrument

The survey was designed to collect data for a DCE, where respondents chose between drone versus ground vehicle delivery options for four different delivery scenarios: delivery of take-out food, last-minute groceries, items from a liquor store, and delivery from a company specializing in delivering prescription medications. However, each scenario may not be applicable to all consumers. To collect more realistic data, the survey first asked questions to gauge whether respondents would ever order delivery from each vendor type. Respondents were then only presented with choice questions for vendor types applicable to them.

The survey design is summarized in Fig. 1. Respondents were first presented with information about the study and after which they provided informed consent. In order to improve data quality, the survey contained 3 attention checks and all data from

[3] At the time of writing, multiple drone delivery services operate in the U.S. delivering take-out food (Shankland, 2023), and Uber announced its Uber Eats delivery service would offer drone delivery as well (Dickey, 2019). For groceries, the major retailer Walmart delivers groceries via drone in seven states and is expanding to more across the country (Rossen, 2023; Guggina, 2022). For liquor store products, there are large online platforms that specialize in delivering alcoholic beverages from local stores (e.g. https://minibardelivery.com, https://drizly.com/) and examples date back to 2014 of using drones to deliver beer to customers (Kelly, 2014; Arthur, 2020). Examples of drone delivery for prescription medications were previously provided.

[4] https://github.com/aberke/drones-consumer-privacy

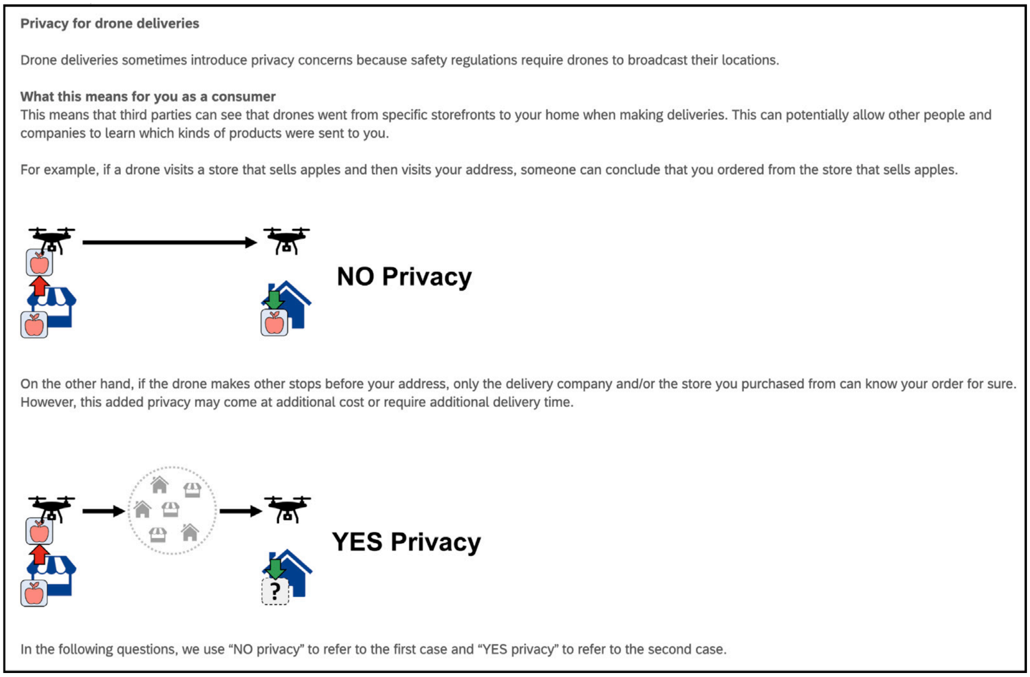

Fig. 2. Description of "NO Privacy" versus "YES Privacy" in the drone delivery options as shown in the survey.

participants who failed any attention check were excluded from analysis. More information about the survey is in the Appendix, which includes further description of the attention checks, with figures displaying how they were shown to participants. A copy of the survey with all questions and their answer options is included as supplementary material.

The survey consisted of 3 main parts: (1) consumer behavior questions, (2) SP mode choice questions, and (3) socio-demographic questions. The first part started with an attention check, then the consumer behavior questions, followed by an additional attention check. The consumer behavior questions asked respondents how often (on average) they make online shopping purchases (i.e., e-commerce), order take-out food delivery to their home, and purchase groceries online, with answer options ranging from "More than once a week" to "Never." They were also presented with questions asking whether they would ever order items for delivery to their home from a liquor store or a company specializing in prescription medications. For the prescription medications, they were asked to consider a scenario where a company that specializes in delivering prescription medications offers service in their area at a price similar to local pharmacies. For these questions, they could answer "Yes"/"No"/"I don't know".

Respondents then proceeded to an explanation of the choice questions where they would choose between drone and ground vehicle delivery options. This included an explanation of consumer privacy for drone deliveries. Fig. 2 shows how this was presented in the survey. Respondents were told that drone deliveries sometimes introduce privacy concerns because safety regulations require drones to broadcast their locations:

> "This means that third parties can see that drones went from specific storefronts to your home when making deliveries. This can potentially allow other people and companies to learn which kinds of products were sent to you."

"YES/NO Privacy" for drone delivery options were then described to them, where "YES Privacy" might involve a drone making other stops before their address to obscure their order from outside observers. Respondents were warned "this added privacy may come at additional cost or require additional delivery time".

Respondents were then shown a series of choice questions. Blocks of choice sets were generated using efficient experimental design methods, where each block contained choice questions for a single vendor type. Each block was preceded by a page introducing the respondent to the choice scenario for the corresponding vendor type. Choice questions for that vendor type were then shown one at a time on separate pages.

For each vendor type, the corresponding blocks and choice questions were only shown to respondents who indicated they would order delivery from that vendor type in the earlier questions (i.e., did not answer "Never" or "No"). If a respondent indicated they would order delivery from only one vendor type, they were shown a random subset of 12 questions for that vendor, and no questions for any other vendor. Otherwise, the respondent was shown a random subset of three questions for each vendor type that they indicated they would order from, answering a maximum of 12 questions in total. The order in which the vendor-specific blocks of questions were presented was randomized. The choice questions were followed by another attention check, which was disguised as a choice question where participants were directed to select both choices rather than just one (see Appendix Fig. A.9).

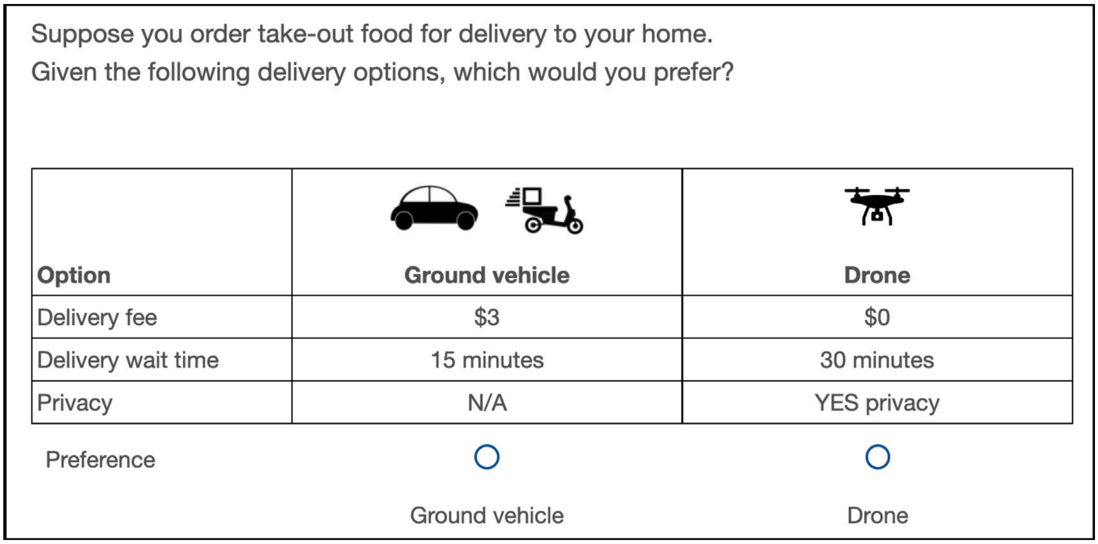

Fig. 3. Example mode choice question.

Participants were then asked questions to collect socio-demographic data. The USPS study (U.S. Postal Service Office of Inspector General, 2016), which this work adds nuance to, found that perspectives on the concept of drone delivery differed by consumer groups defined by gender, age, rural versus urban, and geographic region, as well as whether consumers were frequent e-commerce customers. Similarly, our survey also then asked for gender, age, residential area (urban/suburban/rural/I don't know) and U.S. state of residence in order to analyze differences across these consumer groups as well. In addition, our survey asked for race, household income and residence type (private home/apartment/other). Income was included because unlike the USPS study, the cost of delivery is a key component in the analysis and sensitivity to cost could be moderated by participant's income levels. Race was included to help better assess the representativeness of the survey sample compared to the U.S. population. Residence type was included because the mechanics of drone delivery to different residence types may differ, potentially impacting participants' perceived feasibility of delivery, or planning by delivery service providers. All questions were multiple choice.

The survey was implemented using the Qualtrics survey software.[5] A link to a public preview of the survey is included in Appendix A.

3.2. Choice questions

Each choice question was displayed with a consistent format, with an example shown in Fig. 3. Each asked the respondent to consider a scenario where they ordered a product from the vendor for delivery to their home. They were then asked their preference between two delivery options: ground vehicle and drone, which were presented with varying delivery fees and wait times. The delivery fee and wait time attributes each had 4 levels and are shown for each vendor type in Table 1. In addition, there was a binary attribute for drone privacy, which was displayed as either "YES Privacy" or "NO Privacy" for the drone option, as described above. This attribute was not included for ground vehicle (marked with "N/A"). Attribute levels were the same for take-out food, liquor store items, and last-minute groceries. For these, delivery fees ranged from $0 to $5 and delivery wait times ranged from 15 to 45 min, based on commonly available delivery services in the U.S.[6] For prescription medications, attribute values were determined based on guidance from a pharmacist, with delivery fees and wait times across a much broader range of $0 to $10 and 30 min to 1 day, respectively. Attribute value ranges were also guided by prior research, which suggests that attribute values should be realistic and cover a range that is both wide but not too wide, as a wide range theoretically leads to better parameter estimates with smaller standard error, while too wide a range can lead to alternatives perceived as highly dominant (Rose and Bliemer, 2009).

With the attributes defined, blocks of choice questions were generated programmatically and imported into the Qualtrics survey software, using procedures guided by previous work (Weber, 2021). These procedures are further detailed in Appendix A. While a full factorial design, using all combinations of attribute levels to create questions, could theoretically be used, this would not be preferable as it would include choice questions with a dominant alternative better in both cost and time. While there are numerous ways to reduce a full factorial design to a fractional design for optimal parameter estimation (Rose and Bliemer, 2009), research has shown that when the value of time has an unknown or high variance prior (such as in our case), then a random design with

[5] The survey was implemented using Qualtrics software. Copyright © 2023 Qualtrics. Qualtrics and all other Qualtrics product or service names are registered trademarks or trademarks of Qualtrics, Provo, UT, USA.

[6] Delivery cost and wait times were based on U.S. data for UberEats and Grubhub.

Table 1
Attribute levels for SP survey used in discrete choice experiment.

Level	Vendor type					
	Take-out food, Liquor store, Last-minute groceries			Prescription medications		
	Delivery fee	Delivery time	Drone privacy	Delivery fee	Delivery time	Drone privacy
0	$0	15 min	NO privacy	$0	30 min	NO privacy
1	$1	20 min	YES privacy	$1	2 h (120 min)	YES privacy
2	$3	30 min		$5	6 h (360 min)	
3	$5	45 min		$10	1 day (1440 min)	

Note: Time and cost attribute level values were the same for vendor types take-out food, liquor store, and last-minute groceries; values for prescription medications were different. The binary values for drone privacy ("NO/YES Privacy") were consistent across all vendor types.

dominant alternatives removed can be most efficient (Walker et al., 2018). Given this, we generated a random fractional factorial design by first generating a full factorial design, excluding all choice questions with a dominant alternative, and then randomly sampling blocks of 100 choice questions for each vendor type from this subset, without replacement.

3.3. Data collection

Survey participants were recruited via the online platform Prolific.[7] Recent studies have shown Prolific participants provide high-quality data (Douglas et al., 2023) and their responses for surveys about privacy perceptions can be representative of the larger U.S. population (Tang et al., 2022). Participants were offered $1 USD for completing the survey, with an estimated 5-minute completion time ($12/h). Eligibility was limited to U.S. residents with English fluency who were 18 years or older. Furthermore, participants were recruited to match a 50/50 male/female balance in order to better test the impact of gender in the experiment. Participants were recruited until a sample of 4000 complete responses were recorded, after excluding participants who failed a preliminary attention check.

An initial sample of 1500 responses were collected in August 2022 in order to ensure the survey process collected data as expected. This initial sample showed that the survey had a median completion time of 4.5 min and that the number of responses for each vendor type was well balanced. Data were then collected from the remaining 2500 of the total 4000 participants in September 2022. There is no overlap in participants from the two data collection periods. No major changes were made to the survey before recruiting the rest of the participants. See the Appendix for further details.

3.4. Delivery mode choice models

Discrete choice models were specified separately for each of the vendor-specific choice scenarios to yield one set of models per vendor type. Each was specified as a panel mixed logit model (Train, 2009), using consistent methods across vendor types, as further described below. Models were estimated using the `PandasBiogeme` software (Bierlaire, 2020).

We model the systematic utility V for individual n who chooses alternative i from one of the k choice questions as: $V_{nik} = ASC_i + \beta_i^{\intercal} * x_{nik}$, where the alternatives (i) are either ground vehicle (GV) or drone (D), x_{nik} is a vector of alternative attributes and the individuals' consumer characteristics, and $\beta_i^{\intercal}$ is the transpose of the vector of coefficients associated with all variables. In addition, the models include interaction effects between consumer variables and drone privacy, when applicable. ASC_i is the alternative specific constant.

Since the models are estimated using panel data, where each individual, n, contributed multiple survey responses, the ASC values are specified to handle an agent effect. Each ASC is modeled as a random variable drawn from a normal distribution, where the mean and standard deviation are parameters estimated from the data, capturing the heterogeneity in overall delivery mode preferences across individuals.

Models were developed iteratively, where the inclusion of variables beyond cost, time, and drone privacy was determined by testing variables for statistical significance at the $p = 0.05$ level. For each vendor, the ASC for ground vehicle (ASC_{GV}) was normalized to 0 following tests identifying ground vehicle as the minimum variance alternative (Walker et al., 2007). Models were first developed around alternative attributes (cost, time, privacy). Consumer variables were then tested for inclusion in each resulting vendor model and a consistent set of these variables was then added to each model by including them in the drone alternative's systematic utility function (V_D). Estimated values for ASCs and consumer variable coefficients can then be interpreted for the drone option relative to the ground vehicle option.

Here, we describe how the systematic utility functions were developed around alternative attributes, with more details about consumer variables further below. Drone privacy was coded as a dummy variable (1 = "YES Privacy"; 0 = "NO Privacy") and included in the systematic utility function for the drone option. Previous work has shown that consumers highly value free delivery (Nguyen et al., 2019). To handle a nonlinear effect of a cost of $0 on the estimation of the cost parameter, we included a dummy variable indicating whether an alternative was free (cost = 0) alongside the cost variable, after testing for significance. The likelihood ratio

[7] https://prolific.co

test was used to determine whether the cost and time variables should be specified as generic or alternative specific (Ben-Akiva et al., 1985). This yielded different specifications across vendor types, where time is generic for all vendors except take-out food, while cost is alternative specific for the liquor store and prescription medications vendor types, and generic for take-out food and last-minute groceries.

For all vendors except prescription medications, the dollar and minute values shown in the choice questions were used in the models directly (see Table 1). For prescription medications, time was modeled with attribute levels instead of values (i.e., 0 to 3 instead of 30 min to 1440 min (1 day)). This was to more realistically define and model time trade-offs for prescription medications, where differences in wait times vary widely. Such varied differences result in highly nonlinear perceptions of time differences, e.g., the difference between 2 h and 6 h versus 6 h and 1 day may feel similar. Multiple specifications were tested, where a linear specification with attribute levels yielded the best and most interpretable results.

The systematic utility functions, excluding the consumer variables, are shown below.

Systematic utility functions for take-out food:

$$V_{GV} = \beta_{cost} * GV_{cost} + \beta_{free} * GV_{free} + \beta_{GV_{time}} * GV_{time}$$

$$V_D = ASC_D + \beta_{cost} * D_{cost} + \beta_{free} * D_{free} + \beta_{D_{time}} * D_{time} + \beta_{privacy} * D_{privacy}$$

Systematic utility functions for liquor store:

$$V_{GV} = \beta_{GV_{cost}} * GV_{cost} + \beta_{free} * GV_{free} + \beta_{time} * GV_{time}$$

$$V_D = ASC_D + \beta_{D_{cost}} * D_{cost} + \beta_{free} * D_{free} + \beta_{time} * D_{time} + \beta_{privacy} * D_{privacy}$$

Systematic utility functions for last-minute groceries:

$$V_{GV} = \beta_{cost} * GV_{cost} + \beta_{free} * GV_{free} + \beta_{time} * GV_{time}$$

$$V_D = ASC_D + \beta_{cost} * D_{cost} + \beta_{free} * D_{free} + \beta_{time} * D_{time} + \beta_{privacy} * D_{privacy}$$

Systematic utility functions for prescription medications:

$$V_{GV} = \beta_{GV_{cost}} * GV_{cost} + \beta_{free} * GV_{free} + \beta_{time} * GV_{time\_level}$$

$$V_D = ASC_D + \beta_{D_{cost}} * D_{cost} + \beta_{free} * D_{free} + \beta_{time} * D_{time\_level} + \beta_{privacy} * D_{privacy}$$

With the above utility functions, consumer variables were then tested for inclusion. They were included as dummy variables. For gender, “male” was coded as a dummy variable versus “non-male” which was excluded as the reference variable. For race, dummy variables were coded for “Black or African American”, “Asian” and “Other or 2 or more races”, where “White” was excluded as the reference variable. For household income, income groups were aggregated for dummy variables coded as “lower income” (<$50k) and “higher income” ($100k or more), where “medium income” ($50k–$100k) was used as the reference variable. For age, dummy variables were coded for “younger” (<35 years) and “older” (55+ years), where 35–54 years was used as the reference. For residential area, dummy variables were coded for “urban” and “suburban”, and for residence type dummy variables were coded for “private home” and “apartment”. A dummy variable indicating whether a consumer was a frequent e-commerce user (orders more than once per week) was also included.

Any such variables that were statistically significant in one vendor model were included in all models in order to compare the importance of these variables across vendor types. These included the variables for gender, age, residential area, and frequent e-commerce user. These consumer variables were also tested for interaction effects with drone privacy, resulting in interaction effects included for gender and age. While interaction effects were only significant for younger, and not older, consumer variables, they were both included for consistency and analysis purposes. The final model specifications that include the consumer variables, as they were coded and estimated in the PandasBiogeme software, are included in the Appendix (they are excluded here for brevity).

We note that despite the importance of cost in the models, we did not find variables for income groups, or their interaction effects with privacy, to be statistically significant. However, as a robustness check, we re-estimated the final models with variables for income group level included (lower income: <$50k, medium income: $50k–$100k, higher income: $100k or more). We verified that the other coefficients did not then change in significance or in sign. Final models were estimated with 5000 Halton draws from a normal distribution.

4. Results

4.1. Sample composition

A total of 4000 complete participant responses were collected. If participants failed any of the 3 attention checks, all of their data were discarded in order to improve confidence in data quality. This resulted in a sample of $n = 3715$ complete participant responses used in the analyses below. The following sections describe the sample composition with respect to demographics, consumer group, and which vendor types respondents indicated they might order delivery from, which determined which choice set questions they then saw.

Table 2
Sample characteristics.

Characteristic	n	(%)
Total	3715	(100%)
Gender		
Male	1823	(49.07%)
Female	1812	(48.78%)
Other or Prefer not to answer	80	(2.15%)
Race		
White	2752	(74.08%)
Black or African American	259	(6.97%)
Asian	308	(8.29%)
Other and 2 or more races	396	(10.66%)
Age		
18–24 years	600	(16.15%)
25–34 years	1253	(33.73%)
35–44 years	897	(24.15%)
45–54 years	457	(12.30%)
55–64 years	350	(9.42%)
65 or older	158	(4.25%)
Household income		
Less than $25,000	543	(14.62%)
$25,000 to $49,999	938	(25.25%)
$50,000 to $74,999	786	(21.16%)
$75,000 to $99,999	602	(16.20%)
$100,000 to $149,999	516	(13.89%)
$150,000 to $199,999	179	(4.82%)
$200,000 or more	151	(4.06%)
Residential area		
Urban	1020	(27.46%)
Suburban	2047	(55.10%)
Rural	626	(16.85%)
I don't know	22	(0.59%)
Residence type		
Private home	2644	(71.17%)
Apartment	978	(26.33%)
Other	93	(2.50%)
E-commerce frequency		
More than once a week	744	(20.03%)
Multiple times a month	1893	(50.96%)
About once a month	757	(20.38%)
Once in a few months or longer	312	(8.40%)
Never	9	(0.24%)

4.1.1. Sample characteristics

Table 2 provides information about the distribution of the sample characteristics. For gender, the sample closely matches the 50/50 male/female recruitment goal. For race, we aggregate responses to best compare to the U.S. census estimates which include Hispanics in any race category. The categories "White" (74.1%), "Black or African American" (7%) and "Asian" (8.3%) count participants reporting only one race, which we compare to 2022 U.S. census estimates reporting 75.5%, 13.6% and 6.3% for these categories (U.S. Census Bureau, 2021). Note that our sample underrepresents Black and African American participants which may limit the results. 15 survey participants reported their race as American Indian or Alaska Native (0.4%) and 5 as Native Hawaiian or Pacific Islander (0.1%), compared to the U.S. census estimates of 1.3% and 0.3%, respectively. Because these portions are so small, we combine the Alaska Native and Native Hawaiian or Pacific Islander categories with "Other" and "2 or more races" in Table 2 and the following analyses. For household income group, our sample has a median range of $50,000 to $74,999, which spans the median household income estimated by the U.S. census (U.S. Census Bureau, 2021). For age, our sample lacks a representative amount of older participants, with only 13.7% 55 years or older (versus 2021 U.S. census estimate of 29.7%), which we note as a limitation in our findings that report differences by age groups. Despite this, our sample median age group is 35–44 years, which spans the U.S. median age of 38 estimated by the U.S. Census Bureau for 2021 (U.S. Census Bureau, 2022a). The sample's distribution across residential areas is also consistent with the U.S. population in terms of the largest numbers of people residing in suburban areas, then urban, and then rural (Pew Research Center, 2018). Table 2 also reports on respondents' residence type, where private home is most common. In addition, it includes how frequently respondents make online shopping purchases for delivery to their home (e-commerce), which is a variable used in the following analyses. The majority of the sample uses e-commerce multiple times per month and less than 1% never uses e-commerce.

In terms of geographic distribution across U.S. states of residence, the survey sample closely matches the U.S. population, as reported in the 2022 U.S. Census Bureau population estimates (U.S. Census Bureau, 2022b), with a Pearson correlation coefficient of 0.986. U.S and sample populations by state of residence are shown in the Appendix Table B.6.

Table 3
Percent of sample who would order delivery from each vendor type, by consumer group.

Variable	Vendor type					
	All	None	Take-out food	Liquor store	Groceries	Prescription medications
Total	42.7%	2.4%	81.1%	64.1%	69.4%	89.4%
Gender						
Male	41.6%	2.6%	82.0%	64.6%	66.9%	88.4%
Non-male	43.7%	2.3%	80.3%	63.6%	71.8%	90.5%
Race						
White	42.4%	2.4%	79.8%	64.2%	69.6%	89.7%
Black or African American	49.0%	1.2%	88.4%	63.7%	76.8%	91.1%
Asian	37.0%	4.2%	84.4%	59.1%	63.0%	87.3%
Other or 2 or more races	44.7%	2.3%	83.1%	67.2%	67.9%	88.1%
Household income						
Less than $25,000	35.7%	3.3%	74.4%	59.9%	65.0%	89.3%
$25,000 to $49,999	41.4%	2.9%	80.5%	63.8%	68.0%	89.2%
$50,000 to $74,999	44.5%	1.7%	82.1%	66.2%	72.6%	89.9%
$75,000 to $99,999	42.9%	2.5%	82.4%	61.8%	68.8%	90.2%
$100,000 to $149,999	46.7%	2.5%	83.1%	65.9%	72.3%	88.6%
$150,000 to $199,999	48.0%	0.6%	86.0%	69.3%	72.1%	88.3%
$200,000 or more	45.0%	2.0%	86.8%	67.5%	65.6%	90.1%
Age						
18–24 years	31.3%	3.8%	81.7%	59.7%	52.7%	88.3%
25–34 years	46.8%	1.8%	85.9%	69.0%	70.9%	89.8%
35–44 years	49.3%	1.6%	82.3%	66.4%	78.7%	90.5%
45–54 years	46.8%	2.4%	80.5%	66.1%	75.3%	90.6%
55–64 years	31.4%	2.6%	71.4%	54.3%	63.1%	89.7%
65 or older	27.8%	7.0%	58.2%	44.3%	63.9%	81.0%
Residential area						
Urban	48.7%	2.6%	86.1%	67.4%	71.5%	90.4%
Suburban	42.7%	2.3%	83.4%	64.0%	68.7%	88.8%
Rural	33.2%	2.4%	64.9%	59.4%	69.0%	89.9%
I don't know	22.7%	–	100.0%	54.5%	45.5%	90.9%
Residence type						
Private home	42.2%	2.6%	79.7%	63.5%	69.9%	89.4%
Apartment	44.8%	1.7%	85.9%	66.6%	68.1%	89.3%
Other	32.3%	3.2%	71.0%	54.8%	66.7%	91.4%
Online shopping frequency						
More than once a week	59.1%	0.7%	89.4%	71.5%	89.0%	92.6%
Multiple times a month	45.2%	1.8%	82.4%	65.7%	72.3%	91.1%
About once a month	29.5%	4.8%	73.8%	57.3%	55.4%	83.6%
Once in a few months or longer	20.5%	3.8%	72.8%	53.2%	40.4%	86.5%
Never[a]	22.2%	22.2%	44.4%	55.6%	22.2%	77.8%

[a] Note: Fewer than 0.25% of respondents ($n = 9$) indicated they never shop online.

4.1.2. Responses by vendor and consumer group

From the sample of 3715 respondents there were a total of $N = 36{,}297$ choice questions answered. Respondents answered up to 12 choice questions and were only presented with choice questions for vendor types which they might actually order delivery from. The number of responses therefore varied by vendor type: $N = 9{,}528$ for take-out food, $N = 7{,}269$ for liquor store, $N = 8{,}019$ for last-minute groceries, and $N = 11{,}481$ for prescription medications.

Table 3 shows the percentage of respondents who said they would order delivery from each vendor type and breaks down these responses by consumer group. Each cell in the table indicates the percentage from the given consumer group (row) who indicated they would order delivery from the given vendor type (column) and hence participated in the choice experiment for that given vendor type. For example, 82% of male respondents indicated they order take-out food delivery to their home, and then answered choice questions about take-out food delivery, while only 64.6% of male respondents indicated they might order products from a liquor store to their home and then answered choice questions about liquor store delivery. The "All" column indicates the percent of the sample who answered they would order delivery from all four vendor types, and then answered three choice questions for each vendor type. This included 42.7% of all respondents. The "None" column indicates the portion of the sample who do not or would not order delivery for any of the vendor types. They therefore did not answer any choice questions and were not included in the mode choice models. This included 2.4% of all respondents. The remaining 54.9% of respondents answered they would order delivery from some subset of the vendor types. These data should be considered alongside the following results because they indicate differences in the distributions of the consumer groups that were included in the analysis.

Overall, respondents indicated they were most likely to order prescription medications for delivery and least likely to order delivery from liquor stores. (Many respondents explained in free-response comments that they would not order from a liquor store because they do not drink.) Gender (male versus non-male) was nearly balanced across vendor types, which was desired

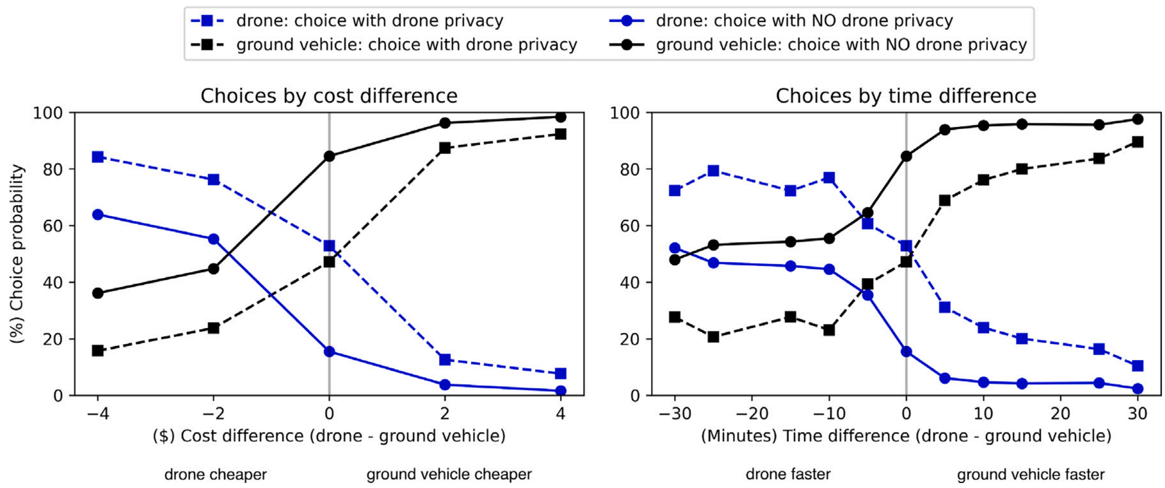

Fig. 4. Choice probability for drone versus ground vehicle by cost and time differences. Data aggregated across vendor types, excluding prescription medications (where cost and time values were different). Choice probability is the percent of times the option was chosen when presented. Left: Choices by cost difference, with data limited to choices where wait times for the two options are the same, and choices where one option is free are excluded (N = 5,400). Right: Choices by time difference, with data limited to choices where cost is the same between options (N = 12,643).

for estimating differences in gender-based preferences. Some differences can be found between consumer groups. For example, respondents residing in rural areas were the least likely to order take-out food for delivery. Age was also a differentiator, with older respondents less likely to order delivery. In particular, 7% of the respondents age 65+ indicated they would not order delivery from any of the vendor types, which further limited the number of older respondents in the sample upon which the models were built. As to be expected, the most frequent e-commerce users were also the most likely to order delivery from any of the vendors.

4.2. Mode choice by cost and time differences and consumer group

Before presenting results from the choice models, we first present a visual analysis of the data.

4.2.1. Choice probability by cost and time differences

Fig. 4 plots the rate at which respondents chose drone versus ground vehicle delivery, given cost and time differences between the two options. The vertical axis shows the “choice probability” as the percent of times an option was chosen given the cost or time difference, which is shown on the horizontal axis. Choices with and without drone privacy are shown separately, using square and circular markers, respectively. Data are aggregated across the take-out food, liquor store, and groceries vendor types since their delivery fee and wait time values were the same across attribute levels (see Table 1). Data for prescription medications are excluded from these plots because that vendor type had different cost and time values.

Choices by cost difference are shown in the left panel of Fig. 4. Data are restricted to choices with the same wait time for the drone and ground vehicle options, so that the trade-off only involves the cost difference and privacy (and not time). Furthermore, choices where one, but not both, of the options had a delivery fee of $0 (i.e., free) are excluded, due to our findings that reducing a cost to free had a nonlinear significant effect. Given these constraints, the plot includes a total of N = 5,400 responses, with 19%–25% of the total responses for each vendor type: 2396/9528 for take-out food, 1378/7269 for liquor store, and 1626/8019 for last-minute groceries.

Choices by time difference are shown in the right panel of Fig. 4, where data are restricted to choices with the same delivery fee for the drone and ground vehicle options, in order to take cost out of the trade-off. With this restriction, the plot includes a total of N = 12,643 responses, with 24%–43% of the total responses for each vendor type: 2290/9528 for take-out food, 2848/7269 for liquor store, and 3485/8019 for last-minute groceries. We note there are small bumps in this plot for choices with drone privacy where drone is the better option, which we attribute to noise.

Data detailing the number of choices and choice probabilities for each cost and time differences displayed in the plots, separated by vendor type, are provided in the Appendix (including for prescription medications). See Tables D.7–D.14.

These plots display how preferences for drone versus ground vehicle change as cost or time differences vary, and the extent to which drone privacy increases the choice probability for the drone option. In the cost differences plot, the horizontal axis indicates the cost difference for drone versus ground vehicle options (for choices where time is the same). Likewise, in the time differences plot, the horizontal axis indicates the time difference between drone versus ground options (for choices where cost is the same). For each plot, at the value 0 on the horizontal axes, both the delivery fees (cost) and wait times are the same for the drone and ground vehicle options. Points on the left side of the horizontal axis represent choices where the drone option is better in terms of cost and time: For the cost differences plot, the left side represents choices with lower drone delivery fees, and for the time differences plot

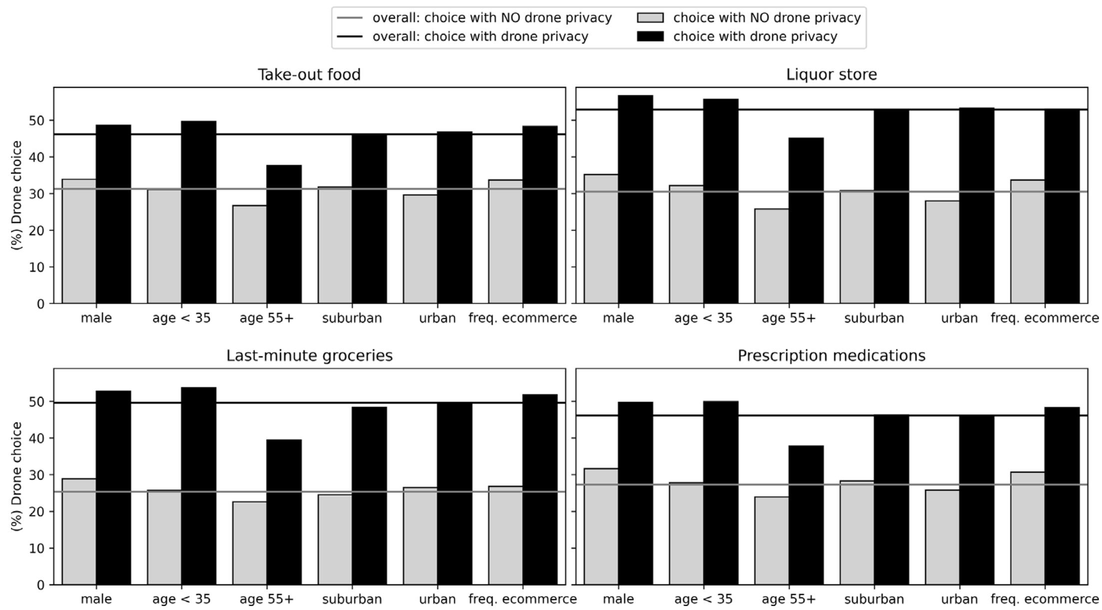

Fig. 5. Delivery preference by consumer group and vendor type.

the left side represents choices with smaller wait times for drone. Whereas points on the right side of the horizontal axis represent choices where the ground vehicle option is better.

For choices where the cost and time are the same, the two plots show the same information. They show that in such a choice where there is no drone privacy the ground vehicle option is chosen more than 80% of the time, i.e., more than 4 times as often as the drone option. This strong preference for ground vehicle delivery is displayed by the large gap in choice probability values (circular markers) for the drone versus ground vehicle options. However, this gap is closed when there is drone privacy (square markers) — when there is drone privacy and cost and time are the same, the choice probabilities for drone and ground vehicle are nearly the same. Overall, the plots show that privacy consistently increases preference for the drone option — the choice probability for drone is consistently higher for choices with drone privacy versus without drone privacy. This is shown by the vertical difference between the blue circular versus square markers at each point on the horizontal axes.

The plots also allow examining the horizontal distance between the lines connecting choice probability values for choices with versus without drone privacy. This horizontal gap can be projected to the horizontal axis, representing the value of privacy with respect to cost or time. For example, in the choices by cost difference plot, there is around a $2 horizontal gap for drone choice probability of 50%. We can compare this value of privacy displayed in the plot to the value of privacy estimates from the mode choice models.

In addition, the shape of the plots complement the model results. Their s-shaped curves support the use of a random utility logit model, as used in our analyses. If respondents were choosing purely based on cost and time, then we might expect any point on the left or right side of the horizontal axes to lie on the extreme values of 0 and 100% choice probabilities. However, this is not the case. By comparing the left and right sides of each plot, we can also see differences in how choice probabilities change when drone is cheaper/faster versus when ground vehicle is cheaper/faster. (If there were no differences, we would expect the curves to be symmetric across 0 cost/time difference.) On the right side of each plot, as the ground vehicle option becomes better than the drone option, the choice probability for ground vehicle increases to a greater extent than does the drone option on the left-hand side of each plot. In other words, improving the drone option (i.e., making it cheaper/faster) has a smaller impact on shifting choices versus improving the ground vehicle option. This indicates some hesitancy among respondents in choosing drone delivery, even when it is the better option in terms of time and cost. This is particularly the case for the choices with no drone privacy.

While these plots are useful for visualizing the trade-offs, they are simplified representations of the data and should not be expected to completely match the model results or match consumer preferences. The plots do not incorporate additional variables such as consumer demographics, which impact the model results. For example, older respondents, who were less likely to prefer drone delivery, were underrepresented, so there may be a greater preference for drone delivery displayed in these plots versus for a more representative sample. The choice models control for such effects by incorporating socio-demographic variables.

4.2.2. Choice by consumer group and vendor type

Fig. 5 plots the preference for drone versus ground vehicle delivery by consumer group and vendor type. The vertical axis shows the percent of times drone option was chosen over ground vehicle, counted across all choice questions, regardless of time or cost differences. The horizontal axis separates these values by consumer group, showing separate values for choices with and

Table 4
Delivery mode choice model results for each vendor type (panel mixed logit models).

Parameter	Vendor type							
	Take-out food		Liquor store		Last-minute groceries		Prescription medications[a]	
	Value	Rob. SE	Value	Rob. SE	Value	Rob. SE	Value	Rob. SE
Constants (ASCs)								
Ground vehicle (reference)	0		0		0		0	
drone mean	−1.369**	0.192	−2.335**	0.223	−1.988**	0.177	−2.251**	0.156
drone std dev	1.726**	0.072	2.170**	0.105	1.865**	0.086	1.668**	0.066
Time (minutes)[1]								
generic			−0.086**	0.004	−0.095**	0.004	−0.740**	0.028
ground vehicle	−0.084**	0.004						
drone	−0.094**	0.004						
Cost ($)								
generic	−0.681**	0.024			−0.856**	0.035		
ground vehicle			−0.823**	0.039			−0.374**	0.013
drone			−0.902**	0.042			−0.422**	0.014
free	0.404**	0.068	0.521**	0.107	0.285**	0.099	0.247**	0.064
drone privacy	1.251**	0.136	2.044**	0.184	1.789**	0.154	1.868**	0.139
Consumer attributes								
freq. e-commerce	0.297**	0.107	0.370**	0.143	0.229*	0.116	0.262*	0.103
Gender								
male	0.592**	0.123	0.950**	0.153	0.655**	0.138	0.814**	0.118
male × privacy	−0.288*	0.146	−0.476*	0.187	−0.216	0.166	−0.324*	0.140
Age (younger < 35; older 55+)								
younger	−0.109	0.132	0.256	0.162	0.003	0.146	−0.020	0.127
younger × privacy	0.543**	0.157	0.220	0.200	0.365*	0.178	0.419**	0.153
older	−0.440*	0.213	−0.412	0.269	−0.422	0.231	−0.256	0.181
older × privacy	−0.036	0.251	−0.070	0.297	−0.201	0.259	−0.262	0.208
Residential area								
suburban	−0.263*	0.129	−0.243	0.172	−0.426**	0.142	−0.019	0.115
urban	−0.315*	0.143	−0.427*	0.190	−0.292	0.157	−0.106	0.129
Model statistics								
sample size (n)	3014		2381		2577		3323	
observations (N)	9528		7269		8019		11481	
parameters (K)	16		16		15		16	
draws	5000		5000		5000		5000	
init log-likelihood $LL(C)$	−6417.46		−5239.84		−5436.62		−8298.06	
final log-likelihood $LL(\beta)$	−4744.13		−3433.13		−3790.58		−5528.74	
$\bar{\rho}^2$	0.258		0.342		0.300		0.332	
Akaike Information Criterion (AIC)	9520.26		6898.27		7611.15		11 089.48	
Bayes Information Criterion (BIC)	9616.44		6990.67		7698.97		11 187.22	

Note: Coefficient estimated values are shown alongside the robust standard error (Rob. SE); Significant values are marked by * (robust p-value < 0.05) and ** (robust p-value < 0.01);

[a] Time values are for minutes for all vendors except prescription medications; the prescription medications model uses time attribute levels and estimated values should be interpreted differently.

without drone privacy. Horizontal lines represent the overall percent of times drone was preferred for each vendor type regardless of consumer group.

The plots display differences in preferences between consumer groups, comparing them to the overall preferences (horizontal lines), and how these differences vary across vendor types. The consumer groups included in the plots are the same as those included in the final models. Whether a consumer group was significantly different from the overall sample differed by vendor type; the model results in Table 4 show which consumer variables were significant for which vendor types.

These plots show how age and gender play a role. Male respondents chose drone delivery more often and older respondents (age 55+) chose drone delivery less, versus the overall sample. These observations hold for all four vendor types, both with and without drone privacy. However, the preferences for younger respondents (<35) were dependent on privacy. Without drone privacy, their preference for drone delivery mostly matched the overall sample. In contrast, when drone privacy was included, they preferred the drone option more often than the overall sample. These plots also show that respondents who frequently use e-commerce (order more than once per week) are more likely to prefer drone delivery. These observations found visually in these plots can also be found in the model results, where the models present more specific and quantitative differences between consumer groups and vendor types.

4.3. Mode choice model results

This section reports the estimation results of the mode choice models, presented in Table 4. The estimated coefficients, with their robust standard error values, are shown for each variable included in the respective models. These results complement the plots above and reveal the joint effects of all attributes.

Overall the models are well fit,[8] with $\overline{\rho^2}$ values above 0.25. All of the main parameters have the expected sign: The time and cost coefficients are negative, while the dummy variable for free is positive. Furthermore, the drone privacy parameter, which was coded as a dummy variable indicating "Yes/No Privacy" for the drone option, is positive and statistically significant for all vendor models. These values indicate that privacy is a significant attribute in improving the utility and hence likelihood of consumers choosing the drone option.

We remind the reader that specification testing found time to be a generic attribute for all vendor types except take-out food, where the estimated time parameter for drone has a stronger negative magnitude than for ground vehicle. This may indicate that for take-out food, consumers expect drone delivery to be faster and this additional delivery speed is more important for take-out food than for the other vendor types. In addition, cost was generic for the take-out food and last-minute groceries vendor types and alternative-specific for liquor store and prescription medications. Here again, the cost parameter for drone had a stronger negative magnitude than for ground vehicle. Overall, resulting estimates for the alternative specific parameters indicate that consumers are more sensitive to time and cost for the drone option.

Furthermore, the estimated ASC values show that when time and cost are the same, and drone privacy is not included, consumers overall prefer the ground vehicle option. However, for each vendor, the negative drone ASC value is close in magnitude to the positive drone privacy value, indicating that drone privacy can nearly offset the otherwise negative preference for drone. Overall, these results indicate that providing improved privacy or cost or time may be necessary in order for the average customer to choose drone delivery over standard ground delivery options. The estimated values, or values from follow up studies that build upon this work, can be used to predict what delivery pricing and wait times will be necessary to guide a desired share of consumers to prefer drone delivery. However, preferences differ by individual consumer, as shown by the statistically significant standard deviation values for the ASCs, and differ across consumer groups.

Given how the utility models were defined, with consumer variables included in the systematic utility for the drone option (V_D), coefficient estimates for consumer variables can be interpreted for the drone option relative to the ground vehicle option. The model results show that, consistent with previous studies, gender has an effect. Male consumers show a greater preference for drone delivery for all vendor types. In addition, there is a significant interaction effect between gender and drone privacy (for all vendor types excluding last-minute groceries). The estimated parameter is negative, indicating that drone privacy is less important to male consumers versus non-male consumers. Age played a more nuanced role in the mode choice models. Whether a consumer is in the younger age category (<35 years) did not have a significant effect. However, there is a significant interaction effect between the younger age category and privacy for three out of the four vendor types. The resulting values indicate that drone privacy is more important to younger consumers than to their older counterparts. In addition, the model results showed that older consumers (55+ years) are less likely to prefer drone delivery, particularly for take-out food. We note that our sample contained a smaller proportion of older survey participants compared to the U.S. population, which may have weakened the significance of findings for this consumer group. Residential area also had an effect, where coefficients for suburban and urban should be interpreted relative to rural residential areas. These values indicate customers ordering delivery to rural residences may be more amenable to drone delivery options compared to suburban or urban residents. Finally, the model results show that frequent e-commerce shoppers (order more than once per week) are consistently more likely to prefer drone delivery across vendor types.

4.3.1. Value trade-offs for cost, time and drone privacy

Table 5 shows the resulting value of time (VOT) estimates for the ground vehicle versus drone delivery modes, as well as respondents' willingness to pay (WTP) for drone privacy. The values are computed from the mode choice model results (Table 4). VOT values are computed as the ratio of time and cost coefficients ($\beta_{time}/\beta_{cost}$), where generic or alternative specific coefficients are used depending on the vendor type's model specification. Similar to related works using DCE results to estimate consumer WTP for privacy (Potoglou et al., 2015), we compute a monetary value of drone privacy as the ratio between the drone privacy coefficient and drone cost coefficient. Likewise, we compute a time value of drone privacy as the ratio between the drone privacy coefficient and drone time coefficient.

These values are multiplied by −1 to then provide an estimated valuation of drone privacy, in money ($) or time (minutes). These values may be interpreted as the additional delivery fees or wait times that consumers may trade-off for drone privacy. For prescription medications, we do not calculate time-related trade-offs because time coefficients do not directly correspond to minutes.

Overall, the VOT and WTP values are largely consistent across the take-out food, liquor store, and last-minute grocery vendor types. For these vendors, VOT values for both ground vehicle and drone fall in the range of $0.10/minute to $0.14/minute, where values are highest for take-out food. This should be expected given the utility of receiving take-out food as soon as possible after ordering may seem higher to most survey respondents versus the other vendor types.

The WTP values are also largely consistent with Fig. 4. The estimated cost value for drone privacy is about $2 for vendors excluding prescription medications. This value is also reflected in the plot showing choices by cost difference (left panel of Fig. 4). This plot shows that when cost and time are the same for the drone and ground vehicle options, the drone and ground vehicle option are chosen at about the same rate for choices with drone privacy, but the ground vehicle option is chosen at a much higher rate than drone for choices without drone privacy. However, this gap is closed when the drone option is $2 cheaper than the ground vehicle

[8] McFadden (1977) notes "Those unfamiliar with ρ^2 should be forewarned that its values tend to be considerably lower than those of the R^2 index and should not be judged by the standards for a "good fit" in ordinary regression analysis. For example, values of 0.2 to 0.4 for ρ^2 represent an excellent fit" (McFadden, 1977). This work uses the adjusted ρ^2 ($\overline{\rho^2}$) which penalizes additional parameters (K).

Table 5
VOT for ground vehicle versus drone delivery and WTP for privacy.

	Take-out food	Liquor store	Last-minute groceries	Prescription medications
Value of time for ground vehicle ($/minute)	0.12	0.10	0.11	–
Value of time for drone ($/minute)	0.14	0.10	0.11	–
Cost value for drone privacy ($)	1.84	2.27	2.09	4.43
Time value for drone privacy (minutes)	13.24	23.79	18.75	–

option. For the time value of drone privacy, the values range between about 13 and 24 min. Again we can compare these values to the time differences spanned on the horizontal axis of the choices by time difference plot (right panel of Fig. 4), specifically as the distance between values representing choice probabilities with versus without privacy. The plot values vary greatly and their range includes the values estimated from the model.

The exact VOT and WTP values should not be overinterpreted, given that SP experiments suffer from hypothetical bias (Colombo et al., 2020). Instead, we use the values to compare sensitivity to time, cost, and privacy, across the vendor types. For both the liquor store and last-minute groceries vendor types, the VOT values for the ground vehicle and drone alternatives are the same. For the liquor store, cost was an alternative specific attribute in the model, yielding different values for the ground vehicle and drone cost coefficients, yet the differences in these values were not large enough to yield different VOT values. For the take-out food vendor type, the VOT for drone is higher than for ground vehicle, due to the larger negative cost coefficient estimated by the model. Again, this reflects that consumers may require drone delivery to be cheaper or faster than ground vehicle delivery in order to prefer it as an option.

The cost and time values for drone privacy are consistently ordered across the vendor types. The value for drone privacy is lowest for take-out food, then last-minute groceries, and then higher for liquor store. For prescription medications, the cost value for drone privacy is about twice that of the other vendor types.

5. Discussion

5.1. Findings and impact

In this study, we used data from a DCE with U.S. consumers in order to calibrate delivery mode choice models and evaluate consumer demand for drone delivery compared to standard delivery, and how privacy plays a role. We measured consumers' willingness to pay for privacy in drone delivery in terms of both time and money, and revealed differences in preferences across product types and consumer groups. Overall, delivery service customers showed a strong willingness to pay for privacy when it comes to drone delivery. Moreover, results from our survey suggest that either offering privacy-preserving drone deliveries or making drone delivery faster or cheaper than standard delivery will be important in order to make these services competitive. In particular, this study focused on an emerging business model where delivery service companies serve multiple businesses, particularly smaller vendors selling more specific types of products. Recent work has demonstrated how privacy risks for drone deliveries operating under this service model can be mitigated by aggregating orders from different customers and vendors into a single delivery route, at the potential cost of additional delivery wait time or money. This is the first large study to present these risks and trade-offs to potential drone delivery customers and analyze their impact. The delivery service market is large and growing, with U.S. carrier revenue reaching $188 billion in 2021 (Pitney Bowes, 2021). Experts suggest drones can change the delivery service landscape. Yet this may be contingent on consumer receptiveness and our results can inform how privacy may play a role.

Overall, customers in our sample chose ground vehicle as a delivery option 4 times more often than drone when delivery fees and wait times were the same across options and privacy enhancements for the drone option were not offered. However, offering privacy for the drone option closed this gap. Our results also show how this gap could be closed without the privacy enhancement by making the drone option cheaper or faster than ground vehicle delivery.

There is a growing body of literature exploring whether new aerial vehicles, such as delivery drones, will be accepted as an alternative to ground vehicles, and how this may differ across consumer groups. We contribute new results to this literature, given that the specific privacy issue for drone delivery that we study has not yet been examined. Furthermore, our results add nuance to previous studies, with more granular findings made possible by our study design. For example, our results are largely consistent with the 2016 USPS survey on the public perception of drone delivery in the U.S. (U.S. Postal Service Office of Inspector General, 2016). Both studies find that frequent e-commerce users, younger consumers, and male consumers are relatively more receptive to drone delivery, and that female consumers express more privacy concerns. More specifically, frequent e-commerce users and male consumers in our study were more likely to favor drone over ground vehicle delivery versus the overall population, regardless of privacy enhancements, whereas privacy enhancements for drone delivery had a significantly greater positive impact on female consumers and younger consumers. We are also able to show how these preferences vary across product types.

Our study also revealed differences in how consumers valued time and privacy, when compared across the four product types tested in our experiment (take-out food, liquor store items, last-minute groceries, and prescription medications). These product types were chosen both because delivery services are either available or becoming increasingly available for them, and because they appeal to a range of consumer habits and privacy sensitivities. Consumers showed the highest value of time (VOT) for take-out food, and were more sensitive to time for the drone versus ground vehicle option. The higher VOT for take-out food is to be expected, as immediacy of delivery may be more pertinent for take-out food than for the other product types, and the higher VOT for drone delivery is again consistent with the USPS study findings that consumers expect drone delivery to be fast. Despite expressing a higher VOT for take-out food, survey participants expressed the lowest value of privacy for take-out food. The model results valued the trade-off between drone privacy and delivery fees from about $2 to $4.50 and the trade-off between drone privacy and wait time from about 13 min to 24 min. These values represent the compensation needed to make a drone delivery option without privacy enhancements as appealing as the option with privacy, for the average customer. We caution against over-interpreting these values as true estimates, given the hypothetical nature of the study design. Instead, we interpret the differences in the values across product types. The willingness to pay for privacy for the different product types in order of smallest to largest values was take-out food, then last-minute groceries, then liquor store, then prescription medications. The first 3 were close in monetary value, whereas the value for prescription medications was about twice their value. This suggests consumers may be willing to pay much more for privacy when ordering prescription medications for delivery. This is consistent with public awareness around the sensitivity of health-related information. Likewise, participants placing the second highest privacy valuation on liquor store items may be guided by the intuition that a third party learning they ordered such items for delivery, or the frequency with which they do so, is sensitive when compared to take-out food or last-minute groceries. However, there are also real risks to be considered for delivery from vendor types that may seem more mundane, such as take-out food or groceries. This is because within each vendor category there are subcategories that can reveal customers' socio-demographic information or preferences. For example, take-out food vendors or grocery stores can specialize in certain cuisines or offer specialty goods, catering to certain preferences or ethnic or demographic groups. Or any vendor, such as a liquor store, might fall into the categories of upscale or bargain store, where frequent purchases may suggest a customers' income level or how they spend. Future descriptions of the potential privacy risks of drone delivery to consumers should consider including these nuances.

The results from this study can help inform whether businesses should adopt drone delivery services, and how drone delivery services should incorporate privacy considerations into their business models, routing strategies and customer messaging. For example, drone delivery services may incorporate privacy-preserving routing strategies, as described in previous work that also quantified their impact on both privacy and efficiency (Ding et al., 2022). These strategies often involve combining orders from multiple vendors within a route before delivering to customers, potentially incurring delivery delays or other efficiency losses. Customers' willingness to pay for privacy, as shown in this study, may help guide delivery services in making trade-offs between privacy and efficiency in their routing, and communicating the potential benefits to customers.

The differences across product types provide more specific insights. For example, drone delivery services for prescription medications are becoming increasingly common, and customers placed twice as high a value on privacy for this product category relative to other products like groceries. Pharmacies and health organizations may wish to revisit their use of drone delivery and better communicate potential privacy risks to their patients, while drone delivery services may wish to prioritize privacy enhancements when delivering medications. In contrast, customers placed a lower value of privacy on take-out food deliveries relative to other products, as well as a high value of time, where the value of time was higher for drone delivery than for ground vehicle delivery. This indicates that businesses offering take-out food delivery via drone should be ready to offer faster delivery, and the trade-off between improving customer privacy and adding delivery delays may be less worthwhile.

Differences across consumer groups can further inform business decisions by allowing businesses to align knowledge about their customers to findings from this study. For example, businesses serving frequent e-commerce users or those that have largely male customer bases may see more initial adoption of drone delivery options, whereas businesses serving younger or higher proportions of female consumers may wish to prioritize privacy.

There may also be times when improving both privacy and efficiency in a delivery route are well-aligned from a business and operational perspective. For example, when customers order from vendors that are geographically close, it may be efficient to pick up the orders before delivering to either customer. If the resulting privacy enhancement is described to customers, the added wait time might not impact customer satisfaction as negatively. This study may also help guide how delivery services invest in drone technologies. For example, drone privacy is improved when the drone can pick up more customer orders before making deliveries, and a drone must have a large enough capacity to carry multiple items for this privacy improvement to be possible.

5.2. Study limitations

Despite this study's significant findings on customers valuing privacy, whether customers' valuation of privacy will transfer to a real delivery setting, and whether companies will benefit from adopting privacy-preserving strategies, is not yet known. In particular, the findings should be considered in the context of the survey participants and survey design. For example, survey participants were recruited from the online research platform Prolific. It is possible these participants are more familiar with and interested in new and emerging technologies, such as drones, which may limit the extent to which the findings generalize to the larger population. Also, our sample underrepresented certain demographic groups, namely Black and African American and older participants, which can also limit the generalizability of results. Although our results did not show significant differences by race, it is possible that future analyses that include more participants from racial minorities would find results differ along racial lines.

In terms of potential limitations due to survey design, we note the survey described the privacy concern for drone deliveries directly before survey participants were tasked with choosing between delivery options (see Fig. 2). This may have impacted the salience of privacy concerns in their decision making. For example, in a survey-based experiment by Paliński (2022), users of a hypothetical ride-hailing service showed more reluctance to trade their private information for discounts (i.e., placed more value on privacy) when they were first shown information about GDPR (i.e., when privacy considerations were salient). The extent to which our findings transfer to the real delivery setting may then depend on the extent to which the privacy risks are clarified and made salient to delivery service customers. Additional research along the lines of Story et al. (2021) is needed to address how such privacy risks should be communicated in emerging logistics infrastructure settings. Customers' perceptions of such risks may result from public awareness programs or business marketing, which may either harm or benefit the success of drone delivery services depending on how businesses position themselves. For example, while our results may suggest that companies offering drone delivery can better appeal to consumers, and hence improve market share, by offering privacy protective practices, this may depend on how companies communicate the associated benefits to consumers.

Furthermore, the results of our study, and related survey-based works studying privacy, should be interpreted alongside the known "privacy paradox" (Norberg et al., 2007). Namely, prior studies have found a difference between individuals' intentions to disclose personal information versus their actual behaviors (Gerber et al., 2018). These prior works about the privacy paradox highlight the limitations of using a hypothetical survey, as done in this study, yet they otherwise support the study methods. A review of works explaining reasons for the privacy paradox found that a "privacy calculus" was the best explanation, with possibly gained benefits being among the best predictors for both intention to disclose information (i.e., forfeit privacy) as well as actually disclose information (Gerber et al., 2018). A "privacy calculus" framework may well apply to the present study, which evaluated consumers' trade-offs between privacy versus benefits, such as reduced cost and wait time. Regarding the DCE as an experimental design, Glasgow et al. (2021) found no evidence that survey design contributes to the privacy paradox in a test comparing a DCE (within-subjects) survey design to a between-subjects survey design.

Regardless of the unknown relationship between the value of privacy consumers expressed in this study and real consumer behavior, this study revealed significant differences in preferences across consumer groups and vendor types. These differences can still be informative in both drone delivery planning as well as other consumer contexts.

6. Conclusion

This is the first work to describe newly emerging privacy risks to potential drone delivery customers and measure how demand for drone delivery compares to standard delivery, with and without privacy enhancements, in a large discrete choice experiment. We measured consumers' willingness to pay for privacy in drone delivery in terms of both time and money, and evaluated differences in preferences across product types and consumer groups. We find that either offering privacy-enhanced routing or making drone delivery faster or cheaper than standard delivery will be important in order to make these services competitive. Furthermore, the importance of these enhancements differs significantly across product types and consumer groups. This work can inform the development of delivery services, as well as contribute to a broader understanding of how consumers value privacy and methods to estimate that valuation.

Due to the newly emerging nature of the privacy issues studied in this work, this should be considered an initial study, with limitations that motivate future research. To re-emphasize limitations noted in Section 5.2, the sample analyzed in this work underrepresents historically marginalized racial groups and our conclusions must be viewed with this context. Our findings should be strengthened with future analyses that include additional data collected to better represent racial minorities. Further efforts should be made to understand how drone delivery and other emerging technologies may have a disparate impact on demographic minorities to help guide the design of these technologies towards more equitable outcomes.

We also note this study was limited in scope. Future work can build on this study by investigating preferences for a broader, or more detailed, set of product types and expand upon the delivery services offered. In addition, this study surveyed consumers who do not necessarily have access to drone delivery. Consumers' receptiveness to drone delivery and value of privacy will likely evolve as drone delivery becomes more commonplace, and future work that repeats this study's data collection process can study this evolution. Finally, while this work focused on privacy for drone delivery, the methods developed and resulting findings may be applicable to other modes of delivery and customer contexts. Future work can extend this research to address questions about how customer privacy concerns impact preferences in related domains.

CRediT authorship contribution statement

Alex Berke: Conceptualization, Methodology, Software, Visualization, Project administration, Investigation, Formal analysis, Data curation, Writing – original draft. **Geoffrey Ding:** Conceptualization, Methodology, Investigation, Writing – review & editing, Visualization. **Christopher Chin:** Conceptualization, Writing – review & editing. **Karthik Gopalakrishnan:** Conceptualization, Writing – review & editing. **Kent Larson:** Funding acquisition, Writing – review & editing. **Hamsa Balakrishnan:** Funding acquisition, Writing – review & editing. **Max Z. Li:** Funding acquisition, Conceptualization, Writing – review & editing.

Declaration of competing interest

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

Data availability

All code and data used in the survey design and analysis is available in an open source repository: https://github.com/aberke/drones-consumer-privacy.

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Appendix A. Survey

A.1. Participant recruitment

Participant requirements were:

- 18 years or older
- U.S. resident
- English fluency

Participants were sampled to maintain a 50/50 balance of male/female participants to help better test the impact of gender in the experiment.

An initial sample of 1500 participants was used to make sure the survey worked and collected data as expected. Their data are included in results. The 1500 participant sample showed that the survey had a median completion time of 4.5 min and that the number of responses for each vendor type was well balanced. No major changes were made to the survey before recruiting the rest of the participants. Participants were offered $1 to complete the survey, which was advertised with a 5 min estimated completion time ($12/hour). The survey included preliminary attention checks within the first set of questions. Upon failing a preliminary attention check, participants were automatically exited from the survey. Participants were recruited until a total sample of 4000 responses (including the initial 1500) were recorded, excluding participants who were immediately exited from the survey due to failing a preliminary attention check. Data were collected in August and September of 2022.

All participants were recruited using the online platform Prolific (http://prolific.co). We note that other works have addressed concerns about using online platforms, namely Amazon's Mechanical Turk (MTurk), for human-subjects research. In particular, concerns have been raised over the presence of inattentive survey participants and non-human respondents (bots). A 2023 study assessed data quality in online human-subjects research by comparing data from Prolific to MTurk and other similar platforms (Douglas et al., 2023). The researchers concluded that Prolific participants provided high-quality data, in contrast to MTurk. They found participants on Prolific were more likely to pass various attention checks, provide meaningful answers, follow instructions, remember previously presented information, have a unique IP address and geolocation, and work slowly enough to be able to read all the items.

More pertinent to this work, another recent study by Tang et al. assessed the external validity of using Prolific and MTurk to study privacy by comparing data collected from these platforms to that collected by Pew Research, using a survey about privacy and security (Tang et al., 2022). The Pew participants were a subset of Pew Research Center's American Trends Panel, a panel of more than 10,000 U.S. adults recruited and maintained by the Pew Research Center using state-of-the-art techniques. Tang et al. found that Prolific provides good quality, generalizable data for user studies that focus on privacy perceptions.

A.2. Survey instrument

The survey instrument used for the discrete choice experiment was developed using Qualtrics software. A public preview of the survey instrument is available at the following link: https://mit.co1.qualtrics.com/jfe/preview/SV_6mmF0a0AcjAgoqq?Q_CHL=preview

An abbreviated version of the survey instrument is included as supplementary material. For brevity, it only includes a sample of 1 of the 100 generated choice questions for each vendor type. It includes all other questions and answer options shown to participants, as well as notes about the survey logic. It also displays the description of the survey that was shown to potential participants on the Prolific platform in order to recruit them.

The survey design is summarized in Fig. A.6. The survey included more questions than those described in the main text and used in the DCE. In particular, in the first part of the survey there were follow up consumer behavior questions. If respondents indicated they do not/would not order take-out food, prescription medications, or liquor store products for delivery, they were then asked why not.

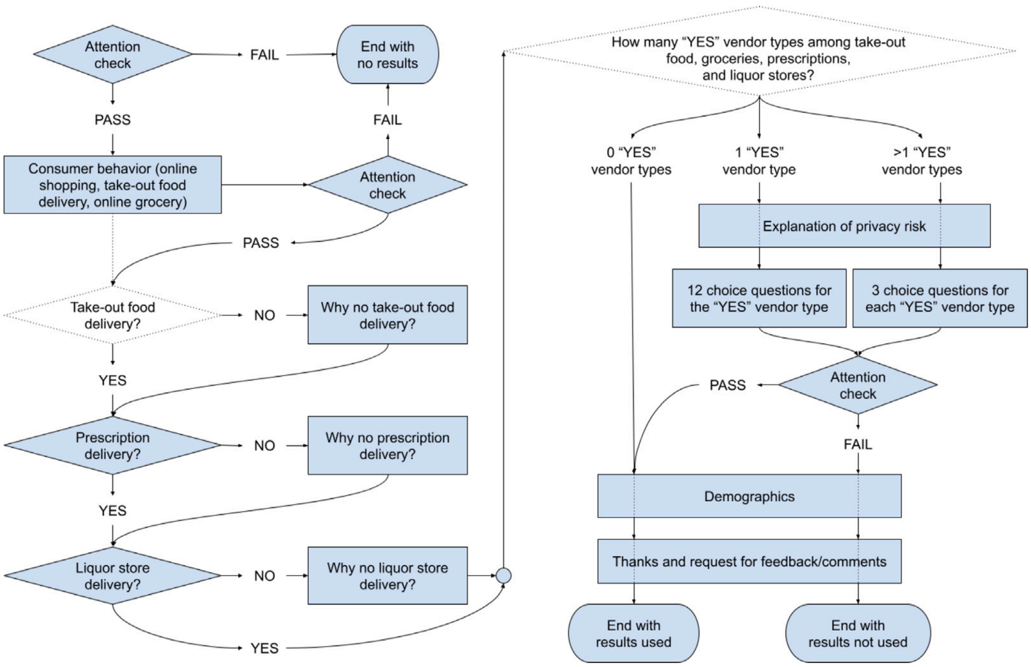

Fig. A.6. Flowchart summarizing survey design (expanded from main text). This includes questions in addition to those described in the main text. In particular, when respondents indicated they would not order take-out food/prescription medications/liquor store delivery, they were then presented with questions asking why.

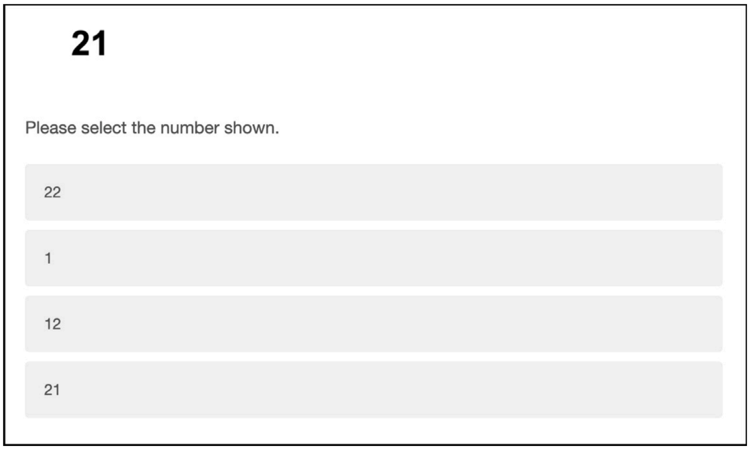

Fig. A.7. Attention check 1 of 3.

A.3. Attention checks

The survey included attention checks in order to help ensure data quality. Participants who failed either of the initial 2 attention checks were immediately exited from the survey. Data from participants who failed any of the 3 attention checks are excluded from analysis.

Attention check 1 is shown in Fig. A.7 as it was displayed to participants. It shows an image of the number 21 and instructs participants to select the number shown from a list of multiple choice options.

Attention check 2 is shown in Fig. A.8 as it was displayed to participants. It came after 3 consumer behavior questions that each asked participants a question of the form "How often (on average) do you __?" with an identical list of answer options. Attention check 2 displays this same list of answer options but unlike the previous 3 questions it instructs participants to select all answer options rather than just one.

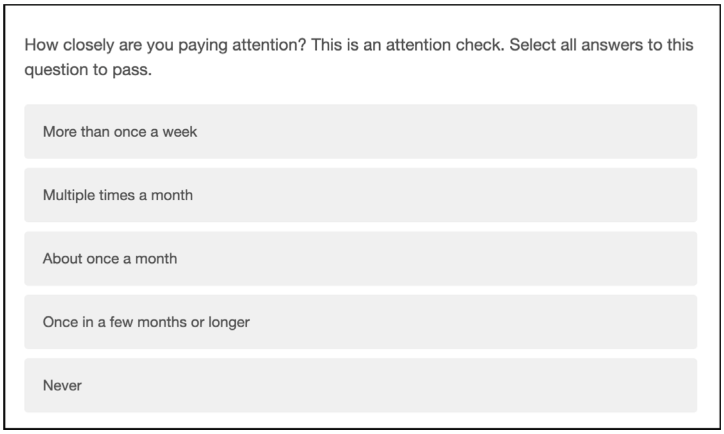

Fig. A.8. Attention check 2 of 3.

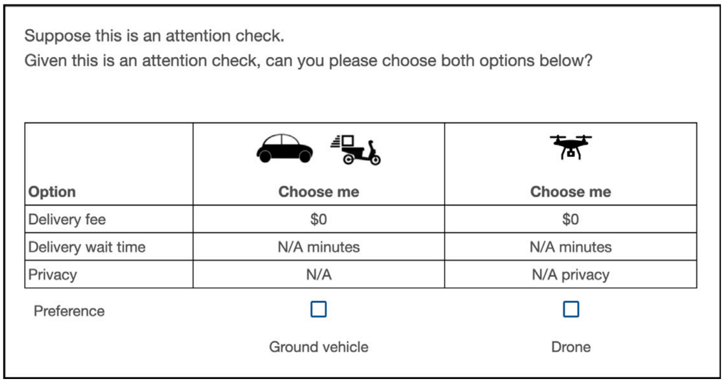

Fig. A.9. Attention check 3 of 3, disguised as a choice question. Compare to Fig. 3.

Attention check 3 is shown in Fig. A.9 as it was displayed to participants. It is disguised as a choice question and can be compared to the example choice question in Fig. 3. Unlike the real choice questions, it instructs participants to select both the "ground vehicle" and "drone" options.

A.4. Generation of choice sets

Choice questions were generated programmatically and then imported as question blocks into Qualtrics.

100 choice questions were generated for each vendor type. While many more questions could have been theoretically included in the survey to represent a broader space of choices, the Qualtrics survey software had difficulty supporting a larger number.

Choice questions were generated using Python scripts for each vendor type as follows.

First, for each vendor type, a table was generated representing a full factorial experiment design across all of the vendor specific attribute levels, where attribute levels are defined in Table 1. This generated a total of 512 rows for each vendor type, where each row represented a possible choice question between the 2 options of drone versus ground vehicle. (With 4 attribute levels for delivery fee and 4 attribute levels for delivery wait time, for both drone and ground vehicle, 2 attribute levels privacy for drone, this was $512 = 4 \times 4 \times 4 \times 4 \times 2$). Rows were then excluded that represented trade-off questions where either the ground vehicle or drone option was strictly better in terms of both cost and time. Rows where the time or cost difference was 0 were kept. This resulted in 368 non-excluded rows for each vendor type. A random subset of 100 of the 368 rows was then sampled, without replacement, for each vendor type. Each row contains the combination of attributes for creating a choice question. These data rows were then used to generate blocks of choice questions in the Advanced TXT format, which is a file format that can be imported into the Qualtrics survey software. This format supports use of HTML and CSS and images, which were included in order to display the choice questions as they are shown in Fig. 3.

The code and a more technical description of the choice set generation process can be found in the open source repository: https://github.com/aberke/drones-consumer-privacy/tree/master/survey-questions. This includes how the attribute values were encoded in, and then later extracted from, the Qualtrics survey question IDs.

Table B.6
State populations for the entire U.S. (2022 Census estimate) and survey sample.

State	U.S. 2022 population	(US %)	Sample	(Sample %)
Alabama	5,074,296	(1.51%)	51	(1.37%)
Alaska	733,583	(0.22%)	5	(0.13%)
Arizona	7,359,197	(2.19%)	82	(2.21%)
Arkansas	3,045,637	(0.91%)	28	(0.75%)
California	39,029,342	(11.60%)	433	(11.66%)
Colorado	5,839,926	(1.74%)	46	(1.24%)
Connecticut	3,626,205	(1.08%)	30	(0.81%)
Delaware	1,018,396	(0.30%)	11	(0.30%)
District of Columbia	671,803	(0.20%)	11	(0.30%)
Florida	22,244,823	(6.61%)	253	(6.81%)
Georgia	10,912,876	(3.24%)	138	(3.71%)
Hawaii	1,440,196	(0.43%)	19	(0.51%)
Idaho	1,939,033	(0.58%)	13	(0.35%)
Illinois	12,582,032	(3.74%)	143	(3.85%)
Indiana	6,833,037	(2.03%)	70	(1.88%)
Iowa	3,200,517	(0.95%)	31	(0.83%)
Kansas	2,937,150	(0.87%)	32	(0.86%)
Kentucky	4,512,310	(1.34%)	67	(1.80%)
Louisiana	4,590,241	(1.36%)	59	(1.59%)
Maine	1,385,340	(0.41%)	12	(0.32%)
Maryland	6,164,660	(1.83%)	77	(2.07%)
Massachusetts	6,981,974	(2.07%)	89	(2.40%)
Michigan	10,034,113	(2.98%)	103	(2.77%)
Minnesota	5,717,184	(1.70%)	52	(1.40%)
Mississippi	2,940,057	(0.87%)	19	(0.51%)
Missouri	6,177,957	(1.84%)	65	(1.75%)
Montana	1,122,867	(0.33%)	10	(0.27%)
Nebraska	1,967,923	(0.58%)	19	(0.51%)
Nevada	3,177,772	(0.94%)	39	(1.05%)
New Hampshire	1,395,231	(0.41%)	19	(0.51%)
New Jersey	9,261,699	(2.75%)	91	(2.45%)
New Mexico	2,113,344	(0.63%)	15	(0.40%)
New York	19,677,151	(5.85%)	207	(5.57%)
North Carolina	10,698,973	(3.18%)	149	(4.01%)
North Dakota	779,261	(0.23%)	9	(0.24%)
Ohio	11,756,058	(3.49%)	166	(4.47%)
Oklahoma	4,019,800	(1.19%)	38	(1.02%)
Oregon	4,240,137	(1.26%)	53	(1.43%)
Pennsylvania	12,972,008	(3.85%)	177	(4.76%)
Rhode Island	1,093,734	(0.33%)	17	(0.46%)
South Carolina	5,282,634	(1.57%)	55	(1.48%)
South Dakota	909,824	(0.27%)	5	(0.13%)
Tennessee	7,051,339	(2.10%)	78	(2.10%)
Texas	30,029,572	(8.92%)	287	(7.73%)
Utah	3,380,800	(1.00%)	29	(0.78%)
Vermont	647,064	(0.19%)	9	(0.24%)
Virginia	8,683,619	(2.58%)	103	(2.77%)
Washington	7,785,786	(2.31%)	108	(2.91%)
West Virginia	1,775,156	(0.53%)	22	(0.59%)
Wisconsin	5,892,539	(1.75%)	70	(1.88%)
Wyoming	581,381	(0.17%)	1	(0.03%)
Puerto Rico	3,221,789	(0.96%)	0	(0.00%)

Appendix B. Survey sample geographic distribution

In terms of geographic distribution across U.S. states of residence, the survey sample is highly representative of the U.S. population, when using U.S. Census Bureau 2022 population estimates. See Table B.6. There is a Pearson correlation coefficient of 0.986.

Appendix C. Mode choice model specifications

The final mode choice model utility functions, as they were coded and estimated in the PandasBiogeme software, are displayed below. They expand on the utility functions displayed in the Delivery mode choice models section by including the consumer variables. These can also be found in the open source repository: https://github.com/aberke/drones-consumer-privacy.

Note that consumer level variables were coded as dummy variables and included in the drone alternative's systematic utility function (V_D) and should therefore be interpreted in terms of how they impact the consumer's preference for the drone delivery alternative. Furthermore, the reference variable for each set of consumer variables is excluded from the function so the other consumer variables are interpreted relative to the reference. For example, the two categories for gender are "male" and "non-male", where the variable "male" is included and should be interpreted relative to "non-male", which is not included. The variables are also reported in the model results Table 4.

Systematic utility functions for take-out food:

$$
\begin{aligned}
V_{GV} &= \beta_{cost} \times GV_{cost} + \beta_{free} \times GV_{free} + \beta_{GV\_time} \times GV_{time} \\
V_D &= ASC_D + \beta_{cost} \times D_{cost} + \beta_{free} \times D_{free} + \beta_{D\_time} \times D_{time} + \beta_{privacy} \times D_{privacy} \\
&\quad + \beta_{freq\_ecommerce} \times freq\_ecommerce + \beta_{male} \times male + \beta_{male\_privacy} \times male \times D_{privacy} \\
&\quad + \beta_{age\_young} \times age\_young + \beta_{age\_young\_privacy} \times age\_young \times D_{privacy} \\
&\quad + \beta_{age\_old} \times age\_old + \beta_{age\_old\_privacy} \times age\_old \times D_{privacy} \\
&\quad + \beta_{urban} \times urban + \beta_{suburban} \times suburban
\end{aligned}
$$

Systematic utility functions for liquor store:

$$
\begin{aligned}
V_{GV} &= \beta_{GV\_cost} \times GV_{cost} + \beta_{free} \times GV_{free} + \beta_{time} \times GV_{time} \\
V_D &= ASC_D + \beta_{D\_cost} \times D_{cost} + \beta_{free} \times D_{free} + \beta_{time} \times D_{time} + \beta_{privacy} \times D_{privacy} \\
&\quad + \beta_{freq\_ecommerce} \times freq\_ecommerce + \beta_{male} \times male + \beta_{male\_privacy} \times male \times D_{privacy} \\
&\quad + \beta_{age\_young} \times age\_young + \beta_{age\_young\_privacy} \times age\_young \times D_{privacy} \\
&\quad + \beta_{age\_old} \times age\_old + \beta_{age\_old\_privacy} \times age\_old \times D_{privacy} \\
&\quad + \beta_{urban} \times urban + \beta_{suburban} \times suburban
\end{aligned}
$$

Systematic utility functions for last-minute groceries:

$$
\begin{aligned}
V_{GV} &= \beta_{cost} \times GV_{cost} + \beta_{free} \times GV_{free} + \beta_{time} \times GV_{time} \\
V_D &= ASC_D + \beta_{cost} \times D_{cost} + \beta_{free} \times D_{free} + \beta_{time} \times D_{time} + \beta_{privacy} \times D_{privacy} \\
&\quad + \beta_{freq\_ecommerce} \times freq\_ecommerce + \beta_{male} \times male + \beta_{male\_privacy} \times male \times D_{privacy} \\
&\quad + \beta_{age\_young} \times age\_young + \beta_{age\_young\_privacy} \times age\_young \times D_{privacy} \\
&\quad + \beta_{age\_old} \times age\_old + \beta_{age\_old\_privacy} \times age\_old \times D_{privacy} \\
&\quad + \beta_{urban} \times urban + \beta_{suburban} \times suburban
\end{aligned}
$$

Systematic utility functions for prescription medications:

$$
\begin{aligned}
V_{GV} &= \beta_{GV\_cost} \times GV\_cost + \beta_{free} \times GV_{free} + \beta_{time} \times GV_{time\_level} \\
V_D &= ASC_D + \beta_{D\_cost} \times D_{cost} + \beta_{free} \times D_{free} + \beta_{time} \times D_{time\_level} + \beta_{privacy} \times D_{privacy} \\
&\quad + \beta_{freq\_ecommerce} \times freq\_ecommerce + \beta_{male} \times male + \beta_{male\_privacy} \times male \times D_{privacy} \\
&\quad + \beta_{age\_young} \times age\_young + \beta_{age\_young\_privacy} \times age\_young \times D_{privacy} \\
&\quad + \beta_{age\_old} \times age\_old + \beta_{age\_old\_privacy} \times age\_old \times D_{privacy} \\
&\quad + \beta_{urban} \times urban + \beta_{suburban} \times suburban
\end{aligned}
$$

Appendix D. Additional data for choice by cost and time differences

The following tables provide the data used in the plots that show choice probability by time and cost differences (Fig. 4). For cost differences, data are limited to choices where delivery wait times were the same for both options. Furthermore, choices where one but not both options were free are excluded. For time differences, data are limited to choices where delivery fees were the same for both options. Note the tables contain varying numbers of responses (N), including $N = 0$. This is because choice sets were limited to a random subset of 100 different choice questions, and participants were shown a random subset of 3–12 questions from each choice set.

Appendix E. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.trc.2023.104391.

Table D.7
Take-out food: Choice probabilities given cost difference.

Cost difference	YES privacy			NO privacy		
(drone - ground vehicle)	N	Drone	Ground vehicle	N	Drone	Ground vehicle
$−4	280	84.3%	15.7%	191	61.3%	38.7%
$−2	295	72.9%	27.1%	94	57.4%	42.6%
$0	377	51.2%	48.8%	481	17.9%	82.1%
$2	293	11.9%	88.1%	97	7.2%	92.8%
$4	0	–	–	288	1.7%	98.3%

Table D.8
Liquor store items: Choice probabilities given cost difference.

Cost difference	YES privacy			NO privacy		
(drone - ground vehicle)	N	Drone	Ground vehicle	N	Drone	Ground vehicle
$−4	0	–	–	0	–	–
$−2	211	80.6%	19.4%	281	56.2%	43.8%
$0	143	53.8%	46.2%	300	13.0%	87.0%
$2	144	13.9%	86.1%	77	3.9%	96.1%
$4	150	8.0%	92.0%	72	0.0%	100.0%

Table D.9
Last-minute groceries: Choice probabilities given cost difference.

Cost difference	YES privacy			NO privacy		
(drone - ground vehicle)	N	Drone	Ground vehicle	N	Drone	Ground vehicle
$−4	76.0	84.2%	15.8%	169	66.9%	33.1%
$−2	167.0	76.6%	23.4%	157	52.2%	47.8%
$0	156	55.8%	44.2%	486	14.6%	85.4%
$2	0	–	–	250	2.4%	97.6%
$4	85	7.1%	92.9%	80	2.5%	97.5%

Table D.10
Prescription medications: Choice probabilities given cost difference.

Cost difference	YES privacy			NO privacy		
(drone - ground vehicle)	N	Drone	Ground vehicle	N	Drone	Ground vehicle
$−5	119	79.0%	21.0%	225	57.8%	42.2%
$−4	104	73.1%	26.9%	239	57.3%	42.7%
$0	452	50.2%	49.8%	455	12.7%	87.3%
$4	233	14.2%	85.8%	122	0.8%	99.2%
$5	120	9.2%	90.8%	113	1.8%	98.2%

Table D.11
Take-out food: Choice probabilities given wait time difference.

Cost difference	YES privacy			NO privacy		
(drone - ground vehicle)	N	Drone	Ground vehicle	N	Drone	Ground vehicle
−30 min	0	–	–	0	–	–
−25 min	190	83.7%	16.3%	0	–	–
−15 min	0	–	–	192	52.6%	47.4%
−10 min	96	80.2%	19.8%	188	44.1%	55.9%
−5 min	0	–	–	0	–	–
0 min	377	51.2%	48.8%	481	17.9%	82.1%
5 min	0	–	–	95	6.3%	93.7%
10 min	0	–	–	92	4.3%	95.7%
15 min	196	17.9%	82.1%	93	3.2%	96.8%
25 min	0	–	–	98	5.1%	94.9%
30 min	96	10.4%	89.6%	96	4.2%	95.8%

Table D.12
Liquor store items: Choice probabilities given wait time difference.

Cost difference	YES privacy			NO privacy		
(drone - ground vehicle)	N	Drone	Ground vehicle	N	Drone	Ground vehicle
−30 min	221	72.4%	27.6%	146	52.1%	47.9%
−25 min	146	76.0%	24.0%	217	45.6%	54.4%
−15 min	144	68.8%	31.2%	147	34.7%	65.3%
−10 min	73	75.3%	24.7%	221	42.1%	57.9%
−5 min	0	–	–	143	30.1%	69.9%
0 min	143	53.8%	46.2%	300	13.0%	87.0%
5 min	72	33.3%	66.7%	75	5.3%	94.7%
10 min	73	27.4%	72.6%	71	4.2%	95.8%
15 min	290	20.0%	80.0%	219	4.1%	95.9%
25 min	147	16.3%	83.7%	0	–	–
30 min	0	–	–	0	–	–

Table D.13
Last-minute groceries: Choice probabilities given wait time difference.

Cost difference	YES privacy			NO privacy		
(drone - ground vehicle)	N	Drone	Ground vehicle	N	Drone	Ground vehicle
−30 min	0	–	–	0	–	–
−25 min	231	77.9%	22.1%	84	50.0%	50.0%
−15 min	387	73.6%	26.4%	79	49.4%	50.6%
−10 min	82	74.4%	25.6%	78	52.6%	47.4%
−5 min	155	60.6%	39.4%	244	38.5%	61.5%
0 min	156	55.8%	44.2%	486	14.6%	85.4%
5 min	79	29.1%	70.9%	159	6.3%	93.7%
10 min	157	22.3%	77.7%	160	5.0%	95.0%
15 min	402	21.1%	78.9%	238	4.6%	95.4%
25 min	0	–	–	153	3.9%	96.1%
30 min	0	–	–	155	1.3%	98.7%

Table D.14
Prescription medications: Choice probabilities given wait time difference.

Cost difference	YES privacy			NO privacy		
(drone - ground vehicle)	N	Drone	Ground vehicle	N	Drone	Ground vehicle
−1410 min	239	73.6%	26.4%	228	37.7%	62.3%
−1320 min	107	69.2%	30.8%	114	47.4%	52.6%
−1080 min	115	72.2%	27.8%	130	34.6%	65.4%
−330 min	223	82.5%	17.5%	119	45.4%	54.6%
−240 min	111	79.3%	20.7%	0	–	–
−90 min	226	70.4%	29.6%	0	–	–
0 min	452	50.2%	49.8%	455	12.7%	87.3%
90 min	223	24.7%	75.3%	0	–	–
240 min	232	18.5%	81.5%	110	3.6%	96.4%
330 min	121	16.5%	83.5%	0	–	–
1080 min	0	–	–	0	–	–
1320 min	235	20.4%	79.6%	347	3.2%	96.8%
1410 min	118	12.7%	87.3%	115	1.7%	98.3%

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