



Article

# Examining the Retail Delivery Choice Behavior in a Technology-Aware Market

Jocelyn Tapia <sup>1</sup>, Paula Fariña <sup>2,\*</sup>, Ignacio Urbina <sup>2</sup> and Diego Dujovne <sup>2</sup>

<sup>1</sup> Universidad Técnica Federico Santa María, Av. España 1680, Valparaíso 2580816, Chile; jocelyn.tapias@usm.cl

<sup>2</sup> Universidad Diego Portales, Vergara 210, Santiago 8370067, Chile; ignacio.urbina@mail.udp.cl (I.U.); diego.dujovne@mail.udp.cl (D.D.)

\* Correspondence: paula.farina@udp.cl

**Abstract:** This study aims to provide valuable insights into consumer preferences for delivery services in online shopping in Chile. The COVID-19 pandemic has accelerated the evolution of delivery and logistics services, leading to increased competition among online stores. Chile, with its highly digitally enabled population and a competitive landscape of online retailers, serves as an ideal reference case for Latin America. By analyzing key delivery attributes such as delivery time, order arrival time range, compensation policies for delivery delays, and delivery prices, we offer valuable insights into consumer behavior. These insights will, in turn, inform the formulation of effective strategies within the online shopping industry. We examine the following aspects: (a) The willingness of consumers to pay for the service attributes; (b) The relative importance assigned to these attributes by consumers; and (c) The relationship between consumer preferences and socioeconomic characteristics. Using Multinomial Logit Models and a database from a Discrete Choice Experiment, we have discovered that the most significant attributes of delivery service are the time until product arrival and the existence of compensation in case of delivery delays. Additionally, we found that consumers are willing to pay more for the same delivery service if the product is large, as large products generally have higher prices. Furthermore, we observed that delivery time preferences vary by gender and for small products, and price sensitivity varies according to educational level, household size, and socioeconomic status. To the best of our knowledge, no previous research of this kind has been conducted for Chile.

**Keywords:** delivery-pricing; willingness-to-pay; Latin America e-commerce; discrete choice models; conjoint analysis



**Citation:** Tapia, J.; Fariña, P.; Urbina, I.; Dujovne, D. Examining the Retail Delivery Choice Behavior in a Technology-Aware Market. *J. Theor. Appl. Electron. Commer. Res.* **2024**, *19*, 1392–1410. <https://doi.org/10.3390/jtaer19020070>

Academic Editor: Danny C.K. Ho

Received: 13 March 2024

Revised: 16 May 2024

Accepted: 22 May 2024

Published: 4 June 2024

**Correction Statement:** This article has been republished with a minor change. The change does not affect the scientific content of the article and further details are available within the backmatter of the website version of this article.



**Copyright:** © 2024 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

## 1. Introduction

In recent years, the online shopping market has expanded worldwide. Specifically, in Chile, in 2021, e-commerce sales grew by 23% compared to the previous year and the percentage of Chilean consumers who buy online reached 63% [1]. This percentage is expected to continue increasing and reach 69% in 2025. During the 2020–2021 period, online sales increased mainly due to quarantines and mobility restrictions, together with the increase in household liquidity. This situation forced the acceleration of digitization processes and generated changes in consumption patterns.

Along with the increase in e-commerce sales, the delivery services market has expanded according to consumers' demands, see [2]. The delivery service may considerably affect the purchase intention of consumers, who may even abandon a purchase when the delivery service is unattractive. The delivery service comprises various attributes which can influence customers' willingness to pay. Therefore, it is crucial to identify the key characteristics that customers value the most. This will provide valuable insights to delivery service providers, enabling them to make more informed decisions.

In this paper we study the demand for delivery service in Chile evaluating the willingness to pay for delivery services. Since standard techniques provide estimations of

willingness to pay that are dependent on the unit of measure, we have also incorporated an adjustment in our estimations. This adjustment enables us to examine the relative importance consumers assign to the various attributes of the delivery service. Additionally, this paper investigates whether there is a relationship between socio-demographic characteristics and the attributes of the delivery service. Building on the works of [3,4], we conducted a Discrete Choice Experiment (DCE). For this purpose, we designed a survey and applied it to 424 consumers in the city of Santiago, Chile. The delivery service attributes we considered are: *delivery time*, *time range of order arrival*, whether there is *compensation* or not in case of not meeting the delivery date, and the *delivery price*. By using the multinomial logit technique, we found that the most crucial attributes of the delivery service for Chilean consumers are the *delivery time* and *compensation*.

Additionally, we found that willingness to pay for delivery service increases with the size of the product, as consumers tend to evaluate delivery costs in relation to product prices, and larger products generally present higher prices. Finally, we identified significant interactions between consumer sociodemographic characteristics and delivery attributes. This fact suggests the existence of consumer segments that value delivery attributes differently. For example, we have observed that females exhibit a stronger preference for a delivery range of 2 to 5 days when it comes to small products, but a relatively lower preference for the same delivery range when it comes to large products. Additionally, we have noticed that consumers with higher educational levels and/or higher socioeconomic status display less price sensitivity.

The rest of the paper is organized as follows: after this introduction, Section 2 describes the state of the art, Section 3 presents the theoretical background; Section 4 describes the methodology used in this paper; Section 5 presents the results and Section 6 discusses and concludes the paper.

## 2. Literature Review

The literature on willingness to pay for delivery services is generally scarce. To our knowledge, no previous research has been conducted on the willingness to pay for delivery services in Chile. Ref. [4] evaluate the willingness to pay for the compensation service in case of delayed delivery in China. They conduct a discrete choice experiment where individuals are presented with a form with 6 sheets. Each slide has 3 alternatives: 2 different compensation services, and an exclusion alternative in which consumers choose not to contract a compensation service. The authors considered the following attributes: Delay probability display (99% probability of on-time arrival, 1% probability of delay, no delay probability display), compensation amount (fixed amount, progressive amount up to 70% of product value), compensation payment method (cash or voucher), penalty for the delivery person (no penalty, delivery person pays compensation, delivery person is penalized in their application score), and the price of the service (0.3 yuan, 0.6 yuan, 0.9 yuan, 1.2 yuan). Their results showed that a progressive compensation scheme has a higher valuation and increased willingness to pay while penalizing deliverymen decreases willingness to pay. However, this study concentrates only in understanding the value of compensation and not on delivery pricing. Moreover, they use a discrete choice experiment, while this work offers better insight by providing the participants with a wider range of alternatives generated by the conjoint methodology.

There are three different works that cover delivery preferences using a similar methodology, but with different objectives. First, ref. [3] investigate Dutch consumer delivery preferences attributes in online retailing across product categories. They implement a conjoint analysis concluding that the most relevant delivery attributes are delivery fee, delivery speed, time slot, delivery date, and daytime/evening delivery, in decreasing order. They also used cluster analysis to identify three segments of consumers, namely a price-oriented, a time- and convenience-oriented, and a value-for-money-oriented segment. Another relevant result of their study was that gender and income showed a relationship with the identified segments. Second, ref. [5] introduce adaptive choice modelling, which

is an improved methodology that builds upon the conjoint analysis, to study how parcel shipping customers make purchase choice decisions about logistics services. The authors found that price, speed of delivery and tracking are the three most important variables when selecting the most relevant option. Their results also show that consumers are not homogeneous, but can be divided into five distinct need-based segments. And third, ref. [6] analyze the preference structures of online grocery consumers using a choice-based conjoint experiments administered online. They found that a significant market advantage can be gained by being simultaneously “best in class” on the top four attributes. Despite being extensively employed in the retail and service sectors: see [7–11] as examples, the conjoint analysis is limited in its application to analyzing delivery attributes. Unlike the former publications, our work is aimed to understand the customer preferences in a latin-american context where there is a technology-aware population, a characteristic scenario of Chile. Moreover, our work shows different conclusions on the behaviour and value given to the aforementioned attributes.

Another group of publications address this topic from different methodological approaches: ref. [12] develop an instrument to identify the key convenience dimensions of online shopping. They found five relevant dimensions of online shopping convenience: access, search, evaluation, transaction, and possession/post-purchase convenience. Ref. [13] investigate the potential of a new service at the interface between retailers and consumers: time-based delivery of parcels. They measure consumers’ willingness to pay for this service through a contingent valuation approach. Their results suggest that the time the customer is available at home and the working hours per week are important sources of the perceived attractiveness of the service, and that consumers who perceive this new service as attractive, represent a market segment that has significant revenue potential. In the Latin American context, a research by [14] examined the impact of delivery attributes, such as delivery time and price, and condition of received orders on Brazilian consumers. Dias et al. also analyze the satisfaction and repurchase intention using artificial neural networks and logistic regressions. The results showed that delivery time and the condition of the received order were the most important characteristics for Brazilian consumers. Furthermore, they discovered that age, educational level, and online shopping frequency affect the importance consumers give to each delivery service attribute. Other relevant articles dealing with delivery service are [15–25].

### 3. Theoretical Background

According to the consumer theory proposed by [26], for an individual, the utility generated by the consumption of a good or service depends on the multiple attributes it possesses. Therefore, the utility generated by the delivery service will depend on the collection of characteristics that it possesses. Changes in the characteristics of the service can change the choices of those who consume the service.

Random utility theory [27–31] considers that the decisions of individuals faced with a discrete set of alternatives can be modeled by comparing the utilities for each alternative. The individual will choose the alternative that provides the greatest utility: This decision process is known to the decision-maker, but not to the researcher who analyzes him/her. The researcher only observes the attributes of the alternative chosen by the decision maker.

Mathematically, the utility generated by alternative  $j$  for a decision maker  $n$  is represented by  $U_{nj}$ , and can be separated into two components:  $V_{nj}$ , which corresponds to the part of the utility explained by the observable variables, and  $\epsilon_{nj}$  which is the unexplained part and is modeled by a random variable. Utility can be represented in linear form, assuming the form:

$$U_{nj} = V_{nj} + \epsilon_{nj} = \beta X_{nj} + \epsilon_{nj},$$

where  $X_{nj}$  represents the vector of attributes of the alternative;  $\beta$  represents a vector of parameters associated with each attribute; and  $\epsilon_{nj}$  represents the unobservable utility.

By assigning a joint distribution to the random vector  $\epsilon_n$ , it is possible to calculate the probability that alternative  $i$  is chosen by person  $n$  as:

$$P_{ni} = \text{Prob}(U_{ni} > U_{nj}, \forall j \neq i) = \text{Prob}(\epsilon_{ni} - \epsilon_{nj} > \beta(X_{nj} - X_{ni}), \forall j \neq i)$$

Different discrete choice models are obtained by different specifications of this distribution. The Gumbel and the Normal distributions are the most commonly used, which give rise to the Multinomial Logit estimation model (MNL) and the Multinomial Probit model, respectively. Both models can be understood as an extension of the simple Logit and Probit models. In this paper we use the MNL model that is described in Section 4.

Willingness to pay is defined by the monetary amount a person would spend for a given attribute of the good or service. It is the marginal rate of substitution between the attribute and the price. This rate can be obtained by differentiating the utility function and calculating the change in an attribute  $A$  and the price that would have to be given to keep utility constant.

$$\Delta V_{nj} = \beta_A \Delta A_{nj} + \beta_P \Delta p_{nj} = 0$$

This implies that the willingness to pay for attribute  $A$  is given by:

$$\frac{\Delta p_{nj}}{\Delta A_{nj}} = -\frac{\beta_A}{\beta_P}$$

The quotient between the coefficient of an attribute  $A$  and the coefficient associated with the price in the case of a linear utility function.

## 4. Materials and Methods

### 4.1. Estimation

The probability of choosing alternative  $i$  by individual  $n$  under the MNL model is:

$$P_{ni} = \text{Prob}(U_{ni} > U_{nj}, \forall j \neq i) = \frac{e^{\beta X_{ni}}}{\sum_j e^{\beta X_{nj}}}$$

$P_{ni}$  represents the probability that individual  $n$  chooses alternative  $i$ . The maximum likelihood method is used to obtain the  $\beta$  estimators. The likelihood function is given by:

$$\max_{\beta} L = \prod_n \prod_i (P_{ni})^{\delta_{ni}},$$

where  $\delta_{ni}$  takes the value 1 if individual  $n$  chooses alternative  $i$  and 0 otherwise.

We analyze three groups of MNL models: The first one seeks to measure the willingness to pay of the attributes using their main effects estimations of coefficients. In this case, price is considered a continuous variable, while the remaining attributes as categorical variables. In the second group of models, both, the price and the remaining attributes are introduced as categorical variables, using the *effect coding* approach ([32]). This variable characterization allows us to determine the relative importance of each attribute (see [3]). Finally, the third group of models explores the presence of interaction between the attributes and the socioeconomic characteristics of the respondents. Each group of models considers both, large and small products separately, allowing for a comparison of estimations between the two product types.

For the first group of models, we consider the suggestion by [33] to omit the global intercept in order to enable better estimations of willingness to pay in MNL regressions. The consumers' willingness to pay for the attributes is approximated by dividing the estimated coefficients of the attributes and the coefficient associated with price:

$$D\hat{P}_j = -\frac{\hat{\beta}_j}{\hat{\beta}_p}$$

where  $DP_j$  is the willingness to pay for attribute  $j$ ,  $\beta_j$  is the coefficient associated with attribute  $j$  and  $\beta_p$  is the coefficient associated with price. The Delta method is used to calculate the standard errors of the willingness to pay since it provides an asymptotic estimator for the standard error:

$$\hat{DP}_j \stackrel{asint}{\sim} N\left(DP_j, \nabla(DP_j)' \Sigma_{DP_j} \nabla(\hat{DP}_j)\right)$$

where  $\nabla(DP_j)$  is the differential of the willingness to pay,  $\Sigma_{DP_j}$  is the variances-covariance matrix of the vector  $(\beta_j, \beta_p)'$ . For the particular case of a linear utility function we have:

$$V(\hat{DP}_j) = \frac{V(\hat{\beta}_j)}{\hat{\beta}_p^2} - 2 \frac{\hat{\beta}_j \text{Cov}(\hat{\beta}_j, \hat{\beta}_p)}{\hat{\beta}_p^3} + \frac{\hat{\beta}_j^2 V(\hat{\beta}_p)}{\hat{\beta}_p^4}$$

In the second group of models, the relative importance of each attribute is calculated directly with the model coefficients. The relative importance of attribute  $j$  is given by:

$$W_j = \frac{I_j}{\sum_{s=1}^m I_s}$$

where  $I_j$  is the importance of the attribute  $j$ ,  $I_j$  is calculated as  $\{\max(\beta_{ij}) - \min(\beta_{ij})\}$ , and  $i$  represents the level of the categorical variable. Note that  $\sum_{j=1}^m W_j = 1$ . Finally, a third group of MNL models that includes interaction effects are used to explore the existence of consumer segments that value delivery attributes differently.

#### 4.2. Survey Design

The survey is composed of two parts: questions about respondent information and the discrete choice experiment. In the first part, questions are asked about socio-demographic data, previous online shopping experiences and aspects that may influence the choice of a delivery service.

The survey is only answered by people who have made online or telephonic purchases in the last six months and who usually use delivery services. The sample was extracted from a panel. The specific details of this extraction process can be found in Section 4.3. In the discrete choice experiment, participants repeatedly select their preferred delivery service within various hypothetical scenarios. Specifically, the questionnaire consists of 10 slides, each of which presents the participant with three different delivery service alternatives. Four different attributes define each delivery service alternative: time to availability of the product (with three options), compensation policy in case of late delivery (with three options), delivery time range (with three options), and delivery cost (with four options). When combined, these attributes generate a total of 108 delivery service alternatives. A comprehensive breakdown of the available options for each attribute can be found in Table 1.

The format of the second part of the survey assumes consumer behavior according to the random utility model [27,28,34] mentioned in Section 3, where the decision maker assigns a utility to each alternative and chooses the one that gives the most utility. It should be remarked that the data collected are *hypothetical* choices. In that sense, it can be understood as a pseudo-experiment: respondents only *declare* their preferences for one alternative.

One of the main characteristics that determines the cost of the delivery service is the size of the product being shipped, for this reason the total number of respondents will be randomly distributed in two surveys that are differentiated by the type of product for which the delivery service is acquired. The first half of the respondents will be asked about the preferred service for the delivery of a large product and the second half will be asked about the preferred service for the delivery of a small product with a price above CL\$30,000 (US\$ 37.62). In both surveys the delivery service will be characterized by the same attributes

differing only in the price range. The delivery service for small products will have as price alternatives CL\$0, CL\$2000 (U\$S 2.51), CL\$3500 (U\$S 4.39) and CL\$5000 (U\$S 6.27), while the service for large products will have as price alternatives CL\$0, CL\$10,000 (U\$S 12.54), CL\$15,000 (U\$S 18.81) and CL\$20,000 (U\$S 25.08).

**Table 1.** Attributes y *delivery* service levels.

| Attributes                 | Levels                                           |                         |
|----------------------------|--------------------------------------------------|-------------------------|
|                            | Small Product                                    | Large Product           |
| Delivery price             | \$0                                              | \$0                     |
|                            | CL\$2500 (U\$S 3.14)                             | CL\$10,000 (U\$S 12.54) |
|                            | CL\$3500 (U\$S 4.40)                             | CL\$15,000 (U\$S 18.81) |
|                            | CL\$4500 (U\$S 5.64)                             | CL\$20,000 (U\$S 25.08) |
| Delivery time range        | 2-h time range                                   |                         |
|                            | 6-h time range (morning or afternoon)            |                         |
|                            | 12-h delivery range (During the day)             |                         |
| Time until product arrival | One day (Next day)                               |                         |
|                            | 2 to 5 days                                      |                         |
|                            | 6 to 15 days                                     |                         |
| Late delivery compensation | No compensation                                  |                         |
|                            | Gift card from the same company                  |                         |
|                            | Money refund directly to the Credit Card account |                         |

The classification between large and small products is required due to the relative difference in delivery process by couriers among them. A large product, such as a bed or refrigerator is generally given a higher delivery price than smaller products, and requires a different type of handling. To the contrary, smaller products, such as a cellular phone or a pair of shoes, can be delivered to concierges or left inside mailboxes without special handling for voluminous packages. This topic has already been addressed in previous literature, see [35,36]. Consequently, we have separated the category in large and small products to adjust the possible delivery pricing to different ranges. The conjoint analysis presented to the participant a number of graphical examples of typical large and small products as guide. The large products were depicted as in Figure 1 and the small products were shown as in Figure 2.



**Figure 1.** Large product graphical description from the conjoint form. Source: own elaboration.



**Figure 2.** Small product graphical description from the conjoint form. Source: own elaboration.

Due to the large number of combinations of possible choice sets, we use the “Modfed” function of the R package “idefix” to reduce the number of choice sets and maximize the information obtained from the responses of each set of alternatives ([37]). One relevant problem in the design of choice sets is the existence of dominant and dominated alternatives ([38]). One alternative dominates another if the former possesses better characteristics

for each of the attributes. In order to solve this problem, an informative prior is used to reduce the number of choice sets with dominant and dominated alternatives. For each type of product, we generated 100 sheets and we divided them into 10 different questionnaires. Each respondent was randomly assigned a 10-sheet questionnaire, and on each sheet, the respondents had to choose between three delivery service alternatives. Tables 2 and 3 present an example of the sheets for large and small product, respectively.

**Table 2.** Large product sheet.

|                                     | Alternative 1   | Alternative 2                   | Alternative 3                                    |
|-------------------------------------|-----------------|---------------------------------|--------------------------------------------------|
| Delivery time                       | 2 to 5 days     | 1 day                           | 6 to 15 days                                     |
| Compensation type for late delivery | No compensation | Gift card from the same company | Money refund directly to the Credit Card account |
| Delivery time range                 | 12-h range      | 2-h range                       | 6-h range                                        |
| Delivery price                      | \$0             | \$15.000                        | \$10.000                                         |

**Table 3.** Small product sheet.

|                                     | Alternative 1   | Alternative 2                   | Alternative 3                                    |
|-------------------------------------|-----------------|---------------------------------|--------------------------------------------------|
| Delivery time                       | 2 to 5 days     | 1 day                           | 6 to 15 days                                     |
| Compensation type for late delivery | No compensation | Gift card from the same company | Money refund directly to the Credit Card account |
| Delivery time range                 | 12-h range      | 2-h range                       | 6-h range                                        |
| Delivery price                      | \$3500          | \$0                             | \$2500                                           |

#### 4.3. The Sample Strategy

A non-probabilistic sample of 424 individuals was selected from a panel of 346,261 Chilean panelists for the purpose of this study. The survey was conducted by a reputable research firm that also supplied the panel. This sampling strategy was chosen to ensure the participation of different segments within the sample. Table 4 presents the size and percentages of population segments. Although the resulting sample is not representative of Santiago, Chile, it is still useful for comparing the willingness to pay between groups with different socioeconomic characteristics.

**Table 4.** Socioeconomic Segments: Frequencies and Percentages. \* ABC1 (the sum of individuals classified as upper class, affluent middle class and emerging middle class), C2 (typical middle class), C3 (lower middle class), D (vulnerable middle class), and E (poor).

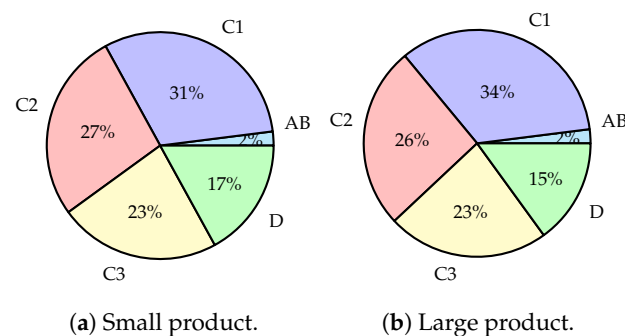
| Socioeconomic Characteristic | Small Product |            | Large Product |            | Total     |            |
|------------------------------|---------------|------------|---------------|------------|-----------|------------|
|                              | Frequency     | Percentage | Frequency     | Percentage | Frequency | Percentage |
| ABC1 *                       | 78            | 37         | 69            | 33         | 147       | 35         |
| C2                           | 56            | 26         | 58            | 2          | 114       | 27         |
| C3                           | 46            | 22         | 49            | 23         | 95        | 22         |
| D                            | 32            | 15         | 36            | 17         | 68        | 16         |
| 18 to 25 years               | 12            | 6          | 14            | 7          | 26        | 6          |
| 26 to 35 years               | 37            | 18         | 45            | 21         | 82        | 19         |
| 36 to 45 years               | 68            | 32         | 73            | 34         | 141       | 33         |
| 46 to 55 years               | 61            | 29         | 54            | 26         | 115       | 27         |
| 55 to 65 years               | 23            | 11         | 20            | 9          | 43        | 10         |
| More than 65 years           | 11            | 4          | 6             | 3          | 17        | 4          |
| Hombres                      | 96            | 45         | 91            | 43         | 187       | 44         |
| Mujeres                      | 116           | 55         | 121           | 57         | 237       | 56         |
| Central Zone                 |               |            |               |            | 24        | 6          |
| North Zone                   |               |            |               |            | 80        | 21         |
| East Zone                    |               |            |               |            | 112       | 27         |
| West Zone                    |               |            |               |            | 24        | 5          |
| South Zone                   |               |            |               |            | 70        | 19         |
| South-East Zone              |               |            |               |            | 90        | 22         |
| Total                        | 212           | 100        | 212           | 100        | 424       | 100        |

## 5. Results

The survey was conducted between 16 and 21 November 2022 in digital format. It garnered 424 responses from residents of the Metropolitan Region of Santiago, Chile. From the total number of participants, 212 answered questionnaires for the large product and 212 for the small product. The people surveyed are part of a panel provided by a statistical consulting firm dedicated to market research in Chile. The sample was segmented by gender, age range and socioeconomic status to explore the delivery preferences of different groups.

### 5.1. Socio-Demographic Characteristics of the Sample

Table 5 shows that female participation in both subsamples was higher than male participation, with 57% and 55% respectively and that age distribution is concentrated in the range between 26 and 55 years old (close to 80%) in both samples. In terms of socioeconomic level, the C1 level is the most represented with 31 and 34% for small and large products, respectively. The participation in the sample decreases as the socioeconomic level decreases (from C1 to D). The least represented level is AB with 2% (see Figure 3).



**Figure 3.** Socioeconomic level of the respondents.

In relation to the educational profile, the Table 5 shows that more than 80% have higher education, whether incomplete, complete or postgraduate. In addition, more than 75% of the sample is employed either as a dependent or self-employed worker, and close to 50% of the respondents live in households with more than 4 members.

**Table 5.** Socio-demographic characteristics of the sample.

| Variable          |                          | Small Product Survey |            | Large Product Survey |            |
|-------------------|--------------------------|----------------------|------------|----------------------|------------|
|                   |                          | Frequency            | Percentage | Frequency            | Percentage |
| Gender            | Male                     | 91                   | 43%        | 96                   | 45%        |
|                   | Female                   | 121                  | 57%        | 116                  | 55%        |
| Age range         | 18 to 25 years           | 14                   | 7%         | 12                   | 6%         |
|                   | 26 to 35 years           | 45                   | 21%        | 37                   | 17%        |
|                   | 36 to 45 years           | 73                   | 34%        | 68                   | 32%        |
|                   | 46 to 55 years           | 54                   | 25%        | 61                   | 29%        |
|                   | 56 to 65 years           | 20                   | 9%         | 23                   | 11%        |
|                   | ≥65                      | 6                    | 3%         | 11                   | 5%         |
| Educational level | Incomplete primary       | 1                    | 0%         | 0                    | 0%         |
|                   | Complete primary         | 2                    | 1%         | 1                    | 0%         |
|                   | Incomplete secondary     | 7                    | 3%         | 3                    | 1%         |
|                   | Complete secondary       | 34                   | 16%        | 26                   | 12%        |
|                   | Incomplete undergraduate | 34                   | 16%        | 35                   | 17%        |
|                   | Complete undergraduate   | 120                  | 57%        | 133                  | 63%        |
|                   | Postgraduate             | 14                   | 7%         | 14                   | 7%         |

Table 5. Cont.

| Variable                 |                    | Small Product Survey |            | Large Product Survey |            |
|--------------------------|--------------------|----------------------|------------|----------------------|------------|
|                          |                    | Frequency            | Percentage | Frequency            | Percentage |
| Main activity            | Student            | 9                    | 4%         | 6                    | 3%         |
|                          | Housekeeper        | 17                   | 8%         | 14                   | 7%         |
|                          | Unemployed         | 17                   | 8%         | 17                   | 8%         |
|                          | Independent worker | 36                   | 17%        | 40                   | 19%        |
|                          | Dependant worker   | 123                  | 58%        | 123                  | 58%        |
|                          | retired            | 8                    | 4%         | 10                   | 5%         |
|                          | Other              | 2                    | 1%         | 2                    | 1%         |
| Number of family members | 1                  | 12                   | 6%         | 11                   | 5%         |
|                          | 2                  | 26                   | 12%        | 26                   | 12%        |
|                          | 3                  | 62                   | 29%        | 64                   | 30%        |
|                          | 4                  | 65                   | 31%        | 64                   | 30%        |
|                          | ≥5                 | 47                   | 22%        | 46                   | 22%        |

### 5.2. Descriptive Analysis of the Survey Results

Online shopping consumers show frequent shopping behavior: more than 80% made their last transaction during the last month before the survey for both small and large products as seen in Figure 4. At the same time, almost everyone who makes remote purchases (97%) uses a delivery service.

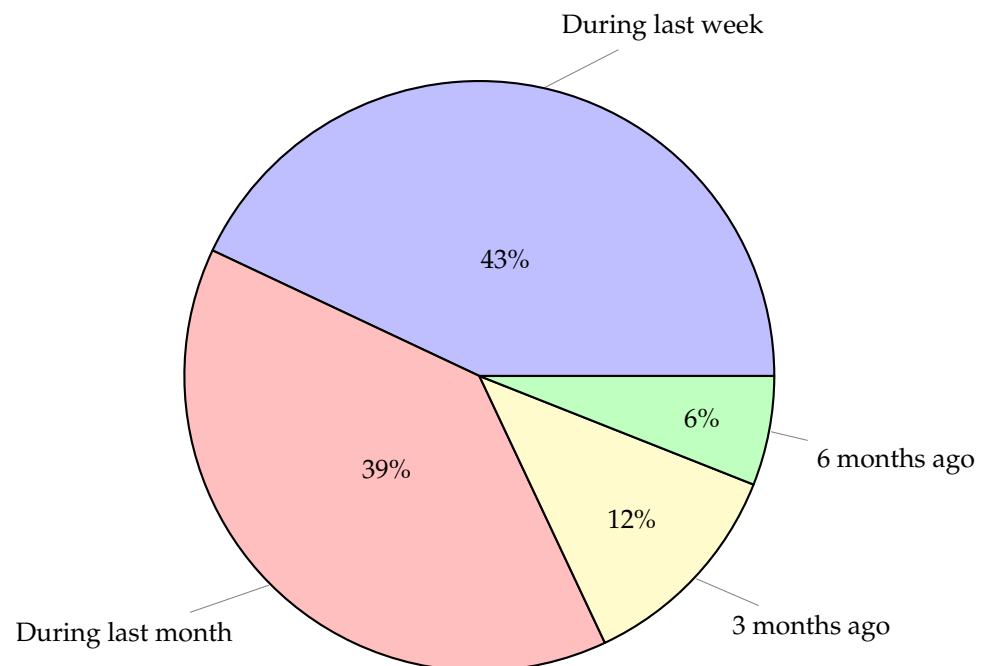
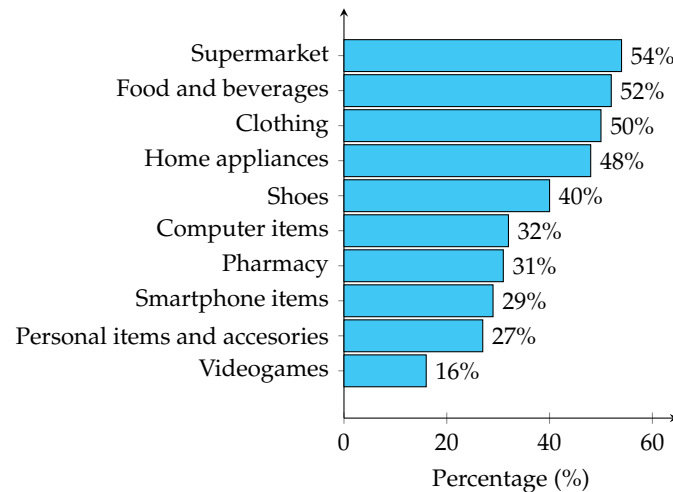


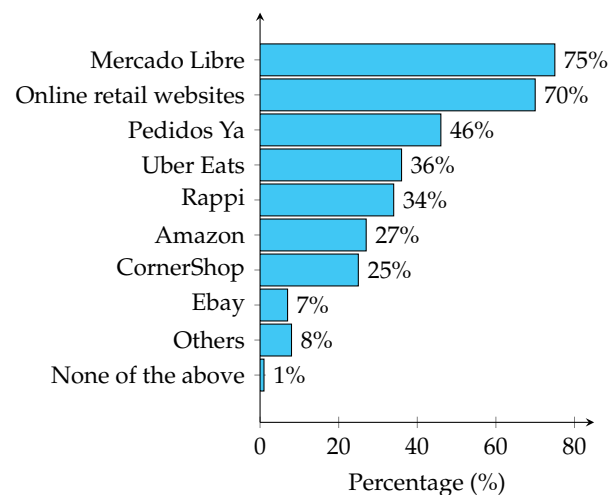
Figure 4. Last order.

The small product categories most frequently purchased by delivery are supermarkets, food and beverages, and clothing, with 54%, 52% and 50%, respectively. The large product category that is most purchased using delivery is white goods and household appliances (see Figure 5).



**Figure 5.** Delivery purchases.

Figure 6 shows that the most used online shopping delivery is Mercado Libre, followed by retail websites.



**Figure 6.** Plataform or APPs use.

### 5.3. Willingness to Pay Estimation

A multinomial logit regression was estimated for the large product sample and another for the small product sample (details in Table A1). Estimates from multinomial logit models were used to approximate the willingness to pay for the delivery service attributes considered in the pseudo-experiment (delivery time, type of compensation for late delivery and delivery range). The results are presented in the Table 6.

For small products, consumers represented in the sample are willing to pay an additional \$1257 (US\$1.50) for same-day delivery relative to a 2–5 day delivery service; and an additional \$4208 (US\$5.30) relative to a 6–15 day delivery service. The results on the type of compensation for late delivery of small products indicate that relative to no compensation for delay, consumers are willing to pay an additional \$1632 (US\$2.00) for a gift card reward and an additional \$1779 (US\$2.20) for cash back reward on the card on which the payment was made.

For large products, consumers represented in the sample are willing to pay an additional \$2858 (US\$3.6) for same-day delivery relative to a 2–5 day delivery service; and an additional \$16,071 (US\$20.1) relative to a 6–15 day delivery service. In addition, they are willing to pay an additional \$6048 (US\$7.6) for a delivery service to receive a gift card reward in case of late delivery, and an additional \$5453 (US\$6.8) to receive the money reward

on the card on which the payment was made, in comparison to not receiving compensation for delay. These amounts are not significantly different from each other at 5% significance.

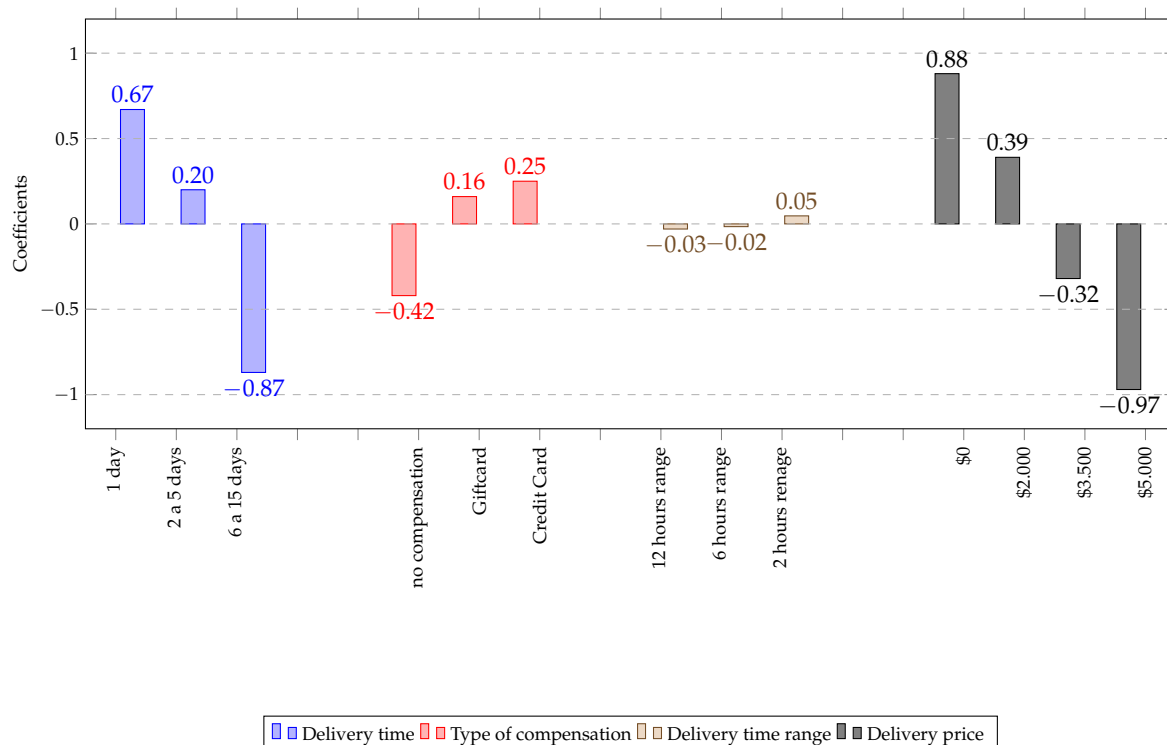
**Table 6.** Estimation of willingness to pay.

| Attributes                                                            | Marginal Willingness to Pay | Small Product    |                                    | Large Product       |                                          |
|-----------------------------------------------------------------------|-----------------------------|------------------|------------------------------------|---------------------|------------------------------------------|
|                                                                       |                             | Average          | Confidence Interval 95%            | Average             | Confidence Interval 95%                  |
| <b>Delivery time</b><br>(Base category: 1 day)                        | Delivery from 2 to 5 days   | −1257<br>(−1.58) | [−1578, −936]<br>(−1.98, 1.17)     | −2858<br>(−3.58)    | [−4377, −1339]<br>([−5.49, −1.68])       |
|                                                                       | Delivery from 6 to 15 days  | −4208<br>(5.28)  | [−4640, −3775]<br>([−5.82, −4.73]) | −16,071<br>(−20.15) | [−18,043, −14,099]<br>([−22.63, −17.68]) |
| <b>Compensation type</b><br><b>Late delivery</b><br>(No compensation) | Giftcard                    | 1632<br>(2.05)   | [1286, 1978]<br>([−5.49, −1.68])   | 6048<br>(7.58)      | [4461, 7636]<br>([5.59, 9.58])           |
|                                                                       | Refund on Credit Card       | 1779<br>(2.23)   | [1341, 2217]<br>([1.61, 2.78])     | 5453<br>(6.84)      | [3395, 7512]<br>([4.26, 9.42])           |
| <b>Delivery time range</b><br>(Base category: 12-h range)             | 6-h range                   | −101<br>(0.13)   | [−530, 327]<br>([−0.66, 0.41])     | −916<br>(−9.15)     | [−2884, 1052]<br>([−3.62, 1.32])         |
|                                                                       | 2-h range                   | 46<br>(0.06)     | [−463, 555]<br>([−0.58, 0.70])     | −1370<br>(−1.72)    | [−3767, 1026]<br>([−4.72, 1.29])         |

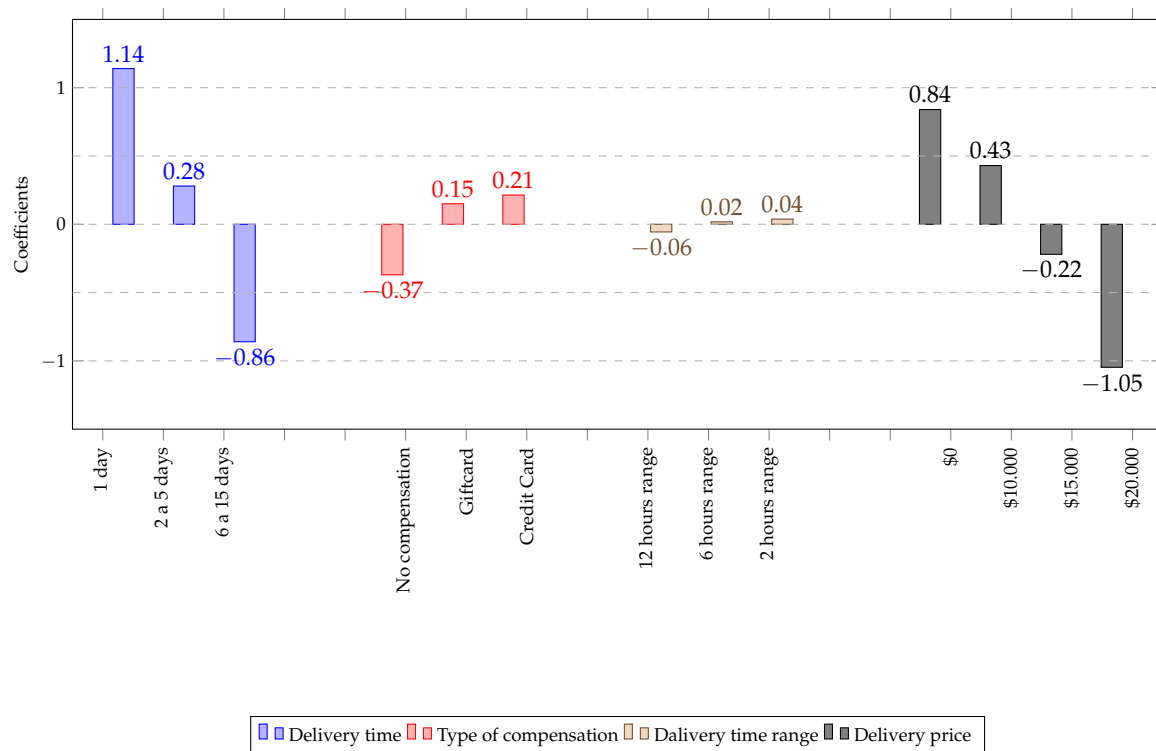
Delivery time range is not significant for the consumers surveyed in any of the surveys (small and large product), which can be seen in the confidence intervals that do not ensure a clear sign of willingness to pay for this attribute.

#### 5.4. Relative Importance of Attributes

A MNL regression was estimated for both groups: The large and small-product sample. The 4 attributes of the delivery service (Time to have the product available, delivery time range, Compensation in case of late delivery, and delivery price) were encoded using *effect coding* to facilitate the interpretation of the results. The model results are presented in Table A2, and the model coefficients for the small- and large-product are shown in Figures 7 and 8, respectively.



**Figure 7.** Small-product model. Coefficients.



**Figure 8.** Large-product model. Coefficients.

The analysis of the coefficient plots for small and large products shows a number of trends and significant differences in consumer preferences towards different attributes of the delivery service. We found that for both small and large products, consumer preference for an alternative decreases as the price increases, with a preference for more affordable alternatives. Additionally, it is observed that the preference for a delivery service significantly increases when the product's delivery time is shorter.

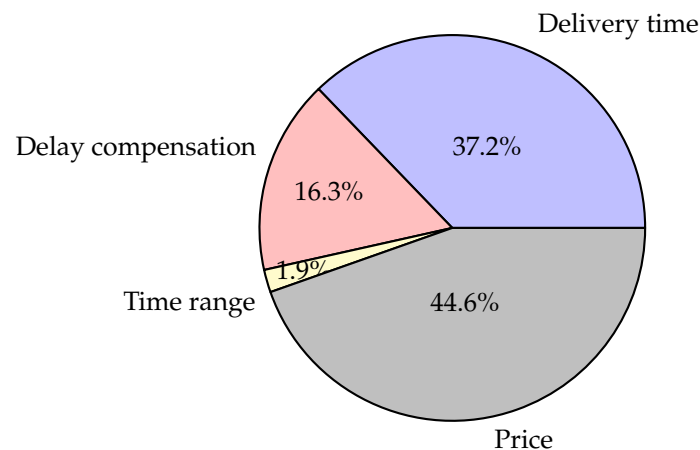
The analysis of compensation in case of late delivery showed that this attribute was found to be relevant in consumers' decision-making. Specifically, the results indicate that consumers value the return option on the store's payment card and *giftcard* compared to alternatives without compensation. However, there are no significant differences between the return on payment card and the *giftcard*.

The analysis of delivery time range, displayed less conclusive results, as no statistical significance was found in its effect on consumer preferences for any product size. This fact suggests that, at least in the analyzed sample, delivery time range is not a determining factor in the choice of *delivery* service. The relative importance obtained for each attribute according to product size is shown in Figures 9 and 10.

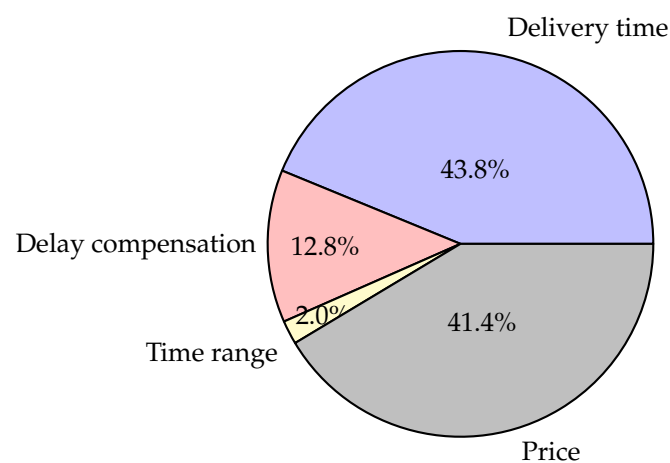
The analysis of the results reveals that for both small and large products, the most important attributes when choosing a *delivery* service are delivery time and price. These two attributes together account for a high proportion of the total importance in both product categories: 81.8% for small products and 85.2% for large products. This suggests that consumers primarily value speed of delivery and cost of service when making their decisions.

In the case of small products, the most influential attribute is price, with an importance of 44.6%. This indicates that for this type of product, the cost of the *delivery* service has a significant impact on consumer preferences. One possible explanation is that small products tend to have a lower unit value, so the cost of delivery may represent a more relevant proportion of the total purchase cost.

On the other hand, for large products, the most relevant attribute is delivery time, with an importance of 43.8%. This trend suggests that, for bulkier products, the speed with which the product is received becomes a critical factor in the choice of *delivery* service. Consumers may be willing to pay a little more for faster delivery, especially for larger items.



**Figure 9.** Relative importance for each attribute for a small product.



**Figure 10.** Relative importance for each attribute for a large product.

For small products, the type of compensation in case of late delivery had an importance of 16.3%. This suggests that consumers consider it relevant to have compensation in case their order is delivered outside the agreed time frame. For large products, this variable showed an importance of 12.8%. As for the delivery time range, this attribute showed an importance close to 2% for both small and large products.

### 5.5. Exploring Consumer Segmentation through Interaction Effects

In addition to service attributes, socio-demographic characteristics of respondents may also have an effect on the choice of a *delivery* alternative. We seek to know whether the valuation of service attributes varies among different groups of respondents, which could help to identify potential market segmentations.

Five socio-demographic characteristics of the respondents are available: gender, educational level, age range, household size and socio-economic level. We studied the interaction that these characteristics have with the 4 attributes of the service: Time to availability of the product, compensation in case of late delivery, time range of delivery and price. The aim was to find out if there is an interaction between a service attribute and a socio-demographic characteristic for each product size (small and large). For this purpose, we calculated 20 logistic regressions to analyze in isolation the interaction of a service attribute of *delivery* with a socio-demographic characteristic. The Tables 7 and 8 show a summary of the sign of the identified interactions, which have a significance level higher than 5%.

**Table 7.** Synthesis of interactions for a small product.

|                   |                     | Socio-Demographic Characteristics |                      |              |              |                             |
|-------------------|---------------------|-----------------------------------|----------------------|--------------|--------------|-----------------------------|
|                   |                     | Gender<br>(Female)                | Educational<br>Level | Age<br>Range | Home<br>Size | Socio-<br>Economic<br>Level |
| Delivery time     | 2 to 5 days         | +                                 | +                    |              |              | +                           |
|                   | 6 to 15 days        | +                                 |                      |              |              |                             |
| Compensation type | Giftcard            |                                   |                      |              | +            |                             |
|                   | Payment card refund |                                   |                      |              | +            |                             |
| Time range        | 6-h range           |                                   |                      | –            |              |                             |
|                   | 2-h range           |                                   |                      |              |              |                             |
| Price             |                     |                                   | –                    |              | +            | –                           |

The analysis of the data shows that the interaction of gender with time to product availability is significant (see Tables 7 and 8). For small products, the interaction between the variable female and time to product availability of 2 to 5 days is positive, so that women have a greater preference for this delivery range compared to men. For large products, the interaction between the female variable and the 2–5 day range is negative, indicating that females have a lower preference for this delivery range compared to males.

**Table 8.** Synthesis of interactions for a large product.

|                   |                     | Socio-Demographic Characteristics |                      |              |              |                             |
|-------------------|---------------------|-----------------------------------|----------------------|--------------|--------------|-----------------------------|
|                   |                     | Gender<br>(Female)                | Educational<br>Level | Age<br>Range | Home<br>Size | Socio-<br>Economic<br>Level |
| Delivery time     | 2 to 5 days         | –                                 | +                    |              |              |                             |
|                   | 6 to 15 days        |                                   |                      |              |              |                             |
| Compensation type | Giftcard            |                                   |                      |              |              | +                           |
|                   | Payment card refund |                                   |                      |              |              |                             |
| Time range        | 6-h range           |                                   |                      |              |              |                             |
|                   | 2-h range           |                                   |                      |              |              |                             |
| Price             |                     |                                   |                      |              |              |                             |

In relation to educational level, we found significant interactions with price for small products (see Table 7) and with the delivery range of 2 to 5 days for both product sizes (see Table 8). For small products, the interaction between price and educational level is negative, implying that as educational level increases, price sensitivity decreases, i.e., people with a higher educational level are less sensitive to price variations. Also, the delivery time of 2 to 5 days has a positive interaction with educational level, indicating that respondents with a higher educational level show a greater preference for 2 to 5 days delivery range for both product sizes.

As for age range, there was a negative interaction with the 2-h delivery range for small products (see Table 7). This suggests that younger people are less sensitive to the 2-h delivery range option compared to older people.

Household size has significant interactions with price for small product (see Table 7) and with the type of compensation in case of late delivery (see Table 7). The interaction between service price and household size is positive, so as household size increases, price sensitivity also increases. Household size has a positive interaction with compensation in case of late delivery, either through *giftcard* or refund on the payment card, so for larger households the alternatives of *delivery* with compensation are more preferred.

The interaction of socioeconomic status with delivery time for small products (see Table 7) shows that the range of 2 to 5 days is more attractive to consumers as the socioe-

conomic status increases. The price of the small-product *delivery* service has a significant interaction with socioeconomic level (see Table 7). The relationship is negative, therefore, as socioeconomic level increases, the effect of price on the preference for an alternative decreases. For large products, socioeconomic status has a positive interaction with compensation through the *giftcard* (see Table 8), so that as socioeconomic status increases, the *giftcard* alternative becomes more preferred.

## 6. Discussion and Conclusions

Since there are no prior studies available on the willingness to pay for delivery attributes in Chile, this study contributes to a better understanding of consumer preferences in the Chilean delivery service market. Our results show that the most important attributes of delivery service are the time until product arrival and the existence of compensation in case of delay in delivery for Chilean consumers buying both small products (e.g., cell phones) and large products (e.g., refrigerators). For each valuable attribute, willingness to pay increases with product size. Large products are generally higher priced and consumers are likely to evaluate the cost of delivery concerning the product price, so they are willing to pay more for the same delivery service if the product is large.

Contrary to our expectations, consumers are unwilling to pay an additional amount for insuring the delivery time range (when comparing 12-h versus 6-h and 2-h ranges). There may be several explanations for this phenomenon; for example, since most of the households surveyed have at least four members, someone from the family could be at home, and they do not need to pay to secure a time slot. The time range attribute is likely more essential for perishable purchases, such as grocery shopping. This is evidenced by supermarkets usually including it as an option. However, these type of products were not included in the pseudo-experiment.

The interactions between socio-demographic characteristics and service attributes have yielded significant results. This suggests the existence of consumer segments that value service attributes differently. We have observed that females exhibit a stronger preference for a delivery range of 2 to 5 days when it comes to small products, but a relatively lower preference for the same delivery range when it comes to large products. Additionally, we have noticed that consumers with higher educational levels and/or higher socioeconomic status display less price sensitivity.

The main limitations of our work are, first, we focus only on the Santiago metropolitan area and this cannot achieve a comprehensive and representative understanding of consumer preferences for delivery services in Chile. Second, our research is related to the methodology used to calculate willingness to pay. We calculate consumers' hypothetical willingness to pay, which may differ from consumers' real willingness to pay, a difference known in the literature as "hypothetical bias". Nevertheless, this method is widely used in the literature because real willingness to pay may be difficult or impossible to obtain, as in our case. Finally, in order to streamline respondents' understanding and avoid overwhelming them with an excessive number of choices, we selectively included the four delivery service features that we considered most important for our analysis. As a result, some potentially valuable features for consumers were omitted from our survey instrument.

In future extensions of our research could explore delivery service preferences in other regions of Chile or conduct segmentation by districts within the metropolitan region. We can also incorporate weighting factors obtained from census data. These weights will enable us to adjust our statistical analysis to accurately reflect the demographics and characteristics of the entire Chilean population. In addition, we can incorporate alternative statistical models, such as random forest, into our analysis. This approach provides a robust framework for handling complex data relationships and can provide valuable insights into our research objectives. Future research could also include further experiments with additional features related to the delivery service that may influence consumer preferences. For example, we intend to explore factors such as delivery traceability [24] and home pickup options in case of product returns. Finally, as mentioned by [3], our research also

contributes an empirical observation that can be used in future meta-analysis studies on the evaluation of delivery attributes.

## 7. Practical Implications

The main practical implications of our research are, first, that this study provides valuable insights into consumer preferences within the Chilean delivery service market, which can aid businesses in segmenting their target audience based on their preferences for delivery attributes. Understanding these preferences allows companies to tailor their services and marketing strategies to better meet the needs of different consumer segments.

Second, by identifying the most important attributes of delivery service for Chilean consumers, businesses can focus on optimizing these aspects to differentiate themselves from competitors. Investing in improving delivery speed and implementing robust compensation policies for delays can increase the perceived value of the service and attract more customers.

Third, the findings regarding willingness to pay for different delivery attributes, especially in relation to product size, provide valuable guidance for pricing strategies. Companies can adjust their pricing models to reflect the value consumers place on delivery attributes, potentially increasing profitability while remaining competitive in the market.

Finally, recognizing the differences in preferences among consumer segments based on socio-demographic characteristics allows businesses to tailor their marketing messages and communication strategies accordingly. For example, targeting female consumers with delivery options that align with their preferences for different product sizes can improve the effectiveness of marketing campaigns.

**Author Contributions:** Conceptualization, J.T., P.F. and D.D.; methodology, P.F. and J.T.; software, I.U.; data curation, I.U. and J.T.; writing—I.U., J.T. and P.F. preparation, D.D.; writing—review and editing, P.F. and D.D.; visualization, P.F.; supervision, J.T.; project administration, D.D.; funding acquisition, D.D. All authors have read and agreed to the published version of the manuscript.

**Funding:** The authors extend their gratitude to the Universidad Diego Portales for providing financial support for this research work. D.D. would like to thank the CYTED AgIoT Project (520rt0011), CORFO CoTH2O “Consorcio de Gestión de Recursos Hídricos para la Macrozona Centro-Sur” (20CTECGH-145896), Proyecto Asociativo UDP “Plataformas Digitales como modelo organizacional” and “WirelessWine” STIC-AmSud (19STIC-09), for their support during the development of this research work.

**Institutional Review Board Statement:** Informed consent was obtained from all subjects involved in the study.

**Informed Consent Statement:** Informed consent was obtained from all subjects involved in the study.

**Data Availability Statement:** The raw data supporting the conclusions of this article will be made available by the authors on request.

**Conflicts of Interest:** The authors declare no conflicts of interest.

## Appendix A

**Table A1.** Results of the Multinomial Logit MNL model.

|                                                | Small Product                  | Large Product                 |
|------------------------------------------------|--------------------------------|-------------------------------|
| <b>Price</b>                                   | −0.0003550982 ***<br>(0.00002) | −0.000076733 ***<br>(0.00000) |
| <b>Delivery time</b><br>(Base category: 1 day) |                                |                               |
| Delivery range 2 to 5 days                     | −0.4465109 ***<br>(0.065)      | −0.2193377 ***<br>(0.064)     |
| Delivery range 6 to 15 days                    | −1.494282 ***<br>(0.103)       | −1.233236 ***<br>(0.100)      |

Table A1. Cont.

|                                                                            | Small Product            | Large Product            |
|----------------------------------------------------------------------------|--------------------------|--------------------------|
| <b>Compensation time late delivery</b><br>(Base category: No compensation) |                          |                          |
| Giftcard                                                                   | 0.5795895 ***<br>(0.070) | 0.4641504 ***<br>(0.069) |
| Refund on payment card                                                     | 0.6319611 ***<br>(0.094) | 0.4185011 ***<br>(0.092) |
| <b>Product delivery time range</b><br>(Base category: 12-h range)          |                          |                          |
| 6-h range                                                                  | −0.03605722<br>(0.077)   | −0.07030105<br>(0.075)   |
| 2-h range                                                                  | 0.01644638<br>(0.093)    | −0.1051504<br>(0.090)    |
| Observations                                                               | 2120                     | 2120                     |
| Log Likelihood                                                             | −1970.200                | −1970.200                |

Note: \*  $p < 0.1$ ; \*\*  $p < 0.05$ ; \*\*\*  $p < 0.01$ .

Table A2. Results of the Multinomial Logit Model-Effect coding.

|                                                                                | Small Product         | Large Product         |
|--------------------------------------------------------------------------------|-----------------------|-----------------------|
| <b>Delivery time</b><br>(Base category: 1 day)                                 |                       |                       |
| Delivery range 2 to 5 days                                                     | 0.206 ***<br>(0.036)  | 0.281 ***<br>(0.035)  |
| Delivery range 6 to 15 days                                                    | −0.876 ***<br>(0.060) | −0.858 ***<br>(0.060) |
| <b>Compensation type for late delivery</b><br>(Base category: No compensation) |                       |                       |
| Giftcard                                                                       | 0.165 ***<br>(0.034)  | 0.153 ***<br>(0.034)  |
| Refund on payment card                                                         | 0.257 ***<br>(0.051)  | 0.214 ***<br>(0.051)  |
| <b>Product delivery time range</b><br>(Base category: 12-h range)              |                       |                       |
| 6-h range                                                                      | −0.016<br>(0.037)     | 0.018<br>(0.037)      |
| 2-h range                                                                      | 0.047<br>(0.048)      | 0.038<br>(0.048)      |
| <b>Price</b><br>(Base category: Price \$0)                                     |                       |                       |
| \$2000 (S)–\$10.000 (L)                                                        | 0.395 ***<br>(0.045)  | 0.427 ***<br>(0.045)  |
| \$3.500 (S)–\$15.000 (L)                                                       | −0.315 ***<br>(0.050) | −0.220 ***<br>(0.048) |
| \$5.000 (S)–\$20.000 (L)                                                       | −0.968 ***<br>(0.066) | −1.047 ***<br>(0.068) |
| Observations                                                                   | 2120                  | 2120                  |
| Log Likelihood                                                                 | −1970.200             | −1970.200             |

Note: \*  $p < 0.1$ ; \*\*  $p < 0.05$ ; \*\*\*  $p < 0.01$ .

## References

1. BlackSip. 2022. Available online: <https://content.blacksip.com/reporte-del-ecommerce-en-chile-2021> (accessed on 17 August 2022).
2. Shang, L.; Liu, Y.; Xu, P. The COVID-19 shock and the ownership of store Chain: Evidence from China's express delivery industry. *Heliyon* **2023**, *9*, e20799. [CrossRef] [PubMed]
3. Nguyen, D.H.; de Leeuw, S.; Dullaert, W.; Foubert, B.P. What is the Right Delivery Option for You? Consumer Preferences for Delivery Attributes in Onlinle Retailing. *J. Bus. Logist.* **2019**, *40*, 299–321. [CrossRef]
4. Pan, R.; Huang, Y.; Xiao, X. Evaluating Consumers' Willingness to Pay for Delay Compensation Services in Intra-City Delivery—A Value Optimization Study Using Choice. *Information* **2021**, *12*, 127. [CrossRef]

5. Garver, M.S.; Williams, Z.; Stephen Taylor, G.; Wynne, W.R. Modelling choice in logistics: A managerial guide and application. *Int. J. Phys. Distrib. Logist. Manag.* **2012**, *42*, 128–151. [CrossRef]
6. Wilson-Jeanselme, M.; Reynolds, J. Understanding shoppers' expectations of online grocery retailing. *Int. J. Retail. Distrib. Manag.* **2006**, *34*, 529–540. [CrossRef]
7. Dellaert, B.; Borgers, A.; Timmermans, H. Consumer activity pattern choice: Development and test of stage-dependent conjoint choice experiments. *J. Retail. Consum. Serv.* **1997**, *4*, 25–37. [CrossRef]
8. Louviere, J.; Johnson, R.; Chrzan, K. Accommodating ideal brands and testing the predictive validity of brand-anchored conjoint analysis: A multiple-choice experiment approach. *J. Retail. Consum. Serv.* **1994**, *1*, 21–29. [CrossRef]
9. Stöckigt, G.; Schiebener, J.; Brand, M. Providing sustainability information in shopping situations contributes to sustainable decision making: An empirical study with choice-based conjoint analyses. *J. Retail. Consum. Serv.* **2018**, *43*, 188–199. [CrossRef]
10. Meyerding, S.G.; Bauchrowitz, A.; Lehberger, M. Consumer preferences for beer attributes in Germany: A conjoint and latent class approach. *J. Retail. Consum. Serv.* **2019**, *47*, 229–240. [CrossRef]
11. Borgers, A.; Vosters, C. Assessing preferences for mega shopping centres: A conjoint measurement approach. *J. Retail. Consum. Serv.* **2011**, *18*, 322–332. [CrossRef]
12. Jiang, L.A.; Yang, Z.; Jun, M. Measuring consumer perceptions of online shopping convenience. *J. Serv. Manag.* **2013**, *24*, 191–214. [CrossRef]
13. Goebel, P.; Moeller, S.; Pibernik, R. Paying for convenience: Attractiveness and revenue potential of time-based delivery services. *Int. J. Phys. Distrib. Logist. Manag.* **2012**, *42*, 584–606. [CrossRef]
14. Dias, E.G.; Oliveira, L.K.d.; Isler, C.A. Assessing the effects of delivery attributes on e-shopping consumer behaviour. *Sustainability* **2021**, *14*, 13. [CrossRef]
15. Javed, M.K.; Wu, M. Effects of online retailer after delivery services on repurchase intention: An empirical analysis of customers' past experience and future confidence with the retailer. *J. Retail. Consum. Serv.* **2020**, *54*, 101942. [CrossRef]
16. Sham, R.; Chong, H.X.; Aw, E.C.; Thangal, T.B.; binti Abdamia, N. Switching up the delivery game: Understanding switching intention to retail drone delivery services. *J. Retail. Consum. Serv.* **2023**, *75*, 103478. [CrossRef]
17. Uzir, M.U.H.; Al Halbusi, H.; Thurasamy, R.; Thiam Hock, R.L.; Aljaberi, M.A.; Hasan, N.; Hamid, M. The effects of service quality, perceived value and trust in home delivery service personnel on customer satisfaction: Evidence from a developing country. *J. Retail. Consum. Serv.* **2021**, *63*, 102721. [CrossRef]
18. Jiang, Y.; Lai, P.L.; Yang, C.C.; Wang, X. Exploring the factors that drive consumers to use contactless delivery services in the context of the continued COVID-19 pandemic. *J. Retail. Consum. Serv.* **2023**, *72*, 103276. [CrossRef]
19. Tsai, P.H.; Chen, C.J.; Hsiao, W.H.; Lin, C.T. Factors influencing the consumers' behavioural intention to use online food delivery service: Empirical evidence from Taiwan. *J. Retail. Consum. Serv.* **2023**, *73*, 103329. [CrossRef]
20. Hoang, H.; Le Tan, T. Unveiling digital transformation: Investigating technology adoption in Vietnam's food delivery industry for enhanced customer experience. *Heliyon* **2023**, *9*, e19719. [CrossRef]
21. Moh'd Anwer, A.S. An investigation of transportation logistics strategy on manufacturing supply chain responsiveness in developing countries: The mediating role of delivery reliability and delivery speed. *Heliyon* **2022**, *8*, e11283. [CrossRef]
22. Shbool, M.A.; Al-Bazi, A.; Al-Hadeethi, R. The effect of customer satisfaction on parcel delivery operations using autonomous vehicles: An agent-based simulation study. *Heliyon* **2022**, *8*, e09409. [CrossRef] [PubMed]
23. Dey, B.K.; Sarkar, M.; Chaudhuri, K.; Sarkar, B. Do you think that the home delivery is good for retailing? *J. Retail. Consum. Serv.* **2023**, *72*, 103237. [CrossRef]
24. Jiang, F.; Tian, S.; Sremac, S.; Huskanovic, E. Analyzing traceability models in e-commerce logistics: A multi-channel approach. *J. Ind. Intell* **2023**, *1*, 203–218. [CrossRef]
25. Andrejic, M.; Pajic, V.; Stankovic, A. Human resource dynamics in urban crowd logistics: A comprehensive analysis. *J. Urban Dev. Manag.* **2023**, *2*, 135–144. [CrossRef]
26. Lancaster, K.J. A new approach to consumer theory. *J. Political Econ.* **1966**, *74*, 132–157. [CrossRef]
27. Ben-Akiva, M.E.; Lerman, S.R.; Lerman, S.R. *Discrete Choice Analysis: Theory and Application to Travel Demand*; MIT Press: Cambridge, MA, USA, 1985; Volume 9.
28. Domencich, T.A.; McFadden, D. Urban Travel Demand—A Behavioral Analysis. 1975. Available online: <https://trid.trb.org/View/48594> (accessed on 1 March 2024).
29. Hensher, D.A.; Johnson, L.W. Behavioural response and form of the representative component of the indirect utility function in travel choice models. *Reg. Sci. Urban Econ.* **1981**, *11*, 559–572. [CrossRef]
30. McFadden, D. Econometric models of probabilistic choice. In *Structural Analysis of Discrete Data with Econometric Applications*; MIT Press: Cambridge, MA, USA, 1981; Volume 198272.
31. Horowitz, J.L.; Bolduc, D.; Divakar, S.; Geweke, J.; Gönül, F.; Hajivassiliou, V.; Koppelman, F.S.; Keane, M.; Matzkin, R.; Rossi, P.; et al. Advances in random utility models report of the workshop on advances in random utility models duke invitational symposium on choice modeling behavior. *Mark. Lett.* **1994**, *5*, 311–322. [CrossRef]
32. Alkharusi, H. Categorical variables in regression analysis: A comparison of dummy and effect coding. *Int. J. Educ.* **2012**, *4*, 202. [CrossRef]
33. Hasan-Basri, B.; Karim, M. The effects of coding on the analysis of consumer choices of public parks. *World Appl. Sci. J.* **2013**, *22*, 500–505.

34. Ben-Akiva, M.; McFadden, D.; Train, K. Foundations of stated preference elicitation: Consumer behavior and choice-based conjoint analysis. *Found. Trends<sup>®</sup> Econom.* **2019**, *10*, 1–144. [[CrossRef](#)]
35. Patowary, M.M.I.; Peulers, D.; Richter, T.; Melovic, A.; Nilsson, D.; Söilen, K.S. Improving last-mile delivery for e-commerce: The case of Sweden. *Int. J. Logist. Res. Appl.* **2023**, *26*, 872–893. [[CrossRef](#)]
36. Borsenberger, C.; Cremer, H.; De Donder, P.; Joram, D. Differentiated pricing of delivery services in the e-commerce sector. In *The Future of the Postal Sector in a Digital World*; Springer: Cham, Switzerland, 2016; pp. 191–211.
37. Traets, F.; Sanchez, D.G.; Vandebroek, M. Generating optimal designs for discrete choice experiments in R: The idfix package. *J. Stat. Softw.* **2020**, *96*, 1–41. [[CrossRef](#)]
38. Crabbe, M.; Vandebroek, M. Using appropriate prior information to eliminate choice sets with a dominant alternative from D-efficient designs. *J. Choice Model.* **2012**, *5*, 22–45. [[CrossRef](#)]

**Disclaimer/Publisher's Note:** The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.