sustainability

MDPI

Article

Assessing the Effects of Delivery Attributes on E-Shopping Consumer Behaviour

Emília Guerra Dias [1], Leise Kelli de Oliveira [1,*] and Cassiano Augusto Isler [2]

[1] Department of Transportation and Geotechnical Engineering, Federal University of Minas Gerais, Belo Horizonte 31270-901, Brazil; egdias16@gmail.com
[2] Transportation Engineering Department, Escola Politécnica, University of São Paulo, Sao Paulo 05508-070, Brazil; cassiano.isler@usp.br
* Correspondence: leise@etg.ufmg.br

Abstract: E-consumer behaviour plays a vital role in e-commerce worldwide. This paper addresses the importance of delivery time, delivery fee, and delivery reception, and the influence of delivery fee and reception on e-consumers' behaviour by analysing the following hypotheses: delivery attributes affect e-shopping behaviour, and delivery attributes affect e-consumers' behaviour according to their sociodemographic characteristics. Data were obtained from a web-based survey with Brazilian e-consumers, and logistic regression and artificial neural network models were estimated to assess consumer behaviour. We found that delivery fee willingness to pay and privacy are affected by delivery times according to gender. Delivery fees affect the e-consumer according to gender, the habit of purchasing books and leisure products, privacy, promotions, and pricing, and influence the e-shopping decision by age, purchase of electronic products, and promotions. Delivery reception is relevant according to age, income, gender, frequency of e-shopping, privacy, and pricing. Furthermore, delivery fees influence the e-shopping decision by age, purchase of electronic products, and promotions. Finally, delivery fee, willingness-to-pay, and privacy are characteristics influenced by reception on the e-shopping decision. Further analyses would include the dynamic aspects of e-consumer behaviour and the impacts of COVID-19 in the e-consumption patterns and its effects on e-commerce deliveries.

Keywords: urban freight transport; e-commerce; consumer behaviour; B2C delivery; logistics regression; artificial neural networks

check for updates

Citation: Dias, E.G.; Oliveira, L.K.d.; Isler, C.A. Assessing the Effects of Delivery Attributes on E-Shopping Consumer Behaviour. *Sustainability* **2022**, *14*, 13. https://doi.org/10.3390/su14010013

Academic Editor: Hyunchul Ahn

Received: 1 December 2021
Accepted: 19 December 2021
Published: 21 December 2021

Publisher's Note: MDPI stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Copyright: © 2021 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

The Internet has contributed to the expansion of e-commerce as online personalised purchases have increased considerably in the last decades. From all sales worldwide, e-commerce sales account for 18%. China was the world leader in e-commerce sales in 2020, and the highest percentage growth was observed in Argentina [1]. Brazil and Mexico were the Latin-American leaders in 2020, with 31% and 28%, respectively [1]. Moreover, US$ 112.4 billion were spent in the online market in Brazil, followed by Mexico (31.5 billion) and Colombia (14.5 billion in 2020) [1]. Fashion, shoes, and cosmetics are the leading product categories among Brazilian shoppers. This paper addressed e-commerce in Brazil, an emergent market, which reached 8% of total sales in 2020.

The demand for delivery services has increased due to online shopping [2]. However, the increase of business-to-consumer (B2C) deliveries has worsened urban freight-related problems, such as negative impacts on traffic and pollution and urban mobility reduction [2]. B2C deliveries benefit from the high demand in urban cities [3], although these services generally consider just one package per delivery, thus not allowing for economies of scale [4].

Despite the growth of e-commerce in the Brazilian market, few studies have analysed the impacts of e-commerce deliveries. The focus is usually on the assessment of sustainable

last-mile alternatives. Nogueira et al. [5] analysed the awareness of e-consumers for sustainable last-mile delivery decisions and Oliveira et al. [6] analysed the demand for pick-up points as a sustainable solution for last-mile deliveries. However, the factors influencing delivery services should be known to fulfil customers' expectations and needs [3]. The most common delivery factors reported in the literature are delivery time [5,7–9], delivery reception, and return possibility [7]. Nonetheless, e-consumer behaviour plays a vital role in e-commerce [10], once urban freight policies and practices require understanding how the e- consumers react to it [11]. Therefore, understanding e-consumer behaviour is key to solving the last-mile problem.

The literature related to the effects of e-commerce delivery attributes on consumer behaviour is limited and focuses on supply chain management [12] and e-commerce purchases [8]. Moreover, some research shows delivery's influence on e-shopping [13–16]. More specifically, short delivery times influence e-shopping decisions [12]. Furthermore, Amorim et al. [17] found that delivery time, delivery reception, and the flexibility of delivery reception are critical attributes that considerably influence customer preferences for home deliveries of e-grocery products.

The research question addressed in this paper is how delivery attributes affect e-consumers' behaviour. More specifically, we aim to analyse the effects of delivery attributes (delivery time, delivery fee, and delivery reception) on e-shopping consumer behaviour. Firstly, we estimated a regression model to identify which factors related to e-shopping consumer behaviour related to the delivery attributes. Next, we used artificial neural networks to identify patterns regarding the effects of delivery attributes on e-shopping consumer behaviour. The use of these techniques brings novelty to this study since the usual approaches found in the literature are discrete choice modelling [6–9,18–22], conjoint analysis [8], cluster analysis [8,23], the mixed structural equation model [10], and statistical tests [5].

Thus, the contribution of this paper is threefold. Firstly, we evaluated the effects of delivery attributes on e-shopping consumer behaviour. Second, we used alternative methods to analyse e-customers behaviour. Finally, we analysed the consumer behaviour in e-commerce in an emerging market, where the number of studies is still minimal [24]. Findings support the development of sustainable delivery strategies. Most e-commerce deliveries are destined for the home/workplace of the buyer. While strategies such as pick-up points are still incipient in Brazil [18], the absence of strategies to meet home delivery needs efficiently is unsustainable in the long term with the growth of e-commerce and the increasing number of orders, and thus the number of deliveries, by the free shipping strategy [25]. Therefore, it is essential to identify how delivery attributes have influenced e-consumer behaviour in this context.

The outline of this paper is as follows. Section 2 presents the literature review and the hypotheses development. Section 3 describes the data used in this study. Section 4 covers the research method, and Section 5 presents the results. Finally, the discussions and the conclusions are presented in Section 6.

2. Literature Review and Hypotheses Development

This paper analyses delivery fee, delivery time, and delivery reception as delivery factors. Delivery fee is a marketing strategy that influences consumer patterns [8]. Delivery time is a critical factor of e-shopping decisions [12] and is related to the time required to deliver the product to the customer [8]. Product type, age, and education level influence the potential for accepting/rejecting longer delivery times [5]. Also, faster deliveries increase consumer satisfaction, especially when buying hedonic products or purchases out of impulsive behaviour [8]. In addition, e-consumers are more flexible to delivery times than delivery fees [8]. Finally, delivery reception is related to how/when the deliveries are received, including during daytime and the date of deliveries [7,8]. The following sections outline the hypotheses analysed in this paper.

The influence of delivery on e-shopping was evaluated by [5,8]. Nguyen et al. [8] analysed consumer preferences in the following delivery attributes: delivery fee, delivery time, and delivery reception. The authors used a conjoint analysis considering the consumer segments (price, time, and value for money) and their contexts (product type, demographic data, and purchase frequency). Nogueira et al. [5] found that delivery time, delivery fee, and environmental information influence e-commerce purchases. They used the Mann-Whitney test, the Kruskal-Wallis test, and the Spearman correlation test. In addition, Buldeo Rai et al. [7] evaluated the consumer preferences related to delivery price, delivery time, delivery reception, and return opportunities in last-mile deliveries.

Several aspects of e-consumer preferences have been studied, including last-mile options [6,10,18,20,26,27], customer-driven central last-mile micro depot [28], and crowd logistics [23]. Liu et al. [29] evaluated customers travel choices to collect delivery points. Oliveira et al. [6] analysed the importance of various delivery factors (delivery destination, delivery time, information and traceability, and delivery fee) to identify the potential demand for automated delivery stations, representing an alternative to e-commerce deliveries. Yuen et al. [26] studied the factors that influence self-collection services. Xiao et al. [10] examined the effects of final delivery solutions on e-shopping behaviour. Oliveira et al. [18] evaluated the accessibility of collection and delivery points (CDP) considering customer preferences and the coverage area. Iannaccone et al. [20] estimated the market share of pick-up points using customer preferences. From the customers ' perspective, Hagen and Schell-Kopeinig [28] examined the acceptance and willingness-to-pay of deliveries for a central last-mile micro depot. Buldeo Rai et al. [23] investigated the preferences for crowdsourcing among end-consumers.

The environmental and social impacts of B2C deliveries also influence e-customers [9,21] and make them choose sustainable delivery options [9]. The environmental factor increases the tolerance for longer delivery times [9,21] and delivery costs [9]. Consumers choose less convenient delivery destinations, especially when additional economic benefits are offered [9]. Positive environmental information might encourage sustainable delivery choices [19]. Ignat and Chankov [9] evaluated the role of information on e-customers preferences and identified that consumers tend to accept longer delivery times and pay more for environmentally sustainable deliveries.

Sociodemographic characteristics have already been studied in the context of e-shopping consumption [30]. For example, Xiao et al. [10] identified that e-shopping frequency is positively influenced by gender, marital status, and the educational level of the consumers. However, previous research has also shown diverging results. For example, Irawan and Wirza [31] identified an association between sociodemographic characteristics and e-shopping frequency. On the other hand, Yuen et al. [26] did not find an association between consumers demographic characteristics and e-shopping. Also, demographic characteristics do not affect customers intention to use self-collection services [26]. Iannaccone et al. [20] included socioeconomic characteristics to estimate the demand for pick-up points. Buldeo Rai et al. [23] reported that socioeconomic characteristics do not influence crowdsourced last-mile services. However, Liu et al. [27] found that psychographic variables explain e-consumer preferences across different product categories. Also, the sociodemographic variables might capture the indirect effects of delivery attributes [29].

Despite the importance of socioeconomic characteristics for e-commerce, such attributes are mainly analysed only considering new delivery alternatives [23,26], i.e., the influence of socioeconomic characteristics on e-shopping deserves further exploration.

Few studies considered the influence of delivery attributes on e-shopping [13–16]. Further, the influence of e-shopping characteristics has not been largely explored [8]. Some e-shopping characteristics such as product information, customer service [15,16,32], brand selection, privacy, and promotions [16], quality [13,15], pricing [13,15,16], convenience [13,16,32], and security [13,16] present positive impacts on customer satisfaction. Most of the literature focused on analysing the influence of these factors on e-shopping.

According to Cherrett et al. [33], frequent shoppers are more likely to use a greater variety of delivery options, reducing delays to receive the products. The product type and purchase frequency influence consumer perceptions regarding delivery services [16]. Also, Mehmood and Najmi [34] identified positive impacts of service convenience (decision, access, transaction, general benefits, and post-benefits) on customer satisfaction of home deliveries.

Based on the literature, we propose the following hypotheses to answer the research question addressed in this paper: (1) delivery attributes affect e-shopping behaviour, and (2) delivery attributes affect e-consumers' behaviour according to their sociodemographic characteristics.

3. Research Approach

3.1. Data

A questionnaire and related data were obtained from a web-based survey to analyse the hypotheses described in the previous section. Table 1 shows the structure of the questionnaire. The survey was disseminated using social networks between August 2018 and October 2018 among many parts of Brazil. We obtained 615 responses on a sample with a 95% confidence level and 5% error regardless of the country's underrepresentation of different sociodemographic characteristics.

Table 1. Structure of the questionnaire.

Characteristics	Variables	Type of Response
Sociodemographic characteristics	Age	15−24 years old
		25−34 years old
		35−49 years old
		above 50 years old
	Income (in minimum wages *)	less than one wage
		2–4 wages
		4–10 wages
		more than ten wages
	Gender	male
		female
Consumption behaviour	Product type	beauty and clothing products
		electronic products
		books and leisure products
	Frequency of e-shopping	once per month
		more than once per month
	Delivery fee willingness to pay	until 3% of the product price
		until 7% of the product price
		until 10% of the product price
		over than 10% of the product price
E-shopping characteristics	Convenience	5-Likert scale
	Privacy	3-Likert scale
	Promotion	3-Likert scale
	Pricing	3-Likert scale
Delivery attributes	Importance of delivery time	3-Likert scale
	Importance of delivery fee	3-Likert scale
	Importance of delivery reception	3-Likert scale
	Influence of delivery fee	3-Likert scale
	Influence of delivery reception	3-Likert scale

* 1 minimum wage equals BRL 954 in 2018 (US$1.00 ≅ BRL5.50 in November 2021).

We used statistical descriptions to describe the data and presented the data using histograms in the following section. Such initial information from the questionnaire provided insights into the phenomenon analysed in Brazil. The internal consistency of the

responses was evaluated with the Cronbach alpha, which considers the average intercorrelation among answers per question [35]. Cronbach alpha values above 0.7 show responses internal consistency for all variables [36,37].

3.2. Data Analysis

Two analyses were performed in this paper: (i) the significance of sociodemographic characteristics, e-consumption behaviour, and e-shopping characteristics on delivery attributes by using a regression model, and (ii) pattern recognition of the effects of sociodemographic characteristics, e-consumption behaviour, and e-shopping characteristics on the different delivery attributes.

We estimated a regression model to identify the significance of sociodemographic characteristics and e-shopping behaviour on delivery attributes. A model was estimated for each delivery attribute, i.e., the importance of delivery time, delivery fee, delivery reception, influence of delivery fee and delivery reception on the e-shopping decision. The goal is to identify the set of variables with statistical significance that suggest the effects of the delivery attributes on e-consumption behaviour given the sociodemographic characteristics of individuals. Such an approach has been adopted since it provides useful information on the magnitude and statistical significance of the relations among the sociodemographic characteristics and the delivery attributes.

Since the response-type of delivery attributes is categorical (3-Likert scale), we estimated ordinal regression models whose results did not provide a good fit. Then, we estimated the logistic regression model by converting neutral responses to positive and negative responses. The accuracy was compared using a confusion matrix, which indicates the model's overall performance based on the total classifications that it performs correctly [38]. Table 2 shows the accuracy of the models. The conversion of neutral responses to positive responses provided better accuracy in all estimated models, which was used to transform the Likert scale categories into binary responses to estimate logistic regression.

Table 2. Comparison of models' accuracy considering the conversion of neutral responses into positive or negative responses.

Delivery Attribute	Accuracy of Neutral-Positive Conversion	Accuracy of Neutral-Negative Conversion
Importance of delivery time	82%	54%
Importance of delivery fee	84%	70%
Importance of delivery reception	64%	50%
Influence of delivery fee	88%	70%
Influence of delivery reception	60%	57%

A training dataset was created with 85% of the sample to estimate the logistic regression models, while the remaining dataset was used as a testing set. The *t*-test was used to identify the characteristics that significantly influence the delivery attributes, and the multicollinearity was verified with the variance inflation factor (VIF). Interested readers may refer to Washington et al. [39] for further details on logistic regression. Finally, the models were estimated in the R environment.

We used Artificial Neural Networks (ANN) to recognise patterns between the delivery attributes and the independent variables (i.e., sociodemographic characteristics, e-consumption behaviour, and e-shopping characteristics). Neural networks were developed to simulate the human brain, recognising patterns [40]. We implemented a multi-layer perceptron (MLP) with three hidden layers and 11 neurons in this study. The lbfgs function was used to optimise the weights limited to 500 iterations, and the ReLU activation function was used for the hidden layers. The ANN was implemented in Python using the Sci-kit Learn library [41], and the data were standardised before the model estimation. The

backpropagation learning algorithm was used to minimise the output errors, where the results of the ANN were compared to the input data. This procedure adjusts the internal weights in an iterative process [42]. The method has been used to provide further insights about the non-linear and multidimensional relations between the delivery attributes and sociodemographic characteristics, e-consumption behaviour, and e-shopping characteristics that cannot be drawn analytically by the regression models previously described. In the application of the ANN, the reliability of the results was verified by computing the accuracy obtained from the confusion matrix. It should be noted that 85% of the sample was used for training and 15% for validation, similar to the logistic regression model.

Partial Dependence Plots (PDP) were used to verify the relationships between the dependent variables and the independent variables of the ANN models [42,43]. PDPs are widely used for visualising learning models [44] and show the marginal effect of one or two variables on the output of a learning model [43], including linear, monotonous or convex relationships. Zhao and Hastie [44] provide the mathematical modelling of PDPs. The PDPs were obtained using the plot_partial_dependence tool from the Sci-kit Learn library.

4. Results

4.1. Data Description

Table 3 summarises the descriptive statistics of the sample considering both sociodemographic characteristics and e-consumption behaviour. Most of the respondents (87%) are younger than 50, earn between two and 10 minimum wages (49%), and are male (53%). Electronic products are the most common e-commerce purchases. Also, most e-consumers (69%) used to make at least one e-purchase per month at the date of the survey, which results in at least one e-commerce delivery per month. The maximum delivery fee willingness-to-pay is 10% of the product price for 72% of respondents e-consumers.

Figure 1 shows the histograms of the sociodemographic characteristics, e-shopping characteristics, and delivery attributes. The delivery fee influences most e-consumers, and the data revealed the importance of convenience, promotions, and pricing in e-shopping. Data reported in the histograms show that most respondents are between 25 and 34 years old, earn above 10 Brazilian minimum wages and are of both genders. Furthermore, they are more likely to buy electronics, followed by beauty and clothing products, and books and leisure items, and are only willing to pay less than 10% of the product value as a delivery fee. In addition, most e-consumers buy products online at least once a month and consider convenience, privacy, promotion, and pricing as important characteristics when e-shopping. Finally, most of them are influenced by the delivery fee and delivery time, considered the attributes most important for e-shopping. Still, more respondents consider delivery reception less or neutrally important.

Table 3. Data descriptive statistics.

Characteristics	Variables	Type of Response	Frequency	Percentage
Sociodemographic characteristics	Age	15−24 years old	123	21%
		25−34 years old	275	46%
		35−49 years old	121	20%
		above 50 years old	76	13%
	Income	less than one wage	9	2%
		2–4 wages	137	23%
		4–10 wages	235	39%
		more than ten wages	214	36%
	Gender	male	318	53%
		female	277	47%

Table 3. *Cont.*

Characteristics	Variables	Type of Response	Frequency	Percentage
Consumption behaviour	Product type	beauty and clothing products	374	32%
		electronic products	459	40%
		books and leisure products	322	28%
	Frequency of e-shopping	once per month	410	69%
		more than once per month	185	31%
	Delivery fee willingness to pay	until 3% of the product price	96	16%
		until 7% of the product price	133	22%
		until 10% of the product price	262	44%
		over than 10% of the product price	104	17%

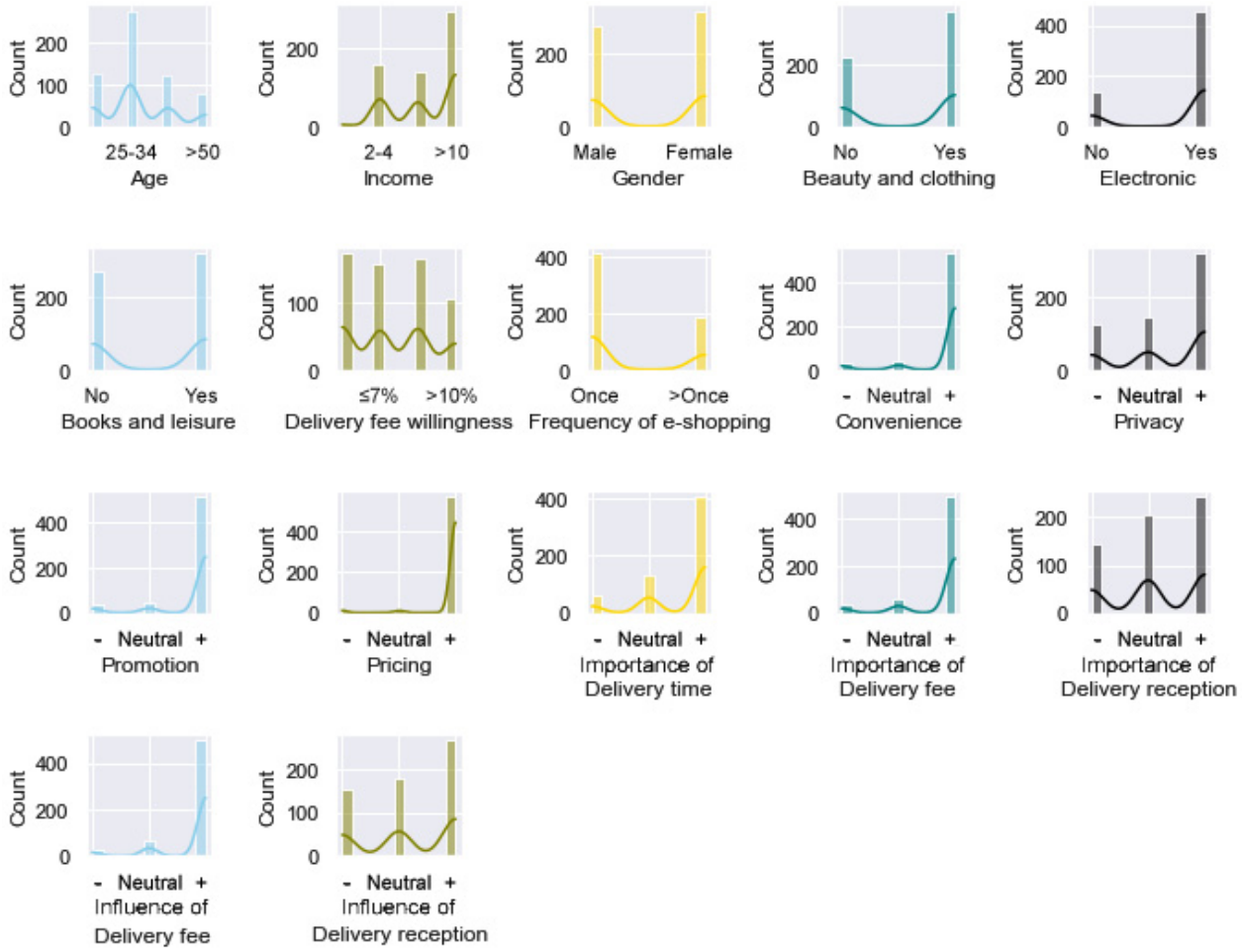


Figure 1. Histogram and Kernel density estimates of e-shopping characteristics and delivery attributes.

Table 4 shows the descriptive statistics of e-shopping characteristics and delivery attributes obtained from the survey in a 3-point Likert scale data format (negative = 1, neutral = 2, positive = 3). These questions investigated the importance of general e-shopping characteristics and delivery attributes on e-shopping. For the delivery attributes, the first

three attributes (i.e., delivery time, delivery fee, and delivery reception) are related to general e-shopping behaviour. The remaining attributes (i.e., delivery fee influence on the e-shopping decision and delivery fee influence on e-shopping decision) are more specific and reflect the final purchase decision. Among e-shopping characteristics, only privacy has neutral responses in the first quartile. Similarly, delivery time and reception also have neutral responses in the first quartile among the delivery attributes.

Table 4. Descriptive statistics of e-shopping characteristics and delivery attributes.

Title 2	Description	Cronbach Alpha	Min	1st Quartile	Median	3rd Quartile	Max
E-shopping characteristics	Convenience	0.783	1	3	3	3	3
	Privacy	0.777	1	2	3	3	3
	Promotion	0.778	1	3	3	3	3
	Pricing	0.780	1	3	3	3	3
Delivery attributes	Importance of delivery time	0.767	1	2	3	3	3
	Importance of delivery fee	0.777	1	3	3	3	3
	Importance of delivery reception	0.770	1	2	2	3	3
	Influence of delivery fee	0.799	1	3	3	3	3
	Influence of delivery reception	0.790	1	1	2	3	3

4.2. Significance of the Effects of Delivery Attributes on E-consumption Behaviour

Table 5 presents the estimated coefficients of the logistic regression model and the significance of the estimations. The variable with statistical significance shows that the delivery attributes somehow affect the e-consumer.

Results show that characteristics such as delivery fee willingness to pay, and privacy are affected by delivery times according to gender. Similarly, delivery fees affect the e-consumer according to gender, the habit of purchasing books and leisure products, privacy, promotions, and pricing, and also influence the e-shopping decision by age, purchase of electronic products, and promotions. In addition, delivery reception is considered by respondents according to their age, income, gender, frequency of e-shopping, privacy, and pricing. Finally, delivery fee, willingness-to-pay, and privacy are characteristics influenced by delivery reception on the e-shopping decision.

4.3. Pattern Recognition

The following sections present the PDPs to recognise patterns related to the effects of sociodemographic characteristics, e-consumption behaviour, and e-shopping characteristics on the different delivery attributes. The effects are analysed and compared considering four patterns: increase, decrease, constant, and complex.

Table 5. Results of the logistic regression models.

Variables		Range	Importance of Delivery Time	Importance of Delivery Fee	Importance of Delivery Reception	Influence of Delivery Fee	Influence of Delivery Reception
Intercept			−3.21 ***	−2.24	−2.00 **	18.72	2.06 ′
Sociodemographic characteristics	Age	25−34 years	−0.48	−0.63	−0.18	−1.14	−0.13
		35−49 years	−0.09	0.36	0.65′	−2.87 **	−0.26
		>50 years	−0.64	−0.57	−0.09	−3.21 **	0.726 ′
	Income	2–4 wages	0.61	−1.58	0.48*	1.23	−0.11
		4–10 wages	0.87	−0.69	0.76	1.27	−0.36
		>10 wages	0.64	−1.50	0.88	0.86	0.36
	Gender	Female	0.92 **	0.89 ′	0.54 **	0.04	0.05
E-consumption behaviour	Product type	Beauty and clothing	−0.27	−0.24	0.11	−0.07	−0.22
		Electronic products	−0.73	−0.42	−0.31	1.92 *	−0.13
		Books and leisure products	0.26	1.03 *	−0.48 *	0.05	−0.03
	E-shopping frequency	> than once by month	−0.18	0.36	−0.48 *	0.41	−0.27
	Delivery fee willingness to pay	Until 7%	−0.69	0.27	−0.29	−0.09	0.24
		Until 10%	−0.70	−0.24	−0.15	−0.48	0.43
		>10%	−1.07 *	−0.88	0.07	−0.29	0.61 *
E-shopping characteristics	Convenience	Neutral	0.19	0.27	0.10	1.39	0.60
		Important	0.52	−0.24	−0.33	0.55	0.40
	Privacy	Neutral	0.55	−0.55	1.19 ***	0.52	0.10
		Important	1.42 **	1.21 **	1.28 *	0.33	0.67 **
	Promotion	Neutral	1.97	18.11	−0.28	−2.39 **	−0.39
		Important	0.65	1.65 **	0.20	−1.06	−0.24
	Pricing	Neutral	19.51	21.32	2.59 **	−15.97	−1.72
		Important	4.37 *	5.13 *	2.09 **	−15.62	−1.54
Accuracy			91%	94%	73%	93%	73%

Significance code: * < 0.001, ** < 0.01; *** < 0.05; ′ 0.1.

4.3.1. Importance of Delivery Time

Figure 2 shows the variable patterns related to the importance of delivery time on e-shopping. Increasing patterns are observed for income, gender, purchase of electronic products, delivery fee willingness to pay, convenience, privacy, and pricing. It suggests that such characteristics are important when delivery times are considered in e-shopping. Conversely, age, some products (beauty and clothing) and promotion are not essential when the effects of the delivery time are considered. Finally, shopping books, leisure products and the frequency of e-shopping are not affected by delivery times.

Figure 3 shows the marginal effects of e-shopping characteristics regarding the importance of delivery time. The pricing e-shopping characteristic is taken as a baseline for comparison. In the different charts, vertical lines indicate that the other variable is more important than pricing considering this delivery attribute. Horizontal lines indicate that the other variable is less critical than pricing for this delivery attribute. Finally, ascending or descending curves with 45-degree or 135-degree slopes (concerning the bottom left corner) indicate that both variables (i.e., the other variable and pricing) have the same importance for this delivery attribute. Therefore, convenience, privacy and promotion are less important than pricing, while delivery fee willingness-to-pay is more relevant than pricing.

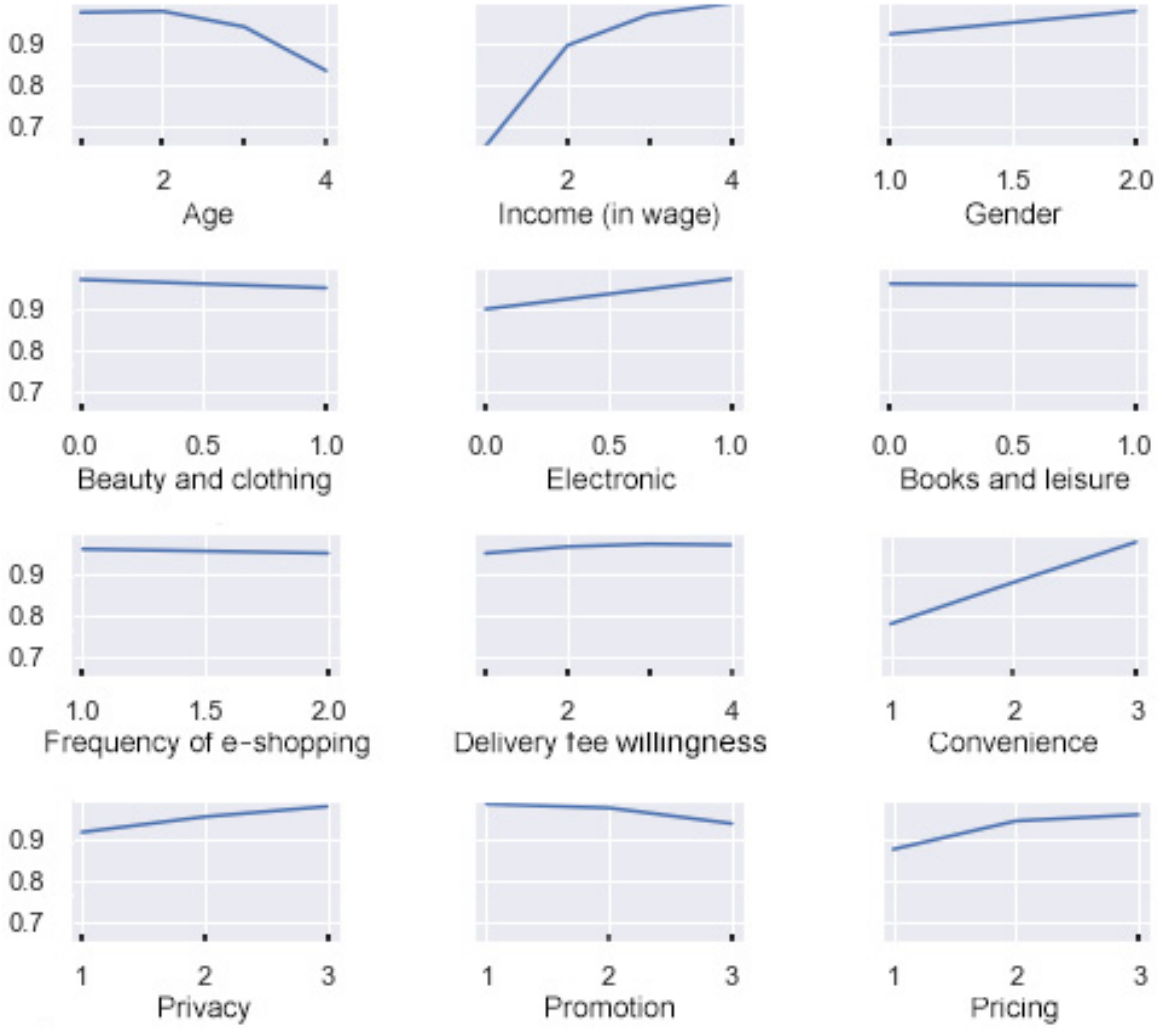


Figure 2. Pattern recognition for the importance of delivery time on e-shopping.

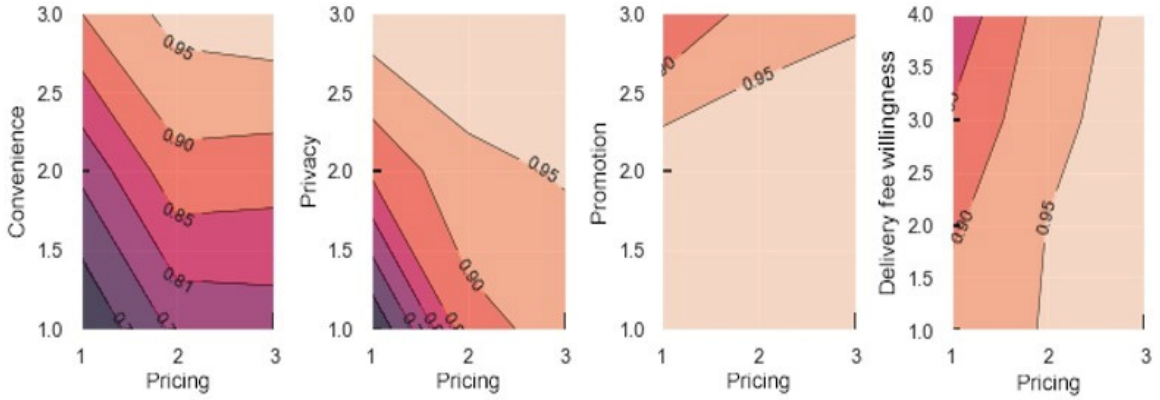


Figure 3. Analysis of marginal effects of the importance of delivery time: comparison between pricing, convenience, privacy, promotion, and delivery fee willingness-to-pay.

4.3.2. Importance of Delivery Fee

Figure 4 shows the pattern analysis for the importance of delivery fees. The analysis by age resulted in a complex pattern with a concave curve: it increases until the 25–34-year-old category (class 2), remains constant, and decreases after the 35–49-year-old category (class 3). Income, electronic products, delivery fee willingness to pay, and privacy showed

increasing patterns, indicating that these variables positively correlated to delivery fee when e-shopping. However, decreasing patterns are observed for convenience, promotion, and pricing, and thus presented negative effects when the importance of delivery fees is analysed. Finally, constant patterns are observed for gender, beauty and clothing products, books and leisure products, and frequency of e-shopping, which suggest their irrelevance regarding the effects of delivery fees.

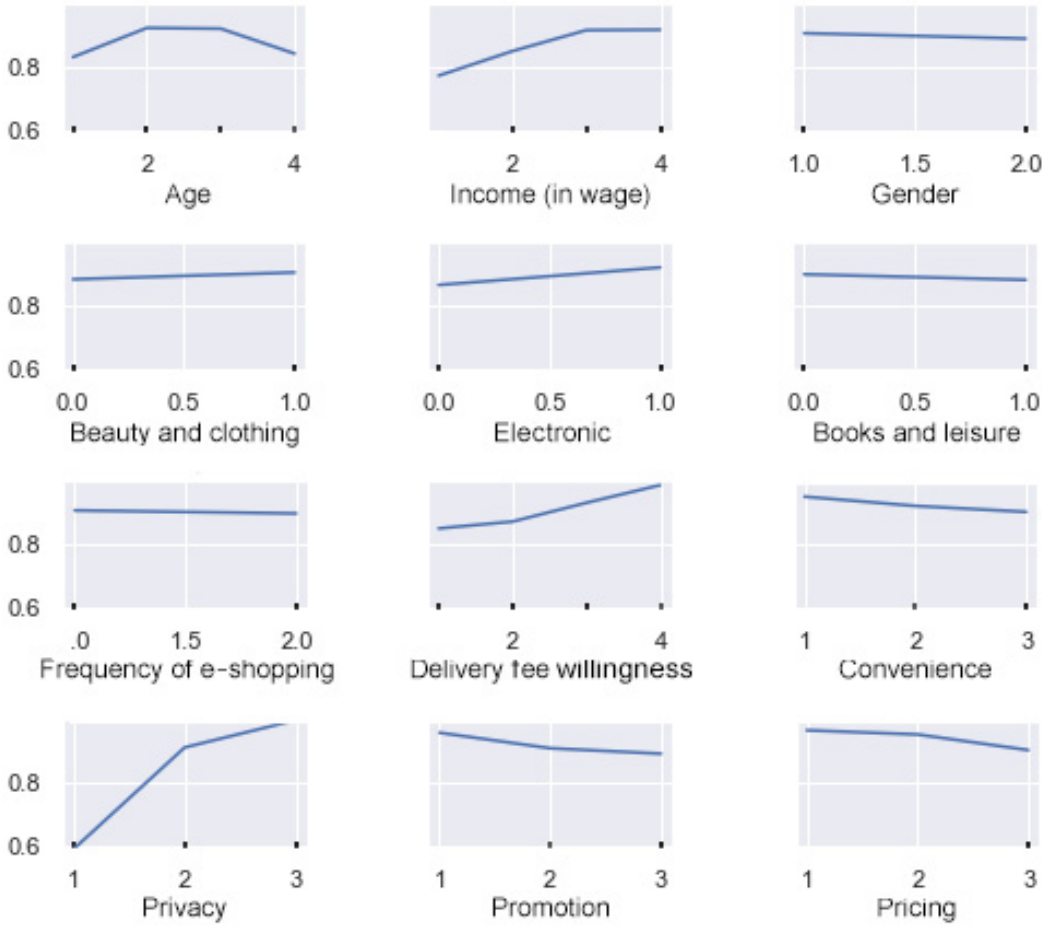


Figure 4. Pattern recognition for the importance of delivery fee on e-shopping.

According to the PDPs of Figure 5, convenience and promotion are less relevant than pricing regarding the importance of delivery fees. In contrast, privacy and delivery fee willingness-to-pay are more relevant than pricing for this delivery attribute.

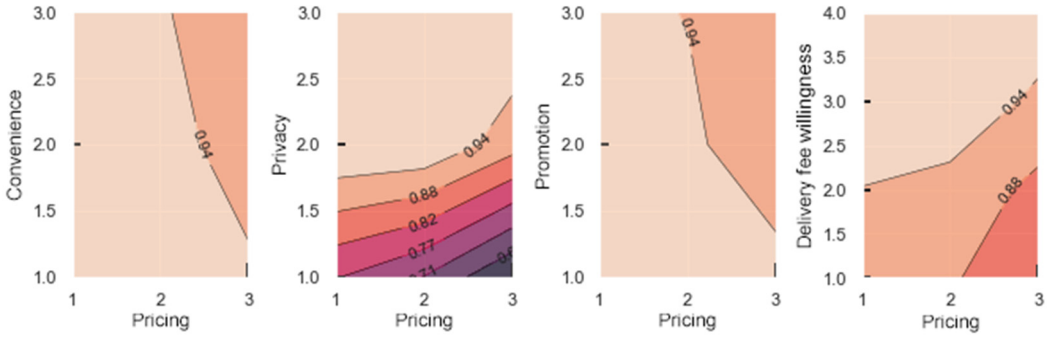


Figure 5. Analysis of marginal effects of the importance of delivery fee: comparison between pricing, convenience, privacy, promotion, and delivery fee willingness to pay.

4.3.3. Importance of Delivery Reception

Figure 6 shows the pattern analysis for the importance of delivery reception. Age, frequency of e-shopping, delivery fee willingness to pay, convenience, and pricing showed increasing patterns; thus, they are positively affected when the importance of delivery reception is assessed. Conversely, income, gender, beauty and clothing products, privacy, and promotion presented decreasing patterns, thus presenting adverse effects when the delivery reception is considered. Finally, flat patterns are observed for electronics and books and leisure products, which indicates that they are not considered when delivery reception is analysed.

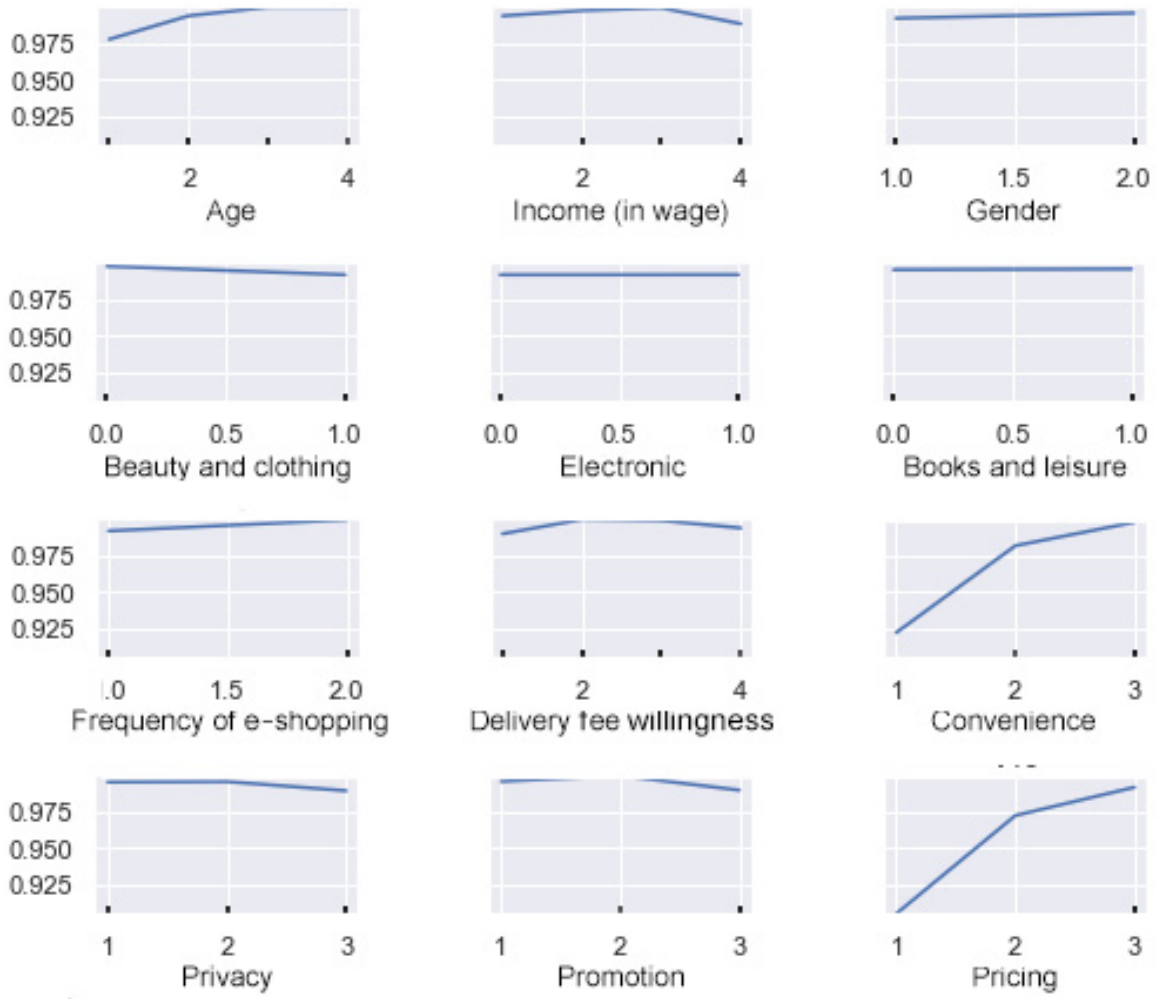


Figure 6. Pattern recognition for the importance of delivery reception on e-shopping.

The PDPs of Figure 7 show that privacy, promotion, and delivery fee willingness-to-pay are less relevant than pricing according to the importance of delivery reception. On the other hand, convenience and pricing are equally likely related to e-consumption when the importance of delivery reception is assessed.

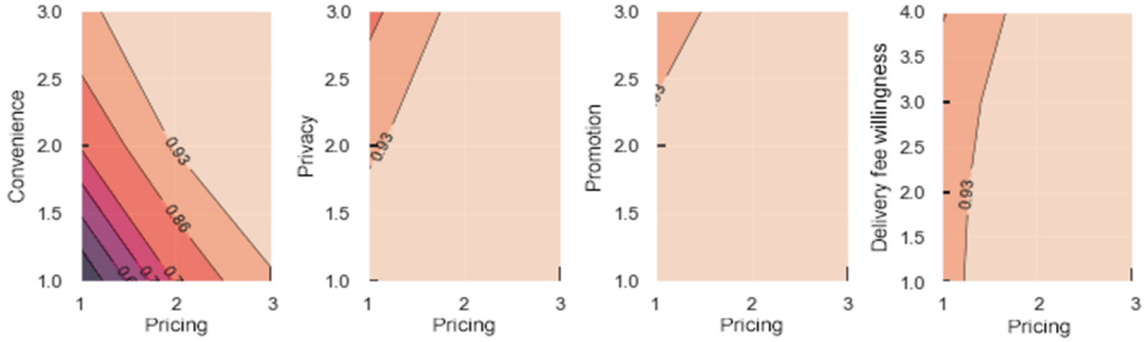


Figure 7. Analysis of marginal effects of the importance of delivery reception: comparison between pricing, convenience, privacy, promotion, and delivery fee willingness to pay.

4.3.4. Influence of Delivery Fee

Figure 8 shows the pattern analysis of how the delivery fee influences the e-shopping decision. The characteristics are of gender and frequency of e-shopping are not considered when that delivery attribute is assessed. Beauty and clothing, electronics, books and leisure products, and promotion are positively correlated to the influence of e-shopping. In contrast, age, income, delivery fee willingness-to-pay, convenience, privacy, and pricing showed decreasing patterns; thus, they are negatively correlated to the delivery fee influence on the e-shopping decision.

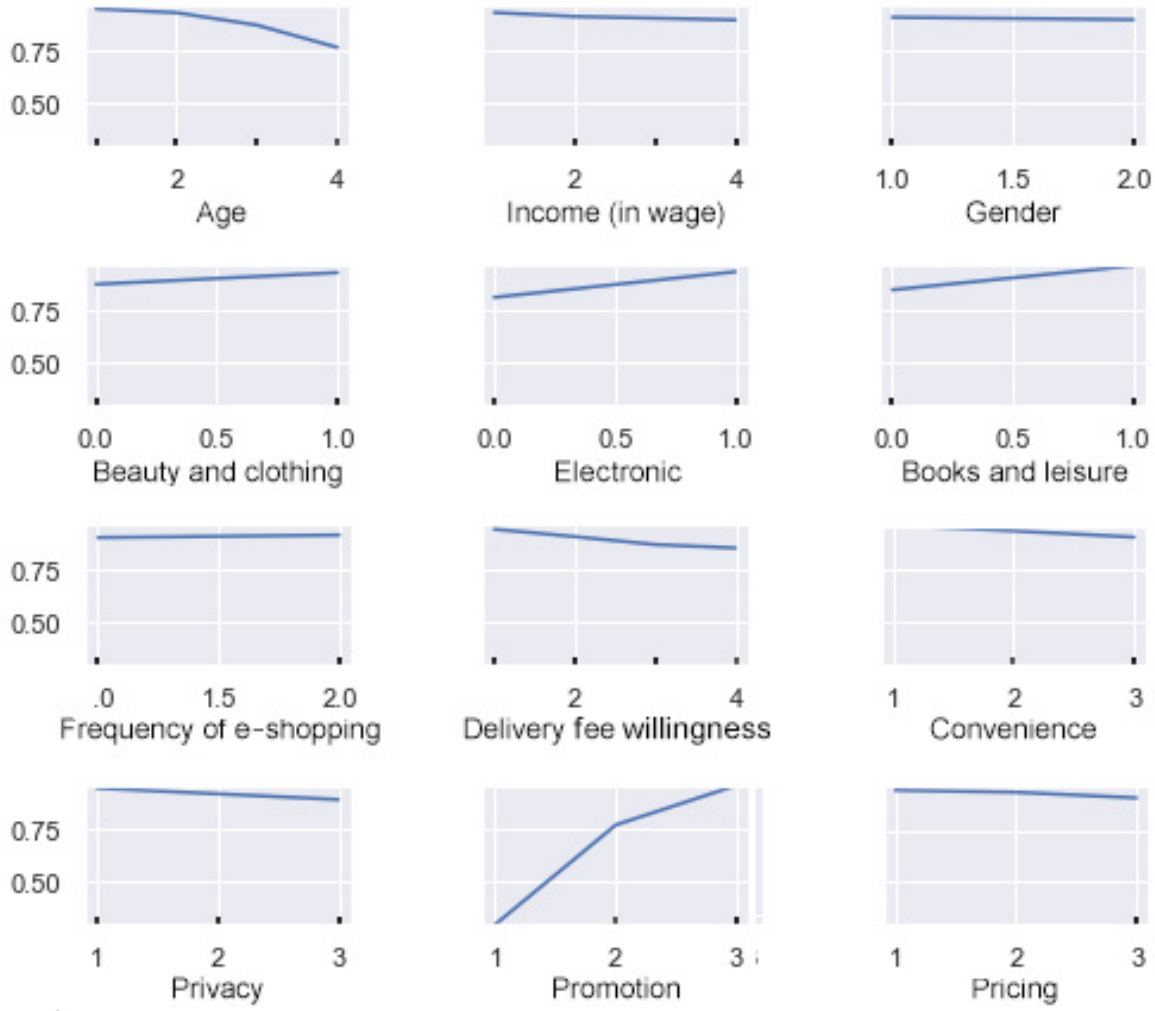


Figure 8. Pattern recognition for the influence of the delivery fee on the e-shopping decision.

For the influence of delivery fee on the e-shopping decision, the PDPs of Figure 9 show that convenience, privacy, and delivery fee willingness-to-pay have similar importance compared to pricing. In addition, promotion is more important than pricing when compared to the influence of the delivery fee.

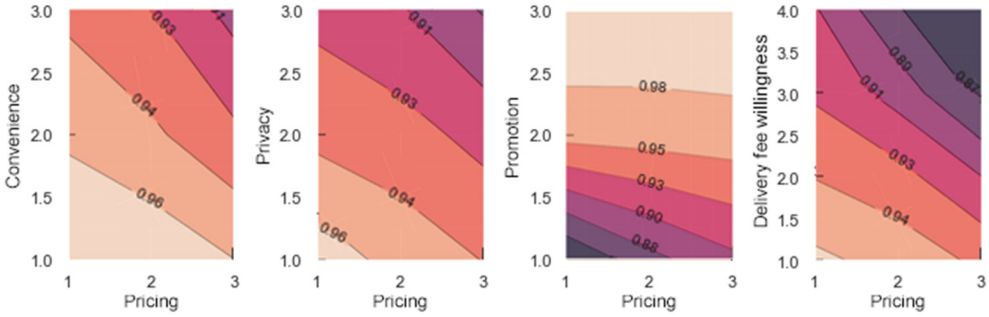


Figure 9. Analysis of marginal effects of the influence of delivery fee on the e-shopping decision: comparison between pricing, convenience, privacy, promotion, and delivery fee willingness to pay.

4.3.5. Influence of Delivery Reception

Figure 10 shows the marginal effects of how the delivery reception influences the e-shopping decision. The frequency of e-shopping has a flat pattern, which indicates no effects for this delivery attribute. Gender, electronic products, book and leisure products, and convenience showed increasing patterns and thus the positive effects of such characteristics. In contrast, age, income, beauty and clothing, delivery fee willingness-to-pay, privacy, promotion, and pricing resulted in decreasing patterns, representing negative effects for the influence of delivery reception on the e-shopping decision.

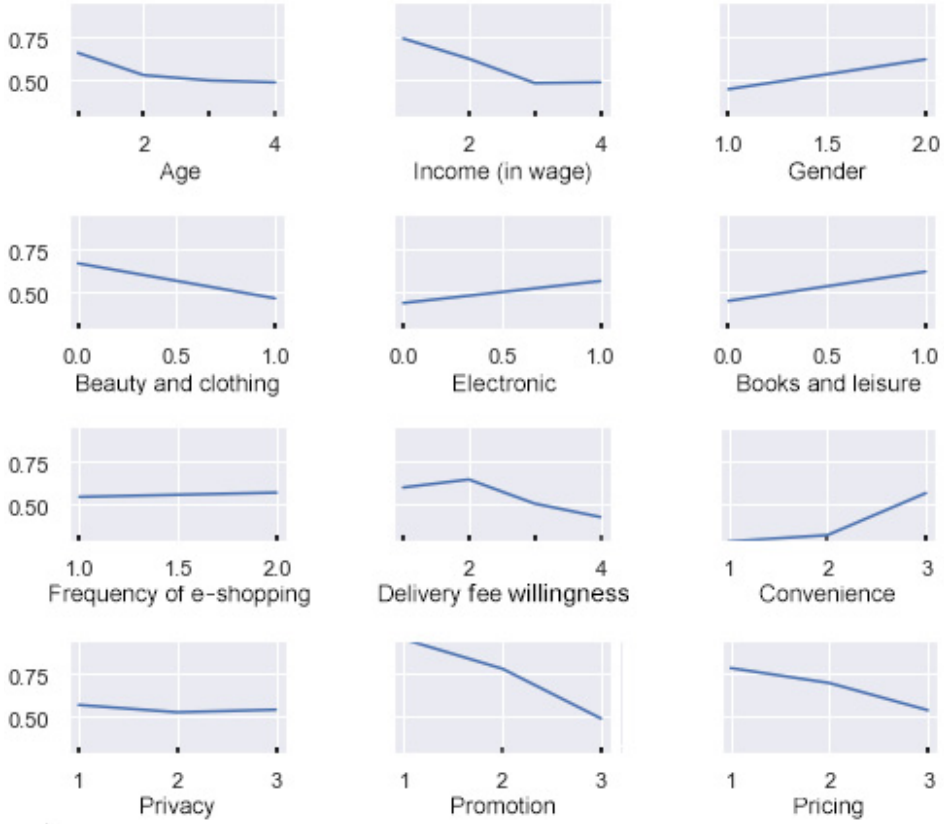


Figure 10. Pattern recognition to evaluate the influence of delivery reception on the e-shopping decision.

Figure 11 shows that privacy and promotion are more important than pricing. At the same time, convenience and delivery fee willingness-to-pay have the same importance as pricing for the influence of delivery reception on the e-shopping decision.

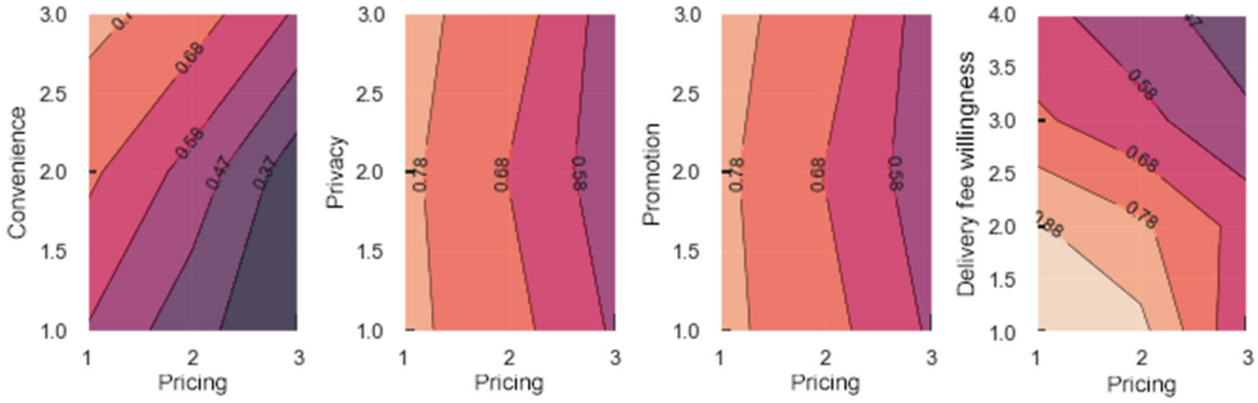


Figure 11. Analysis of marginal effects of the influence of delivery reception on the e-shopping decision: comparison between pricing, convenience, privacy, promotion, and delivery fee willingness to pay.

5. Discussion

The estimated coefficients of the logistic regression models provide insights regarding the effects of the delivery attributes according to the sociodemographic characteristics of e-consumers. For instance, gender is considered when the impacts of delivery time and the influence of delivery fee and delivery reception are assessed. Women are more likely to wait longer for the convenience of online shopping. The influence of delivery reception and delivery fees have a greater effect on e-consumers in the 35–49-year-old age group. The purchase of product types (especially books and leisure products) is influenced by delivery fee and delivery reception, while delivery reception only affects the shopping frequency. Also, delivery fees affect the purchase of electronic products, while all delivery attributes are related to privacy, promotion, and pricing when e-shopping.

Table 6 summarises the estimated effects of the delivery attributes per sociodemographic and e-shopping characteristics obtained from the neural network models. The sign '+' stands for positive effects (increasing patterns), and '−' stands for negative (decreasing patterns). Moreover, constant and complex (concave or convex functions) effects are explicitly indicated. Finally, the degree of dependence for each explanatory variable was estimated as low, medium, or high by comparing THE slopes of the curves: the higher the slope, the greater the importance of the effect of the delivery attribute regarding the independent variable (sociodemographic characteristic, e-consumption behaviour, or e-shopping characteristic).

For the sociodemographic characteristics, age resulted in complex patterns for the importance of delivery fees, which may increase, stabilise, and decrease as age increases. Also, it presents negative medium effects for most of the other delivery attributes. On the other hand, income presented different effects for each delivery attribute, and it showed great relevance related to the importance of delivery times. Additionally, gender showed a low relevance or constant effect for the delivery attributes (except for the delivery reception influence on the e-shopping decision). For e-consumption behaviour, the frequency of consumption showed a constant relationship for most of the delivery attributes. The product type presented different patterns for the different delivery attributes, despite its low relevance or constant effect for most of the delivery attributes. Privacy is relevant mainly for the importance of delivery fees, while pricing is highly relevant to the importance of delivery reception.

Table 6. Results of the neural network models.

Variables		Importance of Delivery Time	Importance of Delivery Fee	Importance of Delivery Reception	Influence of Delivery Fee	Influence of Delivery Reception
Sociodemographic characteristics	Age	Medium (−)	Complex (concave)	Low (+)	Medium (−)	Medium (−)
	Income	High (+)	Medium (+)	Low (−)	Low (−)	Medium (−)
	Gender	Low (+)	Constant	Low (–)	Constant	Medium (+)
E-consumption behaviour	Beauty and clothing products	Low (−)	Constant	Low (−)	Low (+)	Medium (−)
	Electronic products	Low (+)	Low (+)	Constant	Low (+)	Low (+)
	Books and leisure products	Constant	Constant	Constant	Low (+)	Low (+)
	Frequency of e–shopping	Constant	Constant	Low (+)	Constant	Constant
	Delivery fee willingness to pay	Low (+)	Medium (+)	Low (+)	Low (−)	Medium (−)
E-shopping characteristics	Convenience	Medium (+)	Low (−)	High (+)	Low (−)	High (+)
	Privacy	Low (+)	High (+)	Low (−)	Low (−)	Low (−)
	Promotion	Low (−)	Low (−)	Low (−)	High (+)	High (−)
	Pricing	Low (+)	Low (−)	High (+)	Low (−)	Medium (−)

While the logistic regression added robustness to the analysis by statistically validating the estimated coefficients per variable, ANN identified patterns employing a training and learning approach considering the non-linear and multidimensional characteristics about the relations between the variables. Results showed the effectiveness of combining these techniques to analyse consumer behaviour. Table 7 shows the accuracy of the results for these techniques. Although the logistic regression presented better accuracy, the ANN allowed pattern identification complemented by the PDPs.

Table 7. Accuracy between the Logistic Regression and the ANN models.

Delivery Attribute	Accuracy Logistic Regression	Accuracy ANN
Importance of delivery time	91%	82%
Importance of delivery fee	94%	84%
Importance of delivery reception	73%	64%
Influence of delivery fee	93%	88%
Influence of delivery reception	73%	60%

The results converge to the literature. For instance, sociodemographic characteristics and gender are related to delivery attributes, as pointed out by [10], who studied e-shopping frequency. Also, the purchase of different types of products is related to delivery attributes, as shown by [16]. Nevertheless, the influence of delivery attributes regarding e-shopping characteristics has been studied in this paper as a novel approach in the literature contributing to the gap pointed out by [8]. Furthermore, privacy, pricing, and promotion are related to the delivery attributes, as shown by [18,20,21,29], who investigated the impacts of consumer satisfaction on their behaviour.

6. Conclusions

This paper analysed the influence of delivery attributes on e-shopping consumer behaviour. The research hypotheses were: (1) the delivery attributes affect e-consumers'

behaviour according to their sociodemographic characteristics; and (2) delivery attributes affect e-shopping behaviour. The analyses were carried out with Brazilian e-consumers.

For the first hypothesis, the results indicate that the delivery attributes (mainly the delivery fee) affect the behaviour of middle-aged consumers (35–49 years old). For the second hypothesis, we identified that the delivery fee influences the purchase of electronics and books and leisure products. In turn, the importance of delivery attributes is not considered in e-shopping frequency. In summary, the e-consumer gives less importance to delivery fee than to delivery time or delivery reception, and the delivery attributes are considerably related to privacy. In contrast, pricing is more affected by delivery time than delivery fees. Finally, as the importance of promotion increases among e-consumers, it decreases the influence of the delivery attributes.

Consumer behaviour is dynamic and may change over time. Data analysed in this paper was obtained from a survey before the COVID-19 pandemic. In this context, restrictive measures to reduce the virus spread contributed to e-commerce deliveries. It is worth mentioning that the COVID-19 pandemic changed the population's consumption patterns. In this context, in which the online market has gained more importance, meeting the needs of consumers has become essential to increasing market share. Therefore, delivery attributes are increasingly essential to attract new buyers and/or maintain existing customer loyalty. Among the attributes analysed in this article, the delivery fee has become a factor in retaining customers in marketplaces. Many marketplaces have offered subscriptions in exchange for free shipping and reduced delivery time. Therefore, these attributes are being used to increase online shopping.

On the other hand, the Brazilian market is still restricted in terms of delivery reception alternatives, since most deliveries are still destined for the end customer. Alternatives such as pick-up points or lockers are still timid initiatives that are being disseminated, especially in large cities such as São Paulo and Belo Horizonte. Alternative delivery reception could contribute to sustainable urban freight transport. The results found in the Brazilian context would be generalized to other growing markets in Latin America and developing countries such as China, where similar e-consumer behaviour is observed and few alternatives to home deliveries are available.

Changing consumer behaviour and greater awareness of the collective benefits of this initiative need to be further disseminated to consumers. Thus, further research would analyse the changes in consumer behaviour in the post-pandemic scenario and identify the influence of spatial characteristics on e-commerce deliveries. Finally, further analysis would include the proposition and assessment on the effects of public policies on consumer behaviour in urban freight transport and, more specifically, in e-commerce deliveries.

Author Contributions: Conceptualisation, E.G.D. and L.K.d.O.; methodology, E.G.D., L.K.d.O. and C.A.I.; validation, E.G.D., L.K.d.O. and C.A.I.; formal analysis, E.G.D.; data curation, E.G.D.; writing—original draft preparation, E.G.D., L.K.d.O. and C.A.I.; writing—review and editing; E.G.D., L.K.d.O. and C.A.I.; supervision, L.K.d.O. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

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

Data Availability Statement: The data presented in this study are available on request from the corresponding author.

Acknowledgments: This research was funded by National Council for Scientific and Technological Development (CNPq), grant number 303171/2020-0.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Statista. E-Commerce Worldwide. 2021. Available online: https://www.statista.com/topics/871/online-shopping/#dossier-chapter2 (accessed on 12 December 2021).
2. Morganti, E.; Seidel, S.; Blanquart, C.; Dablanc, L.; Lenz, B. The Impact of E-Commerce on Final Deliveries: Alternative Parcel Delivery Services in France and Germany. *Transp. Res. Procedia* **2014**, *4*, 178–190. [CrossRef]
3. Cárdenas, I.; Beckers, J.; Vanelslander, T. E-Commerce Last-Mile in Belgium: Developing an External Cost Delivery Index. *Sustain. Effic. Manag. Issues Urban Goods Transp. New Trends Appl.* **2017**, *24*, 123–129. [CrossRef]
4. Lin, Y.H.; Wang, Y.; He, D.; Lee, L.H. Last-Mile Delivery: Optimal Locker Location under Multinomial Logit Choice Model. *Transp. Res. Part E Logist. Transp. Rev.* **2020**, *142*, 102059. [CrossRef]
5. Nogueira, G.P.M.; de Assis Rangel, J.J.; Shimoda, E. Sustainable Last-Mile Distribution in B2C e-Commerce: Do Consumers Really Care? *Clean. Responsible Consum.* **2021**, *3*, 100021. [CrossRef]
6. de Oliveira, L.K.; Morganti, E.; Dablanc, L.; de Oliveira, R.L.M. Analysis of the Potential Demand of Automated Delivery Stations for E-Commerce Deliveries in Belo Horizonte, Brazil. *Res. Transp. Econ.* **2017**, *65*, 34–43. [CrossRef]
7. Buldeo Rai, H.; Verlinde, S.; Macharis, C. The "next Day, Free Delivery" Myth Unravelled. *Int. J. Retail Distrib. Manag.* **2019**, *47*, 39–54. [CrossRef]
8. Nguyen, D.N.; Leeuw, S.; Dullaert, W.; Foubert, B.P.F. What Is the Right Delivery Option for You? Consumer Preferences for Delivery Attributes in Online Retailing. *J. Bus. Logist.* **2019**, *40*, 299–321. [CrossRef]
9. Ignat, B.; Chankov, S. Do E-Commerce Customers Change Their Preferred Last-Mile Delivery Based on Its Sustainability Impact? *Int. J. Logist. Manag.* **2020**, *31*, 521–548. [CrossRef]
10. Xiao, Z.; Wang, J.J.; Liu, Q. The Impacts of Final Delivery Solutions on E-Shopping Usage Behaviour. *Int. J. Retail Distrib. Manag.* **2018**, *46*, 2–20. [CrossRef]
11. Holguín-Veras, J.; Amaya Leal, J.; Seruya, B.B. Urban Freight Policymaking: The Role of Qualitative and Quantitative Research. *Transp. Policy* **2017**, *56*, 75–85. [CrossRef]
12. Marino, G.; Zotteri, G.; Montagna, F. Consumer Sensitivity to Delivery Lead Time: A Furniture Retail Case. *Int. J. Phys. Distrib. Logist. Manag.* **2018**, *48*, 610–629. [CrossRef]
13. Prebreza, A.; Shala, B. The Trust in Online Shopping during COVID-19: Case Study from Kosovo. *Open Access Libr. J.* **2021**, *8*, e7288. [CrossRef]
14. Vasić, N.; Kilibarda, M.; Kaurin, T. The Influence of Online Shopping Determinants on Customer Satisfaction in the Serbian Market. *J. Theor. Appl. Electron. Commer. Res.* **2019**, *14*, 70–89. [CrossRef]
15. Chincholkar, S.; Sonwaney, V. Website Attributes and Its Impact on Online Consumer Buying Behaviour: An Empirical Study of Online Consumers in Mumbai Region. *Indian J. Sci. Technol.* **2017**, *10*, 1–9. [CrossRef]
16. Lim, H.; Dubinsky, A.J. Consumers' Perceptions of E-shopping Characteristics: An Expectancy-value Approach. *J. Serv. Mark.* **2004**, *18*, 500–513. [CrossRef]
17. Amorim, P.; DeHoratius, N.; Eng-Larsson, F.; Martins, S. Customer Preferences for Delivery Service Attributes in Attended Home Delivery. *Chic. Booth Res. Pap.* **2020**. [CrossRef]
18. Oliveira, L.K.; Oliveira, R.L.M.; Sousa, L.T.M.; Caliari, I.P.; Nascimento, C.O.L. Analysis of Accessibility from Collection and Delivery Points: Towards the Sustainability of the e-Commerce Delivery. *Urbe Rev. Bras. Gest.* **2019**, *11*, e20190048. [CrossRef]
19. Buldeo Rai, H.; Broekaert, C.; Verlinde, S.; Macharis, C. Sharing Is Caring: How Non-Financial Incentives Drive Sustainable e-Commerce Delivery. *Transp. Res. Part Transp. Environ.* **2021**, *93*, 102794. [CrossRef]
20. Iannaccone, G.; Marcucci, E.; Gatta, V. What Young E-Consumers Want? Forecasting Parcel Lockers Choice in Rome. *Logistics* **2021**, *5*, 57. [CrossRef]
21. Caspersen, E.; Navrud, S. The Sharing Economy and Consumer Preferences for Environmentally Sustainable Last Mile Deliveries. *Transp. Res. Part Transp. Environ.* **2021**, *95*, 102863. [CrossRef]
22. Marcucci, E.; Gatta, V.; Le Pira, M.; Chao, T.; Li, S. Bricks or Clicks? Consumer Channel Choice and Its Transport and Environmental Implications for the Grocery Market in Norway. *Cities* **2021**, *110*, 103046. [CrossRef]
23. Buldeo Rai, H.; Verlinde, S.; Macharis, C. Who Is Interested in a Crowdsourced Last Mile? A Segmentation of Attitudinal Profiles. *Travel Behav. Soc.* **2021**, *22*, 22–31. [CrossRef]
24. Janjevic, M.; Winkenbach, M. Characterizing Urban Last-Mile Distribution Strategies in Mature and Emerging e-Commerce Markets. *Transp. Res. Part Policy Pract.* **2020**, *133*, 164–196. [CrossRef]
25. Ebit; Nielsen Webshoppers. 2021. Available online: https://www.ebit.com.br/ (accessed on 12 December 2021).
26. Yuen, K.F.; Wang, X.; Ng, L.T.W.; Wong, Y.D. An Investigation of Customers' Intention to Use Self-Collection Services for Last-Mile Delivery. *Transp. Policy* **2018**, *66*, 1–8. [CrossRef]
27. Liu, H.; Huang, Y.; Wang, Z.; Liu, K.; Hu, X.; Wang, W. Personality or Value: A Comparative Study of Psychographic Segmentation Based on an Online Review Enhanced Recommender System. *Appl. Sci.* **2019**, *9*, 1992. [CrossRef]
28. Hagen, T.; Scheel-Kopeinig, S. Would Customers Be Willing to Use an Alternative (Chargeable) Delivery Concept for the Last Mile? *Urban Transp. Plan. Policy Chang. World Bridg. Gap Theory Pract.* **2021**, *39*, 100626. [CrossRef]
29. Liu, C.; Wang, Q.; Susilo, Y.O. Assessing the Impacts of Collection-Delivery Points to Individual's Activity-Travel Patterns: A Greener Last Mile Alternative? *Transp. Res. Part E Logist. Transp. Rev.* **2019**, *121*, 84–99. [CrossRef]

30. Song, Z. The Geography of Online Shopping in China and Its Key Drivers. *Environ. Plan. B Urban Anal. City Sci.* **2021**, 23998083211002188. [CrossRef]
31. Irawan, M.Z.; Wirza, E. Understanding the Effect of Online Shopping Behavior on Shopping Travel Demand through Structural Equation Modeling. *J. East. Asia Soc. Transp. Stud.* **2015**, *11*, 614–625. [CrossRef]
32. Lim, H.; Widdows, R.; Hooker, N.H. Web Content Analysis of E-grocery Retailers: A Longitudinal Study. *Int. J. Retail Distrib. Manag.* **2009**, *37*, 839–851. [CrossRef]
33. Cherrett, T.; Dickinson, J.; McLeod, F.; Sit, J.; Bailey, G.; Whittle, G. Logistics Impacts of Student Online Shopping—Evaluating Delivery Consolidation to Halls of Residence. *Transp. Res. Part C Emerg. Technol.* **2017**, *78*, 111–128. [CrossRef]
34. Mehmood, S.M.; Najmi, A. Understanding the Impact of Service Convenience on Customer Satisfaction in Home Delivery: Evidence from Pakistan. *Int. J. Electron. Cust. Relatsh. Manag.* **2017**, *11*, 23–43. [CrossRef]
35. Cortina, J.M. What Is Coefficient Alpha? An Examination of Theory and Applications. *J. Appl. Psychol.* **1993**, *78*, 98–104. [CrossRef]
36. Gliem, J.A.; Gliem, R.R. Calculating, Interpreting, and Reporting Cronbach's Alpha Reliability Coefficient for Likert-Type Scales. In Proceedings of the 2003 Midwest Research to Practice Conference in Adult, Continuing, and Community Education, Columbus, OH, USA, 8–10 October 2003; pp. 82–88.
37. Taber, K.S. The Use of Cronbach's Alpha When Developing and Reporting Research Instruments in Science Education. *Res. Sci. Educ.* **2018**, *48*, 1273–1296. [CrossRef]
38. Visa, S.; Ramsay, B.; Ralescu, A.; VanDerKnaap, E. Confusion Matrix-Based Feature Selection. In Proceedings of the 22nd Midwest Artificial Intelligence and Cognitive Science Conference, Cincinnati, OH, USA, 16–17 April 2011; pp. 121–127.
39. Washington, S.P.; Karlaftis, M.G.; Mannering, F. *Statistical and Econometric Methods for Transportation Data Analysis*; Chapman and Hall/CRC: Boca Raton, FL, USA, 2003.
40. Schmidhuber, J. Deep Learning in Neural Networks: An Overview. *Neural Netw.* **2015**, *61*, 85–117. [CrossRef]
41. Pedregosa, F.; Varoquaux, G.; Gramfort, A.; Michel, V.; Thirion, B.; Grisel, O.; Blondel, M.; Prettenhofer, P.; Weiss, R.; Dubourg, V.; et al. Scikit-Learn: Machine Learning in Python. *J. Mach. Learn. Res.* **2011**, *12*, 2825–2830.
42. Aschwanden, G.D.; Wijnands, J.S.; Thompson, J.; Nice, K.A.; Zhao, H.; Stevenson, M. Learning to Walk: Modeling Transportation Mode Choice Distribution through Neural Networks. *Environ. Plan. B Urban Anal. City Sci.* **2021**, *48*, 186–199. [CrossRef]
43. Friedman, J.H. Greedy Function Approximation: A Gradient Boosting Machine. *Ann. Stat.* **2001**, *29*, 1189–1232. [CrossRef]
44. Zhao, Q.; Hastie, T. Causal Interpretations of Black-Box Models. *J. Bus. Econ. Stat.* **2021**, *39*, 272–281. [CrossRef]