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Modelling Consumers' Preferences for Time-Slot Based Home Delivery of Goods Bought Online: An Empirical Study in Christchurch

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Abstract: Due to the remarkable growth in online retail sales in New Zealand, a large number of parcels are needed to be delivered to consumers' doorsteps. Home deliveries in major New Zealand cities (e.g., Christchurch) typically occur between 9 a.m. and 6 p.m. on weekdays, when many home delivery attempts fail. This leads to adverse effects, such as vehicular traffic in residential areas and greater air pollution per parcel delivered. However, home deliveries outside of typical business hours (i.e., before 9 a.m. and after 5 p.m.) might be worthwhile to help subside the above issues. Therefore, this study investigated consumers' preferences for receiving home deliveries during various times, such as early morning, morning, afternoon, late afternoon, and evening. The data used in this study were obtained via an online survey of 355 residents of Christchurch city. Non-parametric tests, namely the Friedman test, Wilcoxon signed-rank test, and ordinal logistic regression, were carried out to examine consumer preferences for the above time slots. The results showed that consumers preferred the late afternoon (3 p.m. to 6 p.m.) time slot the most for receiving home deliveries. It appeared that the off-peak delivery option is less likely to draw the desired consumer patronage and is thus less likely to assist in lowering the number of unsuccessful home deliveries, the transportation costs incurred by service providers, traffic congestion, and pollution in urban areas.

Keywords: online shopping; home delivery; greenhouse gas; off-hour delivery; New Zealand

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1. Introduction

A considerable proportion of the global human population (i.e., 55% in 2018) lives in urban areas [1], which occupy only 30% of the total land area inhabited by humans and 3% of the total land area of the world [2]. However, more people are moving to urban areas, mainly in their quest to achieve economic growth in terms of better employment, income, health, education, and social and recreational opportunities. To meet their requirements for economic growth and well-being, they depend on urban passenger and freight transport infrastructures, which enable the movement of people and goods [3]. Moreover, urban areas typically consume more goods than they produce, and consequently, their dependence on goods transported from the outside of the city has increased over the years [4]. The demand for personal travel and goods transport has therefore been increasing. Consequently, adverse traffic impacts, such as congestion, compromised safety of road users, high transport costs, air pollution, and degraded social space, have become increasingly common for urban dwellers [5–7]. For example, in New Zealand, where 86% of the population resides in urban areas, about 20% of the country's total greenhouse gas emissions each year come from the transport sector [8]. In addition, a huge portion (i.e., 90%) of those transport emissions is caused by road transport, with 67% being contributed by light vehicles (i.e., passenger cars and light commercial vehicles), which are mainly concentrated in urban areas [9]. It is also worth noting that light passenger vehicles and light commercial vehicles, respectively, constituted 73% and 20% of road travel in New Zealand in 2018 [10], which indicates the significance of both passenger and goods transport in urban areas. Therefore, it is essential to maintain the sustainability (i.e., economic viability, social equity, and environmental acceptability) of both personal travel and goods transport while facilitating economic growth in urban areas [11].

In addition, with the recent advances in information and communication technology (ICT), e-commerce (also referred to as online shopping) has emerged as a new opportunity and a challenge for urban transport systems. For instance, while the increasing adoption of online shopping has the potential to decrease people's shopping travel, the last mile of goods transport (i.e., the final leg of the supply chain of a product) has undergone a considerable transformation in recent years, as the consumer demand for having items (bought online) delivered to the home has increased manifold [12–14]. This, in turn, has become an economic opportunity for businesses (e.g., retailers and freight carriers) involved in the e-commerce and freight logistics sectors. However, at the same time, freight delivery vehicle use in urban areas has also increased [15]. For instance, the volume of domestic parcels delivered by New Zealand Post was 6% higher in 2019 compared to 2018 [16]. This has adverse implications for the urban setting in terms of environmental costs. Note that there are also other components of freight transport that contribute to the adverse traffic and environmental implications, such as the long-haul transport of raw materials and the transport of finished products between manufacturing units and warehouses, but the goods' last-mile transport is often the most expensive (e.g., up to 75% of the total transport cost), least efficient, and most polluting component of the goods supply chain [17–19]. This only aggravates the adverse traffic impacts of increasing online shopping and sales worldwide.

To this end, more recent research [20–30] has sought innovative methods (e.g., delivery via collection-and-delivery points, delivery using cargo bikes, delivery using electric vehicles, crowd-sourced deliveries, delivery via smart home devices, and delivery via mobile lockers) for conducting last-mile deliveries to help mitigate the issues facing urban freight transport systems. However, despite several methods, home delivery has been the most common delivery mode [31]. For instance, a considerable proportion of online buyers in New Zealand prefer home delivery of their online orders, which is typically carried out during the daytime (i.e., 9 a.m. to 6 p.m.) on weekdays [32].

Online shopping customer satisfaction is greatly influenced by delivery performance [33]. For instance, the time between the purchase and delivery of an item must be short and deliveries should be punctual to prevent decreases in customer satisfaction and increases in delivery costs [34]. E-commerce is largely governed by customers, as they are often allowed to return or cancel an order even before the parcel arrives [35]. Therefore, customer preferences and satisfaction related to delivery schedules are of paramount importance for e-commerce and logistics ventures to be successful.

It has been well established that freight deliveries to retailers in the city, when carried out during off-peak hours, have the potential to reduce traffic congestion, travel times and transport costs, and environmental pollution, and to improve traffic safety within urban areas [36–38]. However, the option of delivering online orders to end-consumers during off-peak hours (i.e., 6 a.m. to 9 a.m. or 6 p.m. to 9 p.m.) has not received enough attention. For instance, consumers' preferences for off-hour deliveries (OHDs) of goods bought online have not been adequately studied. Therefore, this study aimed to investigate consumer preferences for OHDs of goods bought online, using Christchurch city as a case study. The data used in the study were obtained via an online survey of residents of Christchurch city. The data were analysed using statistical tests (e.g., Freidman Test) and ordinal logistic regression.

The remainder of this paper is structured as follows: A discussion on studies relating to OHDs is given in Section 2. The adopted research method is described in Section 3. Section 4 is devoted to the description of survey implementation and data collection. Section 5 comprises the statistical analysis carried out to understand consumer preferences for OHDs. Finally, Section 6 concludes this study.

2. Literature Review

It is worth noting that research and policies regarding urban transport planning, up until the past two decades, often neglected the goods transport component of urban transport systems [39,40]. It is mainly in the past two decades that the development and implementation of policies related to urban freight transport have received increased attention [41,42]. For example, a variety of policy measures, such as controlled access to city centres for freight vehicles, the creation of low-emission zones, the relocation of large freight terminals to outer parts of the city, off-peak hour deliveries to retailers, and road pricing or taxes for freight vehicles, have been assessed and implemented in several parts of the world to help make urban areas sustainable and liveable and to foster their economic development [43].

The term 'off-hour delivery (OHD)' has traditionally been used to represent the deliveries conducted to retailers outside of peak hours, with or without the retailers being present. There are typically two types of OHDs to retailers—assisted deliveries (i.e., deliveries performed with receivers being present) and unassisted deliveries (i.e., deliveries performed without receivers being present and through direct access to shop stockrooms). Another method of supplying goods to retailers involves delivery through urban consolidation centres (UCCs), which are restocked during night hours by transport providers, while retailers are supplied whenever they prefer (typically during regular opening hours) by small, environmentally friendly trucks [44].

Several studies investigated various stakeholders' preferences for OHDs. For instance, Aljohani and Thompson [45], Dias et al. [46], Gatta et al. [44], Holguín-Veras et al. [47], and Marcucci and Gatta [4] studied retailers' preferences for receiving OHDs. Similarly, Dias et al. [46], Gatta et al. [44], and Holguín-Veras et al. [48] studied carriers' preferences for conducting OHDs, while some other studies investigated the public administration's viewpoint on OHDs [44] and the local residents' perspectives of OHDs [44].

On the other hand, there are only a few studies [49,50] that investigate consumers' or online shoppers' preferences for receiving OHDs or time-slot-based deliveries. Escudero-Santana et al. [49] investigated customers' preferences for receiving deliveries at one of their preferred locations (e.g., at home, at work, at a familiar home, in a shop, or in a locker), each one associated with a different time slot for the delivery day. The results revealed that a distribution policy with several locations can improve the efficiency of electronic commerce by reducing delivery costs. Similarly, Amorim et al. [51] found that retailers with the capability to tailor their time slot offerings to specific customer segments have the potential to generate approximately 9% more shipping revenue than those who cannot.

Park [50] analysed consumer preferences for the early morning and daytime delivery of grocery items bought online in South Korea. Customers most strongly preferred the early morning (dawn) delivery using a personal icebox, followed by dawn delivery using a market cooler bag, with daytime delivery using a paper box being the least preferable.

Considering the high demand of home delivery for goods bought online and a considerable proportion of failed home deliveries in New Zealand, this study aims to investigate end-consumers' preferences for OHDs of goods bought online, taking Christchurch city as a case study.

3. Research Method

When a response variable of interest is measured on an ordinal scale (e.g., preference for home delivery during the late afternoon time slot: low preference vs. high preference), the ordinal logistic regression method is typically used to account for the intrinsic ordering of the levels of ordinal response variables [52,53]. This is because other types of logit models (e.g., multinomial logit or mixed logit) consider ordinal response variables to be nominal, which means that the information about the ordering of responses would be lost [54].

Ordinal logistic regression assumes that the ordinal response variable represents an underlying continuous latent variable (say ω) that depends on a set of explanatory variables (say x_n; n = 1,2,. . .,k) according to the following linear model:

$$\omega = \alpha_0 + \alpha_1 x_1 + \alpha_2 x_2 + \ldots + \alpha_k x_k + \sigma\varepsilon \quad (1)$$

where α represents the coefficients of the explanatory variables; σ is a constant; ε is a random disturbance term, independent of x_n, and it follows a Standard Logistic distribution.

The variable ω cannot be directly observed, but it can be transformed into Y, an ordinal response variable.

$\theta_1,\ \theta_2,\ \theta_3,\ \ldots,\ \theta_{J-1}$ are cut-off values of the continuous latent variable;

$m = 1,\ 2,\ \ldots,\ j,\ \ldots,\ J$ represents the order of levels of the response variable Y.

In this model, all levels at or below a given cut-off are compared with all levels above that cut-off, for example, Y = 1 or 2 versus Y = 3 or 4 or . . .J. To incorporate the ordinal nature of a response variable, the logit model can be modified by defining the probabilities differently. Let P_{ij} be the probability of an individual (i) falling in level (j) of a response variable, and F_{ij} be the cumulative probability that individual i is in the *jth* level or lower. The cumulative probability can be written as

$$F_{ij} = \sum\nolimits_{m=1}^{j} P_{im} \quad (2)$$

Each value of F_{ij} corresponds to a different dichotomisation of the response variable. The cumulative ordinal logistic model can then be specified as a set of $J-1$ equations as follows:

$$\log\,[\frac{F_{ij}}{1-F_{ij}}] = \beta_j + \beta x_i;\ j = 1,\ 2, \ldots,\ J-1 \quad (3)$$

$$\text{where, } \beta x_i = \beta_1 x_{i1} + \ldots + \beta_k x_{ik}; \quad (4)$$

$$\beta_j = \frac{\alpha_0 - \theta_j}{\sigma}\ \ (\text{threshold values}) \quad (5)$$

$$\beta = \frac{\alpha}{\sigma}\,; \quad (6)$$

The above logistic model is based on the assumption that the coefficients of the explanatory variables are equal across the various (i.e., $J-1$) equations, but the intercept value is different for each equation. This assumption is therefore also referred to as the assumption of parallel lines. The cumulative logit model is also referred to as the 'proportional odds' model, because the odds ratios will remain constant regardless of which of the levels are being compared if the parallel line assumption is met. Therefore, the parallel line assumption is also called as the proportional odds assumption. Equation (3) yields the output in terms of the odds ratios for an individual being in one level or other lower levels rather than in a higher level of the ordinal response variable.

4. Data Collection

Members of a market research company's panel were asked to complete an online survey from May to June 2018 using the Qualtrics software. The respondents had to live in Christchurch, be at least 18 years old, and have made an online purchase within the last 12 months in order to be eligible to participate in the survey. The survey included questions about socio-demographic traits, shopping habits (both in-person and online), travel habits, and attitudes toward missed 'attended deliveries' (i.e., deliveries that required a signature upon arrival) and alternative unattended delivery methods (i.e., collection and delivery points). All questions linked to online purchasing had to be answered regarding things that cannot be delivered via the internet (i.e., travel tickets and hotel bookings were excluded). To strike a balance between the burden on respondents and the information sought, the flow of questions was automated so that only pertinent questions appeared to each respondent based on their initial responses [55].

The panel members provided a total of 418 responses, but only 305 of them were included for the analysis because 113 of them were incomplete. In addition to the online survey administered to panel members of a market research firm, a second online survey with the same sets of questions was also conducted simultaneously among the authors' friends and colleagues. Only 50 of the approximately 100 responses were full and able to be used for the analysis. Therefore, 355 full responses from the two independent sources made up the dataset used in the analysis.

The following is a description of the study's variables. The variable levels were chosen based on data from the census (wherever applicable). However, because their 'anticipated count' value was less than five, which is a requirement for the findings of the descriptive tests to be robust, some levels of a number of variables were later combined.

Socio-demographic factors comprised information on the individual (such as gender, age, educational qualifications, and employment status) as well as the household (e.g., type of dwelling unit, household composition, household size, number of workers in household, number of children below 18 years and below 13 years of age in the household). Table 1 compares the proportions of the sample with the census, demonstrating that the sample reasonably captures the population.

Table 1. Sample characteristics.

Factors	Categories	Sample Values (%)	Census 2013 (%)
Gender	Male	50.7	49.1
	Female	49.3	50.9
Age (years)	18–29	23.4	19.4 *
	30–39	20.9	16.9
	40–49	14.6	18.8
	50–59	14.6	17.8
	60 or more	26.5	27.1

Note: * 20–29 years.

5. Consumer Preference for Time-Slot-Based Home Delivery

5.1. Non-Parametric Tests

Consumer preferences for the various time slots were initially captured in terms of rating on a 10-point Likert scale, with '0' meaning 'no preference' and '10' meaning 'maximum preference'. The time slots considered in this study are defined in Table 2.

Table 2. Definition of home delivery time slots.

Hours of ome Delivery Time Slots	Name of Time Slots	Traditional/Non-Traditional
6 a.m.–9 a.m.	Early morning	Non-traditional
9 a.m.–12 p.m.	Morning	Traditional
12 p.m.–3 p.m.	Afternoon	Traditional
3 p.m.–6 p.m.	Late afternoon	Traditional
6 p.m.–9 p.m.	Evening	Non-traditional

It should be noted that since the response (or dependent) variable and several explanatory variables were ordinal in nature and not normally distributed, parametric tests such as the one-way ANOVA with repeated measures, which requires the data to be normally distributed, could not be used [56]. Thus, non-parametric tests, such as the Friedman test and Wilcoxon signed-rank test, which do not require the data to be normally distributed, were conducted to determine the differences in consumer preferences for various time slots of home delivery.

The Friedman test is the non-parametric counterpart of the one-way ANOVA with repeated measures test, and it is used to test for differences between groups when the dependent or response variable is measured on an ordinal scale [57]. The Friedman test compares the mean ranks between related groups and indicates whether the groups differ or not. It is apparent from Table 3 that, overall, there is a statistically significant difference between the mean ranks of consumer ratings for various time slots of home deliveries (Chi-square = 21.69, $p \leq 0.001$), with the mean rank of the late afternoon time slot being the maximum (3.24) among all the time slots for receiving home deliveries of items bought online.

Table 3. Results of the Friedman tests.

Home Delivery Slots	Mean Score	Standard Deviation	Median Score (IQR)	Mean Ranks
Early morning (6 a.m.–9 a.m.)	4.20	3.82	3.00 (8.0)	2.76
Morning (9 a.m.–12 p.m.)	4.98	3.69	5.00 (7.0)	3.10
Afternoon (12 p.m.–3 p.m.)	4.63	3.60	5.00 (7.0)	2.94
Late afternoon (3 p.m.–6 p.m.)	5.27	3.44	5.00 (6.0)	3.24
Evening (6 p.m.–9 p.m.)	4.88	3.99	5.00 (8.0)	2.96
Test statistic–Chi-Square	21.69		Number of responses	355
Asymptotic significance (p)	<0.001		Degrees of freedom	4

Note: IQR—inter-quartile range.

However, it should be noted that the Friedman test is an omnibus test, i.e., it indicates whether there are overall differences, but does not provide information on which groups differ from each other. Therefore, post hoc tests, namely Wilcoxon signed-rank tests, are required to be conducted on each combination of groups (i.e., time slots), to determine the groups that differ from one another (in terms of consumer preferences in this case). The Wilcoxon signed-rank tests were conducted for 10 combinations of time slots, as shown in Table 4. Given that multiple comparisons were to be made, it was more likely that a result would have been declared statistically significant when it was in fact not (i.e., a Type I error) if the significance level was not adjusted to account for multiple comparisons. Hence, a Bonferroni adjustment on the results obtained from the Wilcoxon tests was needed. The Bonferroni adjustment is made by dividing the significance level used in the Friedman test (in this case, 0.05) by the number of tests or comparisons carried out. Therefore, the new significance level of 0.005 (i.e., 0.05/10) was used to determine the time slots for which consumers had statistically significantly different preferences. This implies that if the p-value is larger than 0.005, there is no statistically significant difference between consumer preferences for both the compared time slots.

Out of the above 10 pairs of time slots that were compared, only two pairs were found to have a statistically significant difference in consumer preferences (Refer to Table 4). The results of the Wilcoxon signed-rank tests are shown only for pairs that had statistically significant differences, i.e., Pair 3 and Pair 8, as shown in Table 5. Note that the non-traditional evening home delivery time slot was not found to have a statistically significant difference in ratings given by consumers. This implies that consumers do not prefer the evening home delivery time slot over other time slots.

Table 4. Combinations of time slots compared.

Pair 1	Home Delivery During Early Morning	Home Delivery During Morning
Pair 2	Home delivery during early morning	Home delivery during afternoon
Pair 3 *	Home delivery during early morning	Home delivery during late afternoon
Pair 4	Home delivery during early morning	Home delivery during evening
Pair 5	Home delivery during morning	Home delivery during afternoon
Pair 6	Home delivery during morning	Home delivery during late afternoon
Pair 7	Home delivery during morning	Home delivery during evening
Pair 8 *	Home delivery during afternoon	Home delivery during late afternoon
Pair 9	Home delivery during afternoon	Home delivery during evening
Pair 10	Home delivery during late afternoon	Home delivery during evening

Note: * statistically significant differences at $p = 0.005$.

Table 5. Results of the Wilcoxon signed-rank tests.

Home Delivery during Late Afternoon vs. Home Delivery during Afternoon				
		N	Mean Rank	Sum of Ranks
Rating for late afternoon < Rating for afternoon	Negative Ranks	94	104.9	9863.5
Rating for late afternoon > Rating for afternoon	Positive Ranks	132	119.6	15,787.5
Rating for late afternoon = Rating for afternoon	Ties	129		
	Total	355		
Test statistic (Z)		−3.017		
Asymptotic significance (two-tailed)		0.003		
Home delivery during late afternoon vs. Home delivery during early morning				
		N	Mean Rank	Sum of Ranks
Rating for late afternoon < Rating for early morning	Negative Ranks	111	135.2	15,011.0
Rating for late afternoon > Rating for early morning	Positive Ranks	173	147.2	25,459.0
Rating for late afternoon = Rating for early morning	Ties	71		
	Total	355		
Test statistic (Z)		−3.777		
Asymptotic significance (two-tailed)		<0.001		

The consumer preference for home delivery during the late afternoon time slot was found to be statistically significantly greater than for home delivery during the afternoon time slot ($Z = -3.017$, $p = 0.003$, Mean rank $_{\text{late afternoon}} = 119.60$). This implies that consumers prefer the late afternoon time slot (3 p.m.–6 p.m.) more than the afternoon time slot (12 p.m.–3 p.m.). Similarly, the consumer preference for home delivery during the late afternoon time slot was also found to be statistically significantly greater than for home delivery during the early morning time slot ($Z = -3.777$, $p \leq 0.001$, Mean rank $_{\text{late afternoon}} = 147.16$). This implies that the late afternoon time slot is preferred more than the early morning time slot too. Therefore, the late afternoon time slot appeared to be consumers' most preferred time slot for receiving home deliveries.

5.2. Ordinal Logistic Regression

It should be noted, however, that the non-parametric tests do not help to describe the possible reasons for differences in consumer preferences for various home delivery time slots. Therefore, the ordinal logistic regression technique that helps investigate the correlation between a response variable and explanatory variables, while controlling for the effect of other factors (e.g., socio-demographics), was adopted to examine the factors governing consumer preferences. Given that the late afternoon time slot was found to be the most preferred time slot for receiving home deliveries, the ordinal logistic regression was carried out only for that time slot, leaving the other four time slots aside.

The consumer preference in terms of ratings for the late afternoon time slot was considered as the dependent (or response) variable, and the ratings were categorised as low preference and high preference, as shown in Table 6. All the remaining variables were treated as predictor (or explanatory) variables.

Table 6. Categorisation of consumer preference.

Ratings on 0 to 10 Scale	**Preference**
0 to 5	Low preference
6 to 10	High preference

Moreover, 19 explanatory variables were initially considered to estimate the model using the OL regression approach in the statistical package for social sciences (SPSS). Of the 19 variables, only 9 turned out to be statistically significant in explaining the variance in consumers' preference for late afternoon home delivery at the end of 12 iterations of the model estimation, with variables that did not turn out to be statistically significant (at the 90% confidence level) being eliminated from the model in the next iteration. The results of the OL regression analysis are given in Table 7.

Table 7. Results of the OL regression.

Preference (Ratings) for Late Afternoon Home Delivery	Estimate	Std. Error	Wald Chi-Square	Odds Ratio	*p*-Value
Low preference	−0.083	0.581	0.020		0.887
High preference (reference level)			–		
Age (years)					
18–29	0.292	0.403	0.523	1.34	0.470
30–39	0.431	0.405	1.133	1.54	0.287
40–49	0.546	0.439	1.548	1.73	0.213
50–59	0.889	0.424	4.403	2.43	0.036
60 or more	0	.	.	1.0	.
Educational qualifications					
Up to NCEA Level 3	0.072	0.273	0.070	1.07	0.791
Trade Certificate	0.824	0.353	5.455	2.28	0.020
Bachelor's Degree or above	0	.	.	1.0	.
Employment status					
Student (full- or part-time)	0.595	0.486	1.500	1.81	0.221
Employed (part-time or full-time)	−0.533	0.287	3.445	0.59	0.063
Unemployed, retired and others	0	.	.	1.0	.
Household composition					
Person living alone	−0.092	0.445	0.043	0.91	0.836
Couple without children	−1.163	0.378	9.465	0.31	0.002
Couple with children	0.247	0.404	0.376	1.28	0.540
Others	0	.	.	1.0	.

Table 7. *Cont.*

Time since first online shopping					
Up to 3 years	−0.738	0.304	5.882	0.48	0.015
4–6 years	0.204	0.286	0.505	1.23	0.477
More than 6 years	0	.	.	1.0	.
Frequency of shopping at physical shops					
4 or more times a week	0.638	0.356	3.213	1.89	0.073
2–3 times a week	0.440	0.279	2.498	1.55	0.114
Once a week or less than once a week	0	.	.	1.0	.
Frequency of visiting supermarkets					
Up to 3 times per month	0.413	0.352	1.381	1.51	0.240
4–5 times per month	−0.631	0.307	4.238	0.53	0.040
6 or more times per month	0	.	.	1.0	.
Number of cars in the household					
None	−1.591	0.544	8.565	0.20	0.003
One	−0.321	0.299	1.150	0.73	0.283
Two or more	0	.	.	1.0	.
Household size					
Up to two	0.868	0.394	4.851	2.38	0.028
More than two	0	.	.	1.0	.
Number of children below 18 years in the household					
None	−0.635	0.370	2.952	0.53	0.086
One or more	0	.	.	1.0	.
Coded dependent variable (n)	1 = Low preference (181); 2 = High preference (174)				
−2 log-likelihood (intercept-only model) = 480.7	−2 log−likelihood (final model) = 415.4				
Chi-square statistic–Likelihood ratio tests = 65.2 ***	Degrees of freedom = 21				
Pseudo R^2 (McFadden) = 0.133					

Note: n—number of cases in each category; ***—statistically significant at 99% confidence level.

The 'high preference' level of the response variable was treated as the reference level. The intercept-only model (i.e., with no variables included) was outperformed by the final model (i.e., with variables included), as the likelihood ratio Chi-square test, which tests whether at least one of the coefficients is not equal to zero, was found to be statistically significant (Chi-square = 65.217, $p < 0.001$, and degrees of freedom = 21). Furthermore, the Pearson Chi-square goodness-of-fit measure (p-value of 0.191) shows that the model is an adequate fit. The McFadden Pseudo R^2 value of 0.133 indicates a moderately good fit, as the Pseudo R^2 values are usually considerably lower than the R^2 value of the ordinary least square (OLS) regression [58,59]. A value between 0.2 and 0.4 denotes an excellent fit for the model and is approximately equivalent to an OLS R^2 value between 0.5 and 0.8 [12,60].

OL regression estimates only one model (except for different intercept values) for all the choice alternatives (or levels). The logit estimates (i.e., log-odds) are coefficients of the explanatory variables included in the model and are relative to the reference level within each of the explanatory variables. For example, the log-odds of scoring higher on the response variable (i.e., high preference for late afternoon home delivery) is 0.292 units higher for consumers aged 18–29 years than those aged 60 years or more, when all the other predictor variables in the model are held constant. In other words, younger consumers are more likely than older ones to prefer home deliveries during the late afternoon time slot.

The standard error values of the estimates indicate the average distance of the observed values from the regression line, and thus show the precision of the model on average, using the units of the response variable. Smaller values are better because they indicate that the observations are closer to the fitted relationship.

The odds ratio is the exponentiation of the logit estimate. It indicates the odds of a level of an explanatory variable (relative to the reference level of the variable) being in a higher level of the response variable than levels lower than that. For example, for respondents aged 18–29 years, the odds ratio of 1.34 indicates that they are 1.34 times more likely to be in the higher level (e.g., high preference) of the response variable (i.e., preference for home delivery during late afternoon) than respondents aged 60 years or more.

Consumers' age turned out to be significantly positively correlated with the preference for late afternoon home delivery. The consumer preference was found to increase with age, but only until the age of 59 years. Note that people aged 60 years or above were found to be less likely to have a high preference for late afternoon home delivery than their younger counterparts. This could be due to the higher likelihood of younger people being away for, say, work or study purposes during the day.

Consumers' educational qualification was found to be significantly negatively correlated with their preference for late afternoon home delivery, with people having higher qualifications, such as a 'bachelor's degree or above', being less likely to have a high preference for late afternoon home delivery than people having Trade Certificates or up to NCEA Level 3 education. This is perhaps due to the fact that 'trade persons' (e.g., plumbers, fitters, and labourers) typically start their work early in the morning and often return from work early compared to their highly qualified counterparts, which makes them available to receive their online orders during the late afternoon time slot. There is an increasing trend of people working from home, which is usually possible only with jobs involving highly qualified people, and hence they may be available to receive their parcels earlier during the day.

Consumers' employment status was found to be significantly correlated with their preference for late afternoon home delivery, with students being more likely and employed people being less likely to have high preference for late afternoon home delivery than unemployed or retired people. This result is partially in line with the above observation that younger people are more likely to prefer late afternoon home deliveries than people aged 60 years or more, who are more towards the retirement age. This could be due to the higher likelihood of unemployed or retired people being available at home during the day. It is important to note that employed people are less likely to have a high preference for late afternoon home deliveries, and perhaps this is due to the short time window available to them compared to retired or unemployed people to receive their parcels after finishing work, which is typically around 5 p.m.

Consumers' household composition was found to be significantly correlated with their preference for late afternoon home delivery, with 'people living alone' and 'couples living without children' being less likely, and those 'living with children' being more likely to have a high preference for late afternoon home delivery than respondents living in households with other types of compositions. This is perhaps due to the higher likelihood of young children being available at home (after finishing school) during the late afternoon.

Consumers' online shopping experience was found to be significantly positively correlated with their preference for late afternoon home delivery, with consumers who began online shopping more than six years ago being more likely to have a high preference for late afternoon home delivery than consumers who started shopping online less than 3 years ago. This is perhaps due to less experienced online shoppers' being mainly older people (given that they are less techno-savvy) who are retired or unemployed, and hence available to receive their orders throughout the day.

Consumers' frequency of shopping at physical shops was found to be significantly positively correlated with their preference for late afternoon home delivery, with people shopping four or more times a week being more likely to have a high preference for late afternoon home delivery than people shopping less frequently. It is possible that people shopping frequently at physical shops are often not available at home earlier during the day.

Consumers' frequency of visiting supermarkets (per month) was found to be significantly correlated with their preference for late afternoon home delivery, with people visiting supermarkets six or more times a month being more likely to have a high preference for late afternoon home delivery than people visiting supermarkets less frequently. It is possible that those who visit supermarkets more frequently are time-rich and are available during the day to receive their parcels.

The number of cars in a household was found to be significantly correlated with consumers' preference for late afternoon home delivery, with people not having cars in their household being less likely to have a high preference for late afternoon home delivery than people having cars in their household. It is possible that those who do not have access to a car may take longer to return home after finishing work, which makes it difficult for them to receive parcels during the late afternoon time slot.

Consumers' household size was found to be significantly correlated with their preference for late afternoon home delivery, with households with up to two people being more likely to have a high preference for late afternoon home delivery than households with more than two people. It is possible that smaller households may not have anybody at home earlier during the day, which makes it difficult for them to receive parcels before the late afternoon time slot.

The number of children below 18 years of age in a household was found to be significantly correlated with consumers' preference for late afternoon home delivery, with households with no children below 18 years of age being less likely to have a high preference for late afternoon home delivery than the households with children aged less than 18 years. It is possible that people from households with no children aged less than 18 years are all working, and hence, they often do not have anybody at home during the day, which makes it difficult for them to receive parcels during the late afternoon time slot.

6. Conclusions

This study investigated consumers' preferences for five different home delivery time slots, namely early morning, morning, afternoon, late afternoon, and evening, for receiving items bought online. The results of statistical tests indicate that consumers prefer the late afternoon (i.e., 3 p.m. to 6 p.m.) time slot over other available times for receiving items bought online. This implies that consumers are less interested in the off-hour delivery time slots, i.e., early morning (6 a.m. to 9 a.m.) and evening (6 p.m. to 9 p.m.) time slots. Therefore, the off-hour delivery option is apparently less likely to reduce failed home deliveries, transport costs for service providers, and traffic congestion and pollution in urban settlements. Given consumers' inclination towards the traditional late afternoon home delivery time slot, service providers and city planners need to come up with strategic plans that can encourage city dwellers to receive their online orders outside of peak traffic hours. For instance, service providers need to formulate operational changes such that small parcels can be delivered to end-consumers at their workplaces or places of education during off-peak hours. Similarly, city planners need to plan to strengthen the infrastructure needed to support courier deliveries in terms of loading and unloading bays and parking spaces for courier service providers near commercial areas. The results of the ordinal logistic regression can be used to understand consumers' socioeconomic background and its correlation with their delivery preferences. The methodology adopted in this study can be replicated for other cities in New Zealand and other countries where online shopping is growing rapidly, leading to an increasing demand for home deliveries.

This study, however, did not consider other newer delivery methods, such as delivery to local shops, locker points, car boots, and unattended home delivery by providing access to house premises. These alternatives can be considered in future studies. Another limitation of this study is that the consumer data used were collected before the COVID-19 pandemic, following which consumers' online shopping behaviour may have changed due to the changes caused by the pandemic in terms of new technologies, modified travel habits, and innovations in logistics. Also, consumer preferences for home delivery time slots for different product types can be considered in future studies.

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References

1. United Nations. *68% Of the World Population Projected to Live in Urban Areas by 2050, Says UN*; United Nations Department of Economic and Social Affairs: New York City, NY, USA, 2018. Available online: https://www.un.org/development/desa/en/news/population/2018-revision-of-world-urbanization-prospects.html (accessed on 26 January 2020).
2. Schirber, M. How Much of the World is Covered by Cities? New Geography. 2005. Available online: https://www.newgeography.com/content/001689-how-much-world-covered-cities (accessed on 26 January 2020).
3. Maparu, T.S.; Mazumder, T.N. Transport infrastructure, economic development and urbanization in India (1990–2011): Is there any causal relationship? *Transp. Res. Part A Policy Pract.* **2017**, *100*, 319–336. [CrossRef]
4. Marcucci, E.; Gatta, V. Investigating the potential for off-hour deliveries in the city of Rome: Retailers' perceptions and stated reactions. *Transp. Res. Part A Policy Pract.* **2017**, *102*, 142–156. [CrossRef]
5. Alfaris, R.E.; Patel, D.; Jalayer, M.; Meenar, M. Barriers Associated with the First/Last Mile Trip and Solutions to Bridge the Gap: A Scoping Literature Review. *Transp. Res. Rec.* **2024**, *2678*, 38–48. [CrossRef]
6. Kmiecik, M.; Wierzbicka, A. Enhancing Smart Cities through Third-Party Logistics: Predicting Delivery Intensity. *Smart Cities* **2024**, *7*, 22. [CrossRef]
7. Saw, K.; Katti, B.K.; Joshi, G.J.; Kedia, A. Travel time reliability evaluation using fuzzy-possibility approach: A case study of an Indian city. *Transp. Plan. Technol.* **2024**, 1–19. [CrossRef]
8. NZ Ministry of Transport. *Climate Change and Energy*; NZ Ministry of Transport: Wellington, New Zealand, 2018; [Government Website]. Available online: https://www.transport.govt.nz/multi-modal/climatechange/ (accessed on 24 October 2019).
9. NZ Ministry of Transport. *Annual Fleet Statistics*; NZ Ministry of Transport: Wellington, New Zealand, 2018; p. 28, [Research Report]. Available online: https://www.transport.govt.nz/assets/Import/Uploads/Research/Documents/The-NZ-Vehicle-Fleet-Report-2018-web-v2.pdf (accessed on 26 December 2023).
10. NZ Ministry of Transport. *Government Policy Statement on Land Transport*; NZ Ministry of Transport: Wellington, New Zealand, 2018; p. 65. Available online: https://www.transport.govt.nz/multi-modal/keystrategiesandplans/gpsonlandtransportfunding/ (accessed on 1 August 2018).
11. De Marco, A.; Cagliano, A.C.; Mangano, G.; Perfetti, F. Factor influencing logistics service providers efficiency' in urban distribution systems. *Transp. Res. Procedia* **2014**, *3*, 499–507. [CrossRef]
12. Kedia, A. *Estimating the Effect of Online Shopping and Collection-Delivery Points on Shopping Travel in New Zealand*; University of Canterbury: Canterbury, New Zealand, 2020. [CrossRef]
13. Lauenstein, S.; Schank, C. Design of a Sustainable Last Mile in Urban Logistics—A Systematic Literature Review. *Sustainability* **2022**, *14*, 5501. [CrossRef]
14. New Zealand Post. The Full Download: 2018 New Zealand eCommerce Review. 2018, p. 69. Available online: https://www.nzpost.co.nz/about-us/media-centre/media-release/new-nz-post-ecommerce-report-shows-fastest-growth-in-regions (accessed on 19 January 2019).
15. Villa, R.; Monzón, A. A Metro-Based System as Sustainable Alternative for Urban Logistics in the Era of E-Commerce. *Sustainability* **2021**, *13*, 4479. [CrossRef]
16. New Zealand Post. New Zealand Post Annual Report. 2019. Available online: https://www.nzpost.co.nz/sites/nz/files/uploads/shared/annual-reports/2019-nz-post-annual-report.pdf (accessed on 27 January 2020).
17. Gevaers, R.; Van de Voorde, E.; Vanelslander, T. Cost modelling and simulation of last-mile characteristics in an innovative B2C supply chain environment with implications on urban areas and cities. *Procedia-Soc. Behav. Sci.* **2014**, *125*, 398–411. [CrossRef]
18. Guerrero, J.C.; Díaz-Ramírez, J. A review on transportation last-mile network design and urban freight vehicles. In Proceedings of the 2017 International Symposium on Industrial Engineering and Operations Management, Bristol, UK, 24–25 July 2017; pp. 533–552.

19. Onghena, E. *Integrators: Werkwijze, Strategieën en Toekomst*; Universiteit Antwerpen: Antwerpen, Belgium, 2008.
20. Beckers, J.R. The Logistics Sector in a Consumer Driven Society: Essays on Location and Network Structure. Ph.D. Thesis, University of Antwerp, Antwerpen, Belgium, 2019. Available online: https://www.uantwerpen.be/popup/kalenderonderdeel.aspx?calitem_id=7573&c=LANDP54&n=113758 (accessed on 18 June 2020).
21. Cárdenas, I. Unlocking the Benefits of Pick-Up Points for Sustainable E-Commerce Distribution in Urban Areas. Ph.D. Thesis, University of Antwerp, Antwerpen, Belgium, 2019. Available online: https://hdl.handle.net/10067/1616840151162165141 (accessed on 9 January 2020).
22. Fikar, C.; Hirsch, P.; Gronalt, M. A decision support system to investigate dynamic last-mile distribution facilitating cargo-bikes. *Int. J. Logist. Res. Appl.* **2018**, *21*, 300–317. [CrossRef]
23. Jaller, M.; Pineda, L.; Ambrose, H. Evaluating the use of zero-emission vehicles in last mile deliveries. *ITS Rep.* **2018**, *2017*. [CrossRef]
24. Kedia, A.; Kusumastuti, D.; Nicholson, A. Acceptability of collection and delivery points from consumers' perspective: A qualitative case study of Christchurch city. *Case Stud. Transp. Policy* **2017**, *5*, 587–595. [CrossRef]
25. Kedia, A.; Kusumastuti, D.; Nicholson, A. Locating collection and delivery points for goods' last-mile travel: A case study in New Zealand. *Transp. Res. Procedia* **2020**, *46*, 85–92. [CrossRef]
26. Rai, H.B. Environmental Sustainability of the Last Mile in Omnichannel Retail. Ph.D. Thesis, Vrije Universiteit Brussel, Ixelles, Belgium, 2019. Available online: https://cris.vub.be/en/publications/environmental-sustainability-of-the-last-mile-in-omnichannel-retail(1e13f586-6499-4451-81a8-907b08b6a2f9).html (accessed on 14 January 2020).
27. Schwerdfeger, S.; Boysen, N. Who moves the locker? A benchmark study of alternative mobile parcel locker concepts. *Transp. Res. Part C Emerg. Technol.* **2022**, *142*, 103780. [CrossRef]
28. Seghezzi, A.; Mangiaracina, R. Smart home devices and B2C e-commerce: A way to reduce failed deliveries. *Ind. Manag. Data Syst.* **2023**, *123*, 1624–1645. [CrossRef]
29. Chen, J.; Li, R.; Ma, J.; An, Q. Stationary versus mobile parcel lockers: Which self-service technology moves the consumers in the last mile of urban areas? *Travel Behav. Soc.* **2024**, *35*, 100742. [CrossRef]
30. Jang, S.; Hong, D.; Lee, C. Exploring the behavioral adoption of automated parcel locker systems under COVID-19. *Transp. Policy* **2024**, *151*, 1–11. [CrossRef]
31. Moussaoui, A.E.E.; Benbba, B.; Andaloussi, Z.E.; Jaegler, A. Logistique urbaine au Maroc: Concepts, état des lieux et pistes d'amélioration. *Rev. Française Gest. Ind.* **2022**, *36*, 71–88. [CrossRef]
32. Kedia, A.; Kusumastuti, D.; Nicholson, A. Effect of online shopping on consumers' shopping travel and goods' last-mile travel: A case study in Christchurch. In Proceedings of the 41st Australasian Transport Research Forum, Canberra, Australia, 30 September 2019.
33. El Moussaoui, A.E.; Benbba, B.; El Andaloussi, Z. Impact of logistics performance on the store image, consumer satisfaction and loyalty: A quantitative case study. *Arab Gulf J. Sci. Res.* **2022**, *41*, 226–239. [CrossRef]
34. Pan, S.; Giannikas, V.; Han, Y.; Grover-Silva, E.; Qiao, B. Using customer-related data to enhance e-grocery home delivery. *Ind. Manag. Data Syst.* **2017**, *117*, 1917–1933. [CrossRef]
35. Pham, T.S.H.; Ahammad, M.F. Antecedents and consequences of online customer satisfaction: A holistic process perspective. *Technol. Forecast. Soc. Chang.* **2017**, *124*, 332–342. [CrossRef]
36. Chowdhury, T.; Vaughan, J.; Saleh, M.; Mousavi, K.; Hatzopoulou, M.; Roorda, M.J. Modeling the Impacts of Off-Peak Delivery in the Greater Toronto and Hamilton Area. *Transp. Res. Rec.* **2022**, *2676*, 413–425. [CrossRef]
37. Holguín-Veras, J.; Hodge, S.; Wojtowicz, J.; Singh, C.; Wang, C.; Jaller, M.; Aros-Vera, F.; Ozbay, K.; Weeks, A.; Replogle, M.; et al. The New York City Off-Hour Delivery Program: A Business and Community-Friendly Sustainability Program. *Interfaces* **2018**, *48*, 70–86. [CrossRef]
38. Ukkusuri, S.V.; Ozbay, K.; Yushimito, W.F.; Iyer, S.; Morgul, E.F.; Holguín-Veras, J. Assessing the impact of urban off-hour delivery program using city scale simulation models. *EURO J. Transp. Logist.* **2016**, *5*, 205–230. [CrossRef]
39. Lindholm, M.E.; Blinge, M. Assessing knowledge and awareness of the sustainable urban freight transport among Swedish local authority policy planners. *Transp. Policy* **2014**, *32*, 124–131. [CrossRef]
40. Muñuzuri, J.; Grosso, R.; Cortés, P.; Guadix, J. Estimating the extra costs imposed on delivery vehicles using access time windows in a city. *Comput. Environ. Urban Syst.* **2013**, *41*, 262–275. [CrossRef]
41. Ballantyne, E.E.F.; Lindholm, M.; Whiteing, A. A comparative study of urban freight transport planning: Addressing stakeholder needs. *J. Transp. Geogr.* **2013**, *32*, 93–101. [CrossRef]
42. Taniguchi, E.; Thompson, R.G. *City logistics: Mapping the Future*; CRC Press: Boca Raton, FL, USA, 2014.
43. Taniguchi, E.; Thompson, R.G.; Yamada, T. Recent trends and innovations in modelling city logistics. *Procedia-Soc. Behav. Sci.* **2014**, *125*, 4–14. [CrossRef]
44. Gatta, V.; Marcucci, E.; Delle Site, P.; Le Pira, M.; Carrocci, C.S. Planning with stakeholders: Analysing alternative off-hour delivery solutions via an interactive multi-criteria approach. *Res. Transp. Econ.* **2019**, *73*, 53–62. [CrossRef]
45. Aljohani, K.; Thompson, R.G. Modelling individual preferences of goods receivers for a Receiver-led delivery consolidation service. *Transp. Res. Part A Policy Pract.* **2021**, *150*, 74–94. [CrossRef]
46. Dias, P.A.P.; Yoshizaki, H.; Favero, P.; Vieira, J.G.V. Daytime or Overnight Deliveries? Perceptions of Drivers and Retailers in São Paulo City. *Sustainability* **2019**, *11*, 6316. [CrossRef]

47. Holguín-Veras, J.; Campbell, S.; Kalahasthi, L.; Wang, C. Role and potential of a trusted vendor certification program to foster adoption of unassisted off-hour deliveries. *Transp. Res. Part A Policy Pract.* **2017**, *102*, 157–171. [CrossRef]
48. Holguín-Veras, J.; Polimeni, J.; Cruz, B.; Xu, N.; List, G.; Nordstrom, J.; Haddock, J. Off-Peak Freight Deliveries: Challenges and Stakeholders' Perceptions. *Transp. Res. Rec.* **2005**, *1906*, 42–48. [CrossRef]
49. Escudero-Santana, A.; Muñuzuri, J.; Lorenzo-Espejo, A.; Muñoz-Díaz, M.-L. Improving E-Commerce Distribution through Last-Mile Logistics with Multiple Possibilities of Deliveries Based on Time and Location. *J. Theor. Appl. Electron. Commer. Res.* **2022**, *17*, 27. [CrossRef]
50. Park, Y.-J. Understanding Customer Preferences of Delivery Services for Online Grocery Retailing in South Korea. *Sustainability* **2023**, *15*, 4650. [CrossRef]
51. Amorim, P.; DeHoratius, N.; Eng-Larsson, F.; Martins, S. Customer Preferences for Delivery Service Attributes in Attended Home Delivery. *Manag. Sci.* **2024**. [CrossRef]
52. McCullagh, P. Regression Models for Ordinal Data. *J. R. Stat. Soc. Ser. B Methodol.* **1980**, *42*, 109–127. [CrossRef]
53. McKelvey, R.D.; Zavoina, W. A statistical model for the analysis of ordinal level dependent variables. *J. Math. Sociol.* **1975**, *4*, 103–120. [CrossRef]
54. Allison, P.D. *Logistic Regression Using SAS: Theory and Application*, 2nd ed.; SAS Institute: Cary, NC, USA, 2012.
55. Kusumastuti, D.; Hannes, E.; Depaire, B.; Vanhoof, K.; Janssens, D.; Wets, G.; Dellaert, B.G.C. An interactive computer-based interface to support the discovery of individuals' mental representations and preferences in decisions problems: An application to travel behavior. *Comput. Hum. Behav.* **2011**, *27*, 997–1011. [CrossRef]
56. Scott, I.; Mazhindu, D. *Statistics for Health Care Professionals*; SAGE Publications: London, UK, 2005. [CrossRef]
57. Laerd Statistics. Friedman Test in SPSS Statistics—How to Run the Procedure, Understand the Output Using a Relevant Example. 2018. Available online: https://statistics.laerd.com/spss-tutorials/friedman-test-using-spss-statistics.php (accessed on 29 May 2022).
58. Dunn, R.; Kusumastuti, D. Why Do You Cycle on That Route? In Proceedings of the IPENZ Transportation Group Conference, Auckland, New Zealand, 7–9 March 2016. Available online: https://ir.canterbury.ac.nz/handle/10092/15303 (accessed on 28 December 2019).
59. Kusumastuti, D.; Nicholson, A. *Mixed-Use Urban Planning and Development*; BRANZ Study Report LR 0481; Building Research Association New Zealand Ltd.: Christchurch, New Zealand, 2017; p. i-87. Available online: https://ir.canterbury.ac.nz/handle/10092/15417 (accessed on 26 December 2023).
60. Domencich, T.A.; McFadden, D. *Urban Travel Demand-A Behavioral Analysis*; North-Holland Publishing: Amsterdam, The Netherlands, 1975. Available online: https://trid.trb.org/view/48594 (accessed on 5 January 2017).

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