Order Fulfilment and Consumer Behaviour in Online Retailing

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Chapter 3: Consumer preferences for delivery attributes in online retailing – A conjoint analysis

Abstract

Online retailers offer a variety of delivery options. The purpose of this study is to investigate how consumers value various attributes of these delivery options such as delivery speed, time slot, time of delivery (e.g., daytime/evening), delivery date, and delivery fee. We study three different product categories – convenience goods, shopping goods, and specialty goods and use conjoint analysis to assess the structure for consumer preferences. Our results show that the most important attribute in shaping consumer preference is the delivery fee, followed by non-price delivery attributes and that preferences for these delivery attributes persist across product categories. We also identify which consumers are most influenced by non-price attributes.

1. Introduction

The Internet has created an online channel for retailers to increase sales significantly as it has attracted a considerable number of consumers who search for, and buy, products online. In 2015, over 43% of shoppers used the Internet to buy products in Europe, while online sales in the market grew by 13.3%, at around €455 billion (Ecommerce Europe, 2016a). Though logistics has been recognized as a main activity in e-fulfilment and an important driver of the growth of the e-commerce sector (Maltz et al., 2004; Turban et al., 2015), logistics brings challenges for online retailers as well. Specifically, last-mile delivery is one of the most important success factors in order fulfilment (Boyer et al., 2009; Esper et al., 2003). From a consumer's perspective, last-mile delivery is an important aspect in their purchase decision (Xing et al., 2010). Recent industry reports have shown that online retailers offer delivery options to consumers, including a variety of delivery fees (comScore and UPS, 2014; MICROS, 2014), delivery speeds (comScore and UPS, 2014; Drapers, 2014), and delivery time (IMRG, 2015b; MICROS, 2014). Although a significant number of studies investigated impacts of delivery on online consumer behaviour, including delivery options (Bart et al., 2005; Otim and Grover, 2006), on-time delivery (Collier and Bienstock, 2006), time-slot (Agatz et al., 2011; Campbell and Savelsbergh, 2006), and delivery fees (Rao et al., 2011a), very little research has examined actual consumer choice in delivery options in online retailing, especially in the fields of logistics and supply chain management (Garver et al., 2012).

Prior studies on last-mile delivery have examined a variety of delivery aspects in online retailing (e.g., shipping fees, on-time delivery, time of delivery, and speed of delivery). Lewis (2006) and Lewis et al. (2006) found that shipping fees significantly impact a consumer's purchase pattern, in terms of order incidence and order size. Online consumers are quite sensitive to delivery time, therefore, this factor has a strong impact on consumer satisfaction and repurchase intentions (Collier and Bienstock, 2006). Consumers highly value distribution punctuality in online retail, including various options for delivery dates, delivery on the first day arranged, and within a specified time slot, and the ability to deliver orders quickly. Improving these delivery elements will thus lead to improved consumer satisfaction (Rao et al., 2011b; Xing et al., 2010). In 2005, Dadzie et al. (2005) had already found a significant impact of delivery in terms of cycle time, as a factor of logistics consumer service, on consumer loyalty. They called for future research on consumer expectations with respect to delivery dates and speeds. However, existing studies mainly investigated how delivery affects online consumer behaviour, whereas the question of how consumers view and value delivery attributes, and make trade-offs among the different delivery attributes, remains virtually unexplored.

The aim of this paper is to investigate consumer preferences for delivery attributes in online retailing. An understanding of these behaviours could help retailers design effective delivery options to maximize consumer satisfaction, and support retailers in implementing suitable delivery strategies to meet consumer expectations. Specifically, the main objective of our research is to empirically examine how consumers value delivery attributes when selecting a delivery option for their online purchases. The selection of delivery attributes is based on the literature and an industry report by Global Webshop Logistics (2014); we examine preferences for three different products. We use conjoint analysis to examine the data, since this type of analysis is well suited for understanding consumer preferences (e.g., in product and service choices) and has been widely adopted in marketing research (Rao, 2014). We used cluster analysis, as supplement to our conjoint analysis, to find consumer segments that have different attribute preference patterns. Using part-worth utilities from the conjoint analysis, a simulation is conducted to investigate how consumer preferences change according to attribute levels.

This paper is structured as follows: first, we discuss the extant literature regarding customer response to delivery attributes. Secondly, we provide a synopsis of the existing literature on conjoint analysis in logistics and supply chain management, and describe how this method is used in our paper. Thirdly, we report on the results of the conjoint analysis, cluster analysis, and simulation. We conclude the paper with a discussion of the results and potential implications.

2. Delivery attributes for an online purchase

In their review of literature on the relationship between order fulfilment and online customer behaviour, Nguyen et al. (2018) found that delivery options have a significant impact on purchase and repurchase intentions in online retailing. Delivery options for online purchases sometimes provide one delivery option (e.g., home delivery) or offer a variety of attributes at various prices (e.g., Barclays (2014), comScore and UPS (2014), IMRG (2015)). Online retailers offer a variety of delivery options to improve consumer satisfaction as well as to gain competitive advantage. Consumers must base their delivery choices on a trade-off among these attributes. However, very little is known about consumer response to delivery attributes. Previous studies only focused on investigating individual delivery attributes (e.g., on-time delivery in Collier and Bienstock (2006), delivery fee in Lewis et al. (2006), or time-slot in Agatz et al. (2011)) rather than examining these attributes jointly. In the current study, we investigate five main delivery attributes in online retailing: delivery speeds, time slots, daytime/evening delivery, delivery dates, and delivery fees. Delivery speed is defined as the lead time between a consumer placing an online order and the consumer receiving the order. As online consumers increasingly want shorter lead times, this demand consequently creates a 'last mile' challenge of increased delivery costs for online retailers (Collier and Bienstock, 2006). A delivery time slot can be defined as the time interval (or time slot) in which online consumers receive their delivery – and therefore represents the time consumers must be present at a location to receive the delivery (Punakivi et al., 2001). Campbell and Savelsbergh (2005) developed methodologies for profit maximization that retailers can use to decide whether to accept or reject a requested time slot. Agatz et al. (2011) indicated that changing the time slot template (e.g., the number of time slots or delivery time windows) over spatial areas influences consumer choice of time slots. Daytime/evening delivery is a convenient attribute, as some households choose specific parts of the day for their housework (Southerton, 2003). Delivery date is another relevant delivery attribute for online consumers (Xing et al., 2010). This may be particularly attractive for those who work late during weekdays and are only at home during the weekend. Furthermore, delivery fees are important for online retailers, as they significantly impact a consumer's purchase pattern, in terms of order incidence and order size (Lewis, 2006). Below, we discuss the delivery attributes that we will consider in more detail in our study.

Options for express delivery and/or standard delivery often define the delivery speed attribute. As a result, speed was included in the online shopping process model by Chen and Chang (2003). Garver et al. (2012) showed that delivery speed is the second most important attribute which consumers consider when shopping online, after delivery fee. In their study, delivery speed had four levels: next day delivery, 3-day delivery, 7-day delivery, and 10-day delivery lead-time. Wilson-Jeanselme and Reynolds (2006) indicated that this attribute was placed on third position in consumer preference structures in online grocery retailing in the UK, after product quality and ordering time. Chen et al. (2014) showed that it was of crucial concern to consumers who shop online for specialty foods, where short delivery lead times directly contribute to the quality of the food upon receipt. The role of delivery speed in improving electronic physical distribution service quality was furthermore confirmed by Xing et al. (2010).

Increasing numbers of retailers have adopted time slots as a way to diversify online services (Agatz et al., 2013; Agatz et al., 2008; Ehmke and Campbell, 2014). Depending on the delivery window length, delivery time slots can be time windows of a few hours long (e.g., 2-hour or 4-hour lengths). A short delivery time window is more convenient for consumers than a long one, as consumers are required to spend less time at home waiting for a delivery. Boyer et al. (2009) used simulation experiments to examine the relationship between customer density, delivery window length and delivery efficiency. Their results indicated that offering shorter window lengths would increase delivery costs. However, when customer density reached a certain level, short window lengths could have the same cost as long window lengths. Providing consumers a choice of delivery time slots therefore created challenges for online retailers. If, for example, a consumer chooses a narrow time slot, it will significantly reduce routing efficiency (Agatz et al., 2011). Campbell and Savelsbergh (2006) also investigated ways to use discounts in order to affect consumer choice of time slides (including 1-hour and 2-hour time slots). Offering different time slots with corresponding fees can serve as a means of differentiation for maximizing revenues of online retailers, since consumers are not homogenous in terms of willingness to pay, time preferences, and flexibility (Agatz et al., 2013).

Delivery during a specific part of the day is offered as more people choose to work alternate shifts and flexible hours (Van Der Lippe, 2007; Southerton, 2003). Households try to balance the time spent at work and at home, so that they have more time to spend at home during the day (Tausig and Fenwick, 2001). Being able to select a delivery date is an attribute that was found to be an important attribute of timeliness, contributing to consumer satisfaction in online retailing (Xing et al., 2010; Xing and Grant, 2006). We argue that offering a choice of delivery during a specific part of the day, or a delivery date, can help online retailers reduce the risk of failed delivery when consumers are not at home.

In practice, many online retailers offer this premium delivery service in addition to standard ones. Several papers report that consumers are sensitive to delivery fees. For example, online consumers have different evaluations and perceptions for the two main delivery fee structures: flat rate and threshold-based free delivery (Koukova et al., 2012). Lewis (2006) and Lewis et al. (2006) found that existing consumers were more responsive to the base level of delivery fees, while new consumers were more responsive to incentives that charged the lowest fee for the largest order size. Becerril-Arreola et al. (2013) also proved that consumer purchase amounts were affected when a threshold was applied to free delivery. Furthermore, consumer satisfaction with delivery fees and online presentation of the fees prior to purchase positively affects consumer retention (Rao et al., 2011a). This attribute has hence been identified in consumer preference structures in two studies, one by Garver et al. (2012) and the other by Wilson-Jeanselme and Reynolds (2006). Delivery fees are even found to be the most important attribute in the former study. As mentioned previously, delivery fees can be used as effective marketing tools for influencing a consumer's decision in choosing a delivery service (Agatz et al., 2013).

3. Methods and procedures

3.1. Conjoint analysis in logistics and supply chain management

Conjoint analysis has gained widespread acceptance in various fields such as marketing, information systems, psychology, and health care. It is a multivariate technique developed to understand consumer decisions and preferences for products and services (Hair et al., 2010). This method can provide good estimates of actual preferences, as respondents are required to evaluate products or services through levels of each attribute and combinations of attributes. The respondents must make trade-offs among the attributes while making their choices.

Although conjoint analysis has also gained increasing attention in operations management (Karniouchina et al., 2009), its application in logistics and supply chain management is still limited (Garver et al., 2012). Reutterer and Kotzab (2000) proposed the traditional conjoint analysis as an appropriate tool for designing a supply chain. They evaluated preferences of supply chain managers for supply chain designs (including make-or-buy decisions, degree of centralization, degree of vertical integration, and performance measuring) and identified four clusters of supply chain managers, based on importance values for the specified designs and corresponding levels. Maier et al. (2002) conducted choice-based conjoint experiments to evaluate transport choices by logistics managers. An adaptive conjoint analysis was used to examine logistics managers' preferences for freight service attributes such as cost, travel time, punctuality, and damage and loss (Danielis et al., 2005). Anderson et al. (2011) identified seven attributes, also via choice-based conjoint analysis, that affected a customer's choice of a logistics service provider, and found three customer segments with different characteristics. Their findings suggest that logistics service providers should focus on improving reliable performance which matters most to customers, and should customize service offerings according to respective customer groups due to the heterogeneity of the preferences for these logistics service attributes. Garver et al. (2012) introduced the use of adaptive choice modeling in logistics to understand the decision-making process of consumers selecting carriers for their online purchase. Their results identified the three most important factors, including price, speed of delivery, and tracking in the selection decision, and revealed five consumer segments. Bask et al. (2013) used conjoint analysis to identify determinants of green purchase behaviour of consumers who were shopping for a specific product: a mobile phone. Four consumer groups were discovered, and the findings helped to design sustainable products from a consumer's perspective.

3.2. Conjoint analysis in the current study

Conjoint analysis is a set of methodologies used to study how customers make choices between products or services, including traditional conjoint analysis, adaptive conjoint analysis, and choice-based conjoint analysis (Hair et al., 2010). An individual's preference is expressed in terms of utility, which is the sum of part-worth estimates placed on each level of each attribute of an object (products or services). Respondents evaluate combinations of attributes when making decisions to choose a specific delivery type and to switch between attributes.

The current study uses the traditional conjoint analysis with a full-profile method. In this method, respondents are presented with individual combinations of the different levels of each of the attributes (a so-called profile), and rate them according to their preference. This method was chosen because of its realistic presentation of profiles to respondents. We use fractional factorial designs to reduce the number of profiles to be evaluated by respondents (Hair et al., 2010; Keen et al., 2004). The general form of a conjoint model can be expressed as:

$$U(X) = \alpha_0 + \sum_{i=1}^{m} \sum_{j=1}^{k_i} \beta_{ij} D_{ij}$$

where $U(X)$ is the overall expected utility of an alternative, α_0 is an intercept, β_{ij} is the utility (known as the part-worth) associated with the j^{th} level $(j = 1,2,\dots,k_i)$ of the i^{th} attribute $(i = 1,2,\dots,m)$, k_i is the number of levels of attribute i, m is the number of attributes, D_{ij}

equals 1 if the j^{th} level of the i^{th} attribute is present (0 otherwise). For identification purposes, the sum of the part-worths β_{ij} for a given attribute *i* are constrained to be zero.

The part-worths can be used to calculate the relative importance values of each attribute, W_i:

$$W_i = \frac{I_i}{\sum_{i=1}^{m} I_i}$$

where I_i is the importance of an attribute ($I_i = \{\max(\beta_{ij}) - \min(\beta_{ij})\}$) for each i. The sum of the relative importance values of all attributes is 1:

$$\sum_{i=1}^{m} W_i = 1$$

3.2.1. Design of the conjoint analysis

The first step of conjoint analysis is the selection of appropriate attributes and their levels. Our study focuses on the B2C market in the Netherlands. In 2015, the Dutch B2C E-commerce industry was worth €16.1 billion, with the expectation to grow to €18.0 billion in 2016 (Ecommerce Europe, 2016b). The Netherlands is one of top 10 countries in terms of E-commerce shares in the Gross Domestic Product and the B2C E-commerce market shares in Europe (Ecommerce Europe, 2016a). Attribute choices were based on a review of the literature discussed in the previous section, and of industry reports on consumer preferences and expectations. In addition, we discussed the attributes with e-fulfilment providers to ensure that the attributes and levels reflect the current market situation. Specifically, we chose the three most applicable levels of delivery speed in an online market: same-day delivery, next-day delivery, and standard delivery (2-5 days). Although time slot lengths vary in practice, depending on online retailers' strategies, three levels of "time slot" were included: 'no time slot', '2 hours', and '4 hours'. These levels were selected because of their prevalence in the Dutch online market (Global Webshop Logistics, 2014; de Leeuw and Spiliotopoulou, 2017). Regarding delivery during specific parts of the day, we selected two commonly applied practices: daytime and evening delivery. We furthermore differentiated delivery service into delivery on weekdays only and delivery on weekends (i.e. Saturday and Sunday). It is common to provide weekday delivery service, but more retailers offer the option for Saturday/Sunday delivery, as well. Delivery fees are dependent on the selected delivery services. The majority of online retailers offered free delivery. We noticed that there are two popular structures of free delivery in online retailing: unconditional free shipping and threshold-based free shipping (Global Webshop Logistics, 2014). The threshold level, based on the value of the order that qualifies for free shipping, varies among (Dutch) online retailers. This variation in threshold levels is related to differences in product values and delivery policies among the online retailers. Since it was not our objective to study customer sensitivity to different threshold levels, we decided to only adopt free shipping without a threshold (i.e. unconditional free shipping) in our questionnaire. For other levels of delivery fees, we also used the Global Webshop Logistics (2014) to set delivery fees to €2.5, €4, €7.5, and €17.5. We piloted the conjoint questions with eight colleagues experienced with online shopping to ensure the clarity of the questions. Five attributes and their levels were finally chosen for consumer evaluations (Table 1).

Attributes	Attribute levels
Delivery speed	▪ Order today and deliver today ▪ Order today and deliver tomorrow ▪ Order today and deliver in 2-5 business days
Time slot	▪ No time slot ▪ 2 hours ▪ 4 hours
Daytime/evening delivery	▪ During daytime ▪ During daytime and evening
Delivery date	▪ Monday to Friday ▪ Monday to Friday as well as Saturday ▪ All days in the week including Sunday
Delivery fee	▪ Free (€ 0) ▪ € 2.5 ▪ € 4.0 ▪ € 7.5 ▪ € 17.5

Table 1: Attributes and attribute levels

Given the five attributes and their levels, a total of 270 (3∗3∗ 2 ∗3 ∗5) profiles were constructed. To reduce the respondent evaluation task, a fractional factorial design was employed by generating an orthogonal design in IBM® SPSS® Statistics Version 21. The number of profiles for each questionnaire was 29, including four holdout profiles serving as validation profiles. Each respondent was presented with the 29 profiles and asked to rate them, on a 7-point scale (1 = very undesirable; 7 = very desirable). The part-worth utilities in the following model were estimated using ordinary least squares:

$$U = \alpha_0 + \sum_{l=1}^{3} \beta_{1l} D_{1l} + \sum_{l=1}^{3} \beta_{2l} D_{2l} + \sum_{l=1}^{2} \beta_{3l} D_{3l} + \sum_{l=1}^{3} \beta_{4l} D_{4l} + \sum_{l=1}^{5} \beta_{5l} D_{5l}$$

where U is the aggregate of the individual preference scores (Utility); α_0 is the intercept; β_{1l}, β_{2l}, β_{3l}, β_{4l}, β_{5l} are the coefficients (i.e. part-worth scores) associated with the levels of the attributes (1) delivery speed, (2) time slot, (3) daytime/evening delivery, (4) delivery date, (5) delivery fee, with D_{1l}, D_{2l}, D_{3l}, D_{4l}, D_{5l} being the dummy variables for each of the attributes.

3.2.2. Product categories

We examine how consumers choose delivery attributes across three product types, as previous studies have identified the need to customize order fulfilment approaches to product types (Ramanathan, 2010, 2011; Thirumalai and Sinha, 2005). For example, Thirumalai and Sinha (2005) differentiated between convenience goods (e.g., groceries), shopping goods (e.g., apparel), and specialty goods (e.g., electronics). Ramanathan (2010) and Ramanathan (2011) identified four product types by distinguishing between low and high price levels and product ambiguity. Investigating the relationships between logistics aspects and online customer behaviour for different types of products was also suggested by Kim and Lennon (2011) and Rao et al. (2011a). In accordance with the product classification by Thirumalai and Sinha (2005), this paper uses three example products representing three different product types in their classification, namely a personal care item (representing convenience goods), a pair of jeans (shopping goods), and a digital camera (specialty goods).

3.2.3. Data collection and sample

An online survey was conducted by an online panel of a market research service, Mobiel Centre. Mobiel Centre (http://www.mobielcentre.nl/en) is the largest field research organization in the Netherlands, providing market research services in various fields such as fast-moving consumer goods, retailing, mobility, and finance. 1,012 respondents had ordered a product online at least once, and participated in the study. They were asked to complete a questionnaire that consisted of three main parts: (i) questions about online shopping experience and perception; (ii) 29 profiles for the three product categories; (iii) questions about demographics. Respondents were randomly allocated across the product categories. We collected 345 responses for convenience goods, 329 responses for shopping goods, and 338 responses for specialty goods. Based on the results of our pretest, seven minutes was used as the lower boundary for the time needed to fill out the questionnaire: respondents who needed less time were dropped from the sample because the quality of their answers could not be guaranteed. Then, sample sizes were further reduced by excluding outliers. Based on the results of an initial conjoint analysis, the candidates for deletion were the ones that had attributes with an extremely high Pearson's R (0.970-1.000), indicating unreasonable preference patterns (Hair et al., 2010). Alternatively, observations that had attributes with a Pearson R lower than the calculated minimum correlation of 0.46[1], or a Kendall's tau for the hold-out observations of 0.40 or lower (Hair et al., 2010), were also candidates for deletion. In our cluster analysis, which we describe later, we also controlled for outliers. Based on the agglomeration schedule from hierarchical clustering, certain cases could be identified as outliers (in the sense that they did not really belong to any cluster). Table 2 summarizes final sample sizes for the conjoint analysis and cluster analysis.

	Total subjects	Convenience goods	Shopping goods	Specialty goods
Conjoint analysis	513	187	169	157
Cluster analysis	507	182	168	157

Table 2: Final sample sizes for conjoint analysis and cluster analysis

4. Analysis and results

4.1. Conjoint analysis

The survey data were analyzed using IBM® SPSS® Conjoint, which performs conjoint analyses using ordinary least squares. The part-worth utilities for individual levels of attributes for the three product categories were estimated. Importance values of these attributes for each product category were calculated using the part-worth utilities. The accuracy of the models was evaluated by assessing the correlation between respondents' ratings and the estimated utilities, namely by calculating Pearson's R and Kendall's tau. Furthermore, the external validity was assessed by calculating the correlations for the holdout profiles. When all three product categories were examined together, we found Pearson's R and Kendall's tau statistics of 0.90 ($p < 0.001$) for the estimation sample, and a Kendall's tau value of 0.66 ($p < 0.100$) for the hold-out sample. These results suggest decent model fit (Cohen, 1988; Evans, 1996). The correlation coefficients for the holdout sample were lower because of the smaller size of the holdout sample. Aggregate importance values for each sample are shown in Figure 1 and the part-worth utilities per level are reported in Table 3.

[1] According to Hair et al. (2010), the minimum correlation (R) should be established so that the adjusted R^2 is at least zero. Using the formula $R^2_{adjusted} = 1 - \frac{(1-R^2)(N-1)}{N-p-1}$ where $R^2_{adjusted} = 0$; $p = 5$ (number of attributes); $N = 25$ (number of profiles/observations per respondent, excluding holdout profiles), we obtained $R = 0.46$

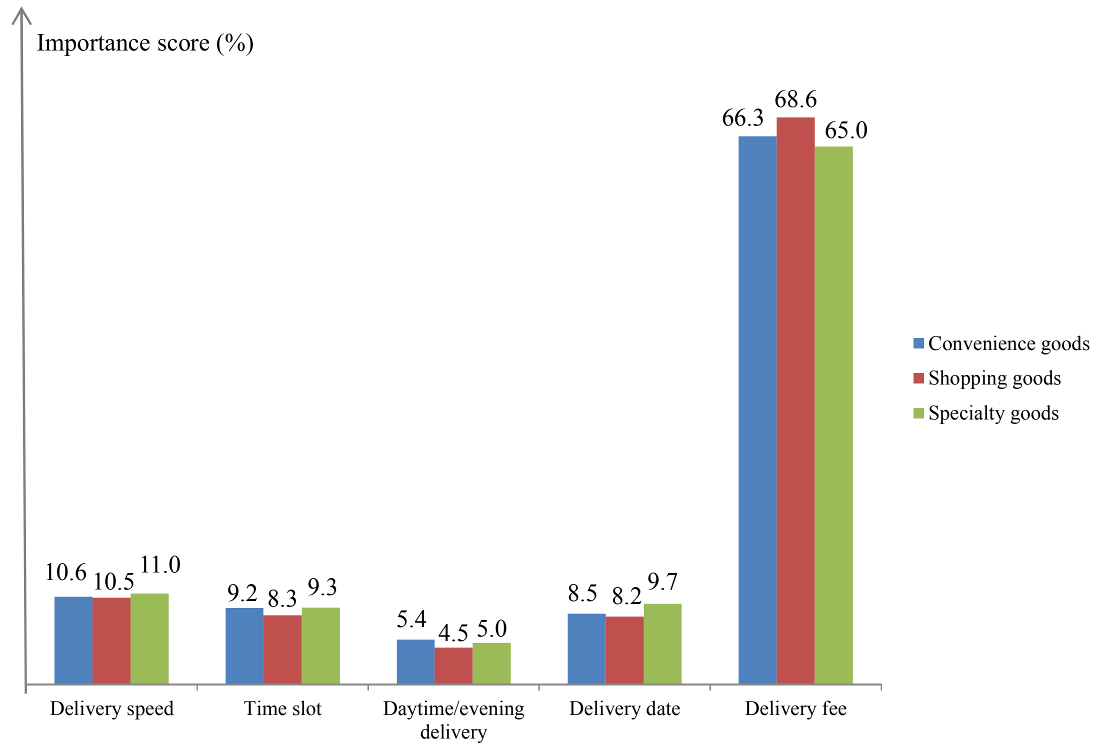

Figure 1: Importance scores for product categories (%)

The results show that *delivery fee* is the most important attribute for three product categories. The importance scores for the other attributes (i.e. *delivery speed*, *time slot*, *daytime/evening delivery,* and *delivery date*) remain roughly the same across product categories. There is a slight difference between the three categories regarding the characteristic that consumers consider to be the third most important attribute. For consumers in the convenience and shopping goods samples, *time slot* is the third most important attribute, while for consumers in the specialty goods sample, it is *delivery date*. This implies that consumers care more about the flexibility in delivery date than about the time slot when ordering high-value specialty goods. Finally, *daytime/evening delivery* is generally rated as the least important attribute.

Attribute	Attribute level	Part-worth utility (standard error)		
		Convenience goods	Shopping goods	Specialty goods
Delivery speed	Order today and deliver today	0.173 [a] (0.049)	0.140[a] (0.051)	0.111 (0.036)
	Order today and deliver tomorrow	0.058 (0.049)	0.108 (0.051)	0.131 [a] (0.036)
	Order today and deliver in 2-5 business days	-0.231 (0.058)	-0.249 (0.061)	-0.242 (0.043)
Time slot	No time slot	-0.145(0.049)	-0.128 (0.051)	-0.144 (0.036)
	2 hours	0.084 [a] (0.049)	0.103[a] (0.051)	0.105 [a] (0.036)
	4 hours	0.060 (0.058)	0.025 (0.061)	0.039 (0.043)
Daytime/evening delivery	During daytime	-0.092 (0.036)	-0.071 (0.037)	-0.079 (0.026)
	During daytime and evening	0.092 [a] (0.036)	0.071[a] (0.037)	0.079 [a] (0.026)
Delivery date	Monday to Friday	-0.045 (0.049)	-0.049 (0.051)	-0.080 (0.036)
	Monday to Friday as well as Saturday	0.058 [a] (0.049)	0.027[a] (0.051)	0.062 [a] (0.036)

Attribute	Attribute level	Part-worth utility (standard error)		
		Convenience goods	Shopping goods	Specialty goods
	All days in the week including Sunday	-0.013 (0.058)	0.022 (0.061)	0.018 (0.043)
Delivery fee	Free (€ 0)	2.326 [a] (0.070)	2.366[a] (0.073)	2.145 [a] (0.051)
	€ 2.5	0.748 (0.070)	0.819 (0.073)	0.731 (0.051)
	€ 4.0	-0.043 (0.070)	-0.012 (0.073)	0.030 (0.051)
	€ 7.5	-1.091 (0.070)	-1.088 (0.073)	-0.926 (0.051)
	€ 17.5	-1.939 (0.070)	-2.085 (0.073)	-1.980 (0.051)

([a] Level with the highest utility)

Table 3: Part-worth utilities per level for product categories

Table 3 reveals that the most preferable combination for consumers is to have a free delivery, a delivery from Monday to Saturday, delivery during daytime and evening, delivery within 2 hours, and same-day delivery (for convenience goods and shopping goods) or next-day delivery (for specialty goods). In line with our expectations, we find that a consumer's intent of choosing a delivery attribute decreases with an increase in delivery fee. Xing et al. (2010) reported that price was the most important variable to consumers in an online delivery context and the findings of Garver et al. (2012) indicated that free delivery had a much higher preference score than paid delivery. Our research confirms these results: the utility values of the second most important attribute, *delivery speed*, show that consumers prefer shorter delivery lead-times over longer ones. This result supports the findings of a study by Wilson-Jeanselme and Reynolds (2006) that found that the preference score for 24-hour delivery was higher than that of 48-hour delivery. Consumer preferences for same-day and next-day delivery over regular delivery (2-5 days) can be explained by the fact that the Netherlands is a small country. As a result, short delivery times are more common than in smaller countries (cf. de Leeuw and Spiliotopoulou (2017)) and as such consumers may be used to short delivery times. From the part-worths of the *time slot* attribute, it can be concluded that consumers prefer a specific time slot (2 or 4 hours), instead of an unknown time, for receiving a shipment at home. It is also interesting to note that consumers prefer receiving shipments throughout the entire week (including weekends), instead of on weekdays only (i.e., from Monday to Friday), which may be due to customer availability. *Daytime/evening delivery* was found to be the least important attribute. Consumers' preference for receiving shipments during daytime or in the evening (as opposed to only during daytime) may be attributed to the fact that many consumers are only at home after working hours.

In the next step, we conducted conjoint analyses for different groups of consumers. Specifically, in each of the categories, we split our sample on the basis of demographic variables and frequency of online purchase (Table 4). We then used one-way analysis of variance (ANOVA) to compare the importance values of the different attributes across groups. The ANOVA analysis indicated that there were significant differences between certain groups, which allowed for several post-hoc analyses between levels of the respective groups. For convenience and shopping goods, we found some significant differences between consumer groups, differing in terms of gender or annual income ($p<0.05$). Specifically, *time slot* was more important for men. An interpretation may be that (as identified in, e.g., a recent study on differences in work life between men and women[2]), in the Netherlands, more men than women are at work during the daytime. In contrast, *delivery fee* was more important for women for these two product categories. For convenience goods, the low-income group had higher importance values than the middle-income group for *delivery fee,* but lower for *time slot*. For shopping goods, the low-income group had higher importance values than the high-income group for *delivery fee,* but lower for *time slot* and *delivery date*. No significant differences in importance values were found for the different education and purchase frequency groups ($p>0.05$). There were no significant differences for specialty goods ($p>0.05$) in importance values across consumer groups for attributes except the age variable. For the specialty goods, the youngest group had the lowest importance values for non-price attributes while *delivery fee* matters most to this age group. Table 4 shows the results of ANOVA analysis and post-hoc comparisons.

Variable	N	Attributes				
		Delivery speed	Time slot	Daytime/evening delivery	Delivery date	Delivery fee
Convenience goods						
Age (years)						
18-20	4	16.967	4.895	4.910	6.828	66.398
21-40	20	9.649	7.368	4.452	7.558	70.971
>40	76	10.433	9.983	5.678	8.881	65.022
Gender						
Male	50	11.217	**10.368**	**6.256**	8.664	**63.496**
Female	50	9.892	**8.116**	**4.542**	8.399	**69.051**
Education						
Low	8	10.091	6.051	4.692	7.912	71.254
Middle	67	10.656	9.491	5.441	9.049	65.363
High	25	10.441	9.625	5.533	7.319	67.083
Income						
Low	24	8.914	**6.303**	4.761	8.313	**71.708**
Middle	36	11.849	**10.434**	5.526	8.443	**63.748**
High	21	10.475	**10.650**	6.090	9.002	**63.783**
Purchase frequency/year						
Low	33	10.596	9.506	5.219	7.885	66.794
Medium	61	10.640	9.064	5.529	8.959	65.808
High	6	9.494	9.706	5.142	7.750	67.909
Shopping goods						

[2]Source: https://www.scp.nl/Nieuws/Nederlandse_vrouwen_werken_al_op_jonge_leeftijd_in_deeltijd (Access on 14 February 2017)

Variable	N	Attributes				
		Delivery speed	Time slot	Daytime/evening delivery	Delivery date	Delivery fee
Age (years)						
18-20	5	13.315	7.511	4.335	**4.307**	70.530
21-40	23	12.416	9.267	4.412	**8.551**	65.352
>40	72	9.639	8.101	4.469	**8.338**	69.451
Gender						
Male	44	10.915	**9.742**	4.933	8.998	**65.411**
Female	56	10.086	**7.226**	4.065	7.558	**71.066**
Education						
Low	13	9.987	8.255	4.414	7.994	69.350
Middle	59	10.709	8.060	4.250	8.017	68.963
High	28	10.129	8.985	4.893	8.674	67.320
Income						
Low	23	10.561	**6.285**	4.493	**5.924**	**72.738**
Middle	30	9.611	**8.708**	4.803	**9.381**	**67.496**
High	17	13.167	**10.934**	4.867	**10.127**	**60.905**
Purchase frequency/year						
Low	34	9.354	8.410	4.406	8.853	68.978
Medium	55	10.585	8.386	4.265	7.761	69.003
High	11	13.113	7.929	5.492	8.360	65.105
Specialty goods						
Age (years)						
18-20	4	**5.775**	**4.151**	3.721	**5.358**	**80.993**
21-40	20	**11.890**	**10.460**	4.144	8.967	**64.537**
>40	76	**10.943**	**9.146**	5.297	**10.092**	**64.519**
Gender						
Male	42	11.657	10.365	5.119	10.708	62.150
Female	58	10.474	8.450	4.935	8.990	67.150
Education						
Low	13	9.436	9.826	5.989	11.266	63.484
Middle	61	11.675	9.850	5.059	9.863	63.553
High	26	10.129	7.586	4.405	8.568	69.313
Income						
Low	32	9.578	7.692	5.157	9.103	68.470
Middle	27	10.381	9.479	5.282	10.578	64.281
High	17	11.856	9.594	4.200	10.803	63.546
Purchase frequency/year						
Low	37	10.658	9.677	5.073	9.625	64.966
Medium	54	11.536	9.314	5.072	10.011	64.067
High	10	9.022	7.297	4.444	8.375	70.862

Remark: Values in bold indicate significant differences ($p < 0.05$) between groups of a variable that have these values.

Table 4: Importance values by demographic variables and frequency of online purchase (%)

4.2. Cluster analysis

We performed a cluster analysis, based on the consumer-level importance values, to identify homogeneous consumer segments. Retailers may use the results of such a cluster analysis to offer different delivery services to different consumer clusters. A two-stage clustering approach (including hierarchical and non-hierarchical methods) was adopted, because of its advantages over either purely hierarchical or purely non-hierarchical methods (Hair et al., 2010; Keen et al., 2004). The cluster analysis was performed with IBM® SPSS® Statistics Version 21. First, hierarchical clustering was used to determine the appropriate number of clusters. This technique uses Ward's method to minimize the sum of squared Euclidean distances between individuals and the centroids of their clusters. As the variables were measured on the same 7-point scale, unstandardized importance values were used as inputs in this first stage. Based on the agglomeration schedules and scree plots produced by the hierarchical clustering results, we found a three- and four-cluster solution for each product category. The cluster solutions in this stage were then used for non-hierarchical clustering in the second stage. Specifically, k-means clustering was used to determine the 'optimal' cluster compositions, given the number of clusters from the first stage. For convenience goods, the three-cluster solution led to relatively comparable clusters in terms of attribute importance patterns. In the four-cluster solution, in contrast, each cluster had more distinct features. Thus the four-cluster solution was chosen for convenience goods. For shopping and specialty goods, in the four-cluster solution, the number of cases for Cluster 4 was less than 10% of all observations, which was considered too small (Hair et al., 2010). Therefore, a three-cluster solution was chosen for these two product categories.

4.2.1. Cluster analysis results for convenience goods

Four clusters were identified for this product category. Table 5 presents details of the four clusters in terms of demographic characteristics and frequency of online purchase.

Variable		**Cluster 1 (N=72)**	**Cluster 2 (N=70)**	**Cluster 3 (N=22)**	**Cluster 4 (N=18)**
Age (years)	18-20	6	3	0	6
	21-40	21	26	5	17
	>40	73	71	95	77
Gender	Male	42	53	54	56
	Female	58	47	46	44
Education	Low	10	10	0	6
	Middle	68	60	73	83
	High	22	30	27	11

Income	Low	31	23	5	28
	Middle	26	41	45	44
	High	19	19	27	17
Purchase frequency/year	Low	32	32	45	22
	Medium	58	64	55	72
	High	8	4	0	6

Table 5: Cluster profiles in terms of demographic variables and frequency of online purchase (%), in the convenience goods category

Table 6 shows importance scores and part-worth utilities for each cluster. Cluster 1 is the largest segment, accounting for 40% (72 cases) of the total number of cases. In this cluster *delivery fee* has a much higher importance than other attributes (importance score: 81%); the other four attributes are relatively unimportant for respondents in this cluster. Consumers in this cluster are mainly low and middle income consumers. This cluster will therefore be referred to as “price sensitives”. Cluster 2 is the second largest segment (38%, 70 cases). This cluster has a preference pattern and demographic profile similar to Cluster 1. However, the important scores of three service attributes (*delivery speed*, *time slot*, and *delivery date*) are larger, at the expense of the *delivery fee* attribute. Since this cluster is most representative of the overall sample (see last column of Table 6), we refer to it as “average shoppers”. Cluster 3 has 22 cases (12%). The importance of *delivery fee* is the lowest across all clusters (importance score: 40%). *Time slot* and *delivery speed* are the two most important non-price attributes (importance score: 19% and 18% respectively). The least important attribute is *delivery date*. Most consumers in this cluster belong to the groups of middle- and high-income consumers. This segment can be labeled as “non-price-oriented”. Cluster 4 contains 18 cases (10%). In this segment, consumers care remarkably much about *delivery date*. The highest utility for this attribute is obtained for delivery on weekdays and Saturday. Compared to segments 1 and 2, *delivery fee* is less important. Most consumers in this cluster have a medium frequency of online purchases (72%, see Table 5). This cluster can be referred to as “delivery date oriented”.

	Cluster 1 (N=72)	**Cluster 2 (N=70)**	**Cluster 3 (N=22)**	**Cluster 4 (N=18)**	**Overall[b] (N=182)**
Constant	3.466	3.411	3.449	3.278	3.424
Delivery speed					
+ Order today and delivery today	0.081[a]	0.256[a]	0.211[a]	0.159[a]	0.172[a]
+ Order today and delivery tomorrow	0.030	0.103	0.020	0.015	0.055
+ Order today and delivery in 2-5 business days	-0.111	-0.359	-0.230	-0.174	-0.227
Importance score (%)	6.037	12.392	18.363	9.277	10.291
Time slot					
+ No timeslot	-0.023	-0.139	-0.348	-0.237	-0.128
+ 2 hours	0.023[a]	0.126[a]	0.102	0.069	0.076[a]
+ 4 hours	0.000	0.013	0.247[a]	0.169[a]	0.052
Importance score (%)	4.963	8.790	18.617	11.707	8.756

	Cluster 1 (N=72)	Cluster 2 (N=70)	Cluster 3 (N=22)	Cluster 4 (N=18)	Overall[b] (N=182)
Daytime/evening delivery					
+ During daytime	-0.051	-0.082	-0.273	0.003[a]	-0.085
+ During daytime and evening	0.051[a]	0.082[a]	0.273[a]	-0.003	0.085[a]
Importance score (%)	3.281	4.771	12.119	5.580	5.150
Delivery date					
+ Monday to Friday	-0.026	-0.112	0.023	0.059	-0.045
+ Monday to Friday as well as Saturday	0.012	0.061[a]	0.041[a]	0.198[a]	0.053[a]
+ All days in the week including Sunday	0.014[a]	0.051	-0.064	-0.257	-0.008
Importance score (%)	4.718	8.129	10.743	22.350	8.502
Delivery fee					
+ Free	2.887[a]	2.470[a]	0.896[a]	1.769[a]	2.375[a]
+ €2.50	0.837	0.893	0.351	0.391	0.755
+ €4	-0.166	-0.090	0.233	0.247	-0.048
+ €7.50	-1.291	-1.182	-0.604	-0.764	-1.114
+ €17.50	-2.266	-2.090	-0.876	-1.642	-1.969
Importance score (%)	81.001	65.918	40.159	51.086	67.304
Correlations					
Pearson's R	0.999	0.994	0.944	0.984	0.996
Kendall's tau	0.923	0.913	0.745	0.926	0.945

[a]Attribute level with the highest part worth
[b] Five outliers were detected and deleted from the overall sample for this product category.

Table 6: Cluster analysis for convenience goods

Clearly, this analysis illustrates that consumers are not homogeneous in how they choose delivery attributes for their online purchases, even though delivery fee is the dominant selection criterion.

4.2.2. Cluster analysis results for shopping goods

Three clusters were identified in the shopping goods category. Table 7 presents details of the three clusters in terms of demographic characteristics and frequency of online purchasing.

Variable		Cluster 1 (N=90)	Cluster 2 (N=21)	Cluster 3 (N=57)
Age (years)	18-20	4	0	7
	21-40	19	24	26
	>40	77	76	67
Gender	Male	40	71	40
	Female	60	29	60
Education	Low	13	14	12
	Middle	61	53	58
	High	26	33	30
Income	Low	27	10	15
	Middle	30	48	16
	High	10	24	15
Purchase frequency/year	Low	34	38	32
	Medium	57	52	54
	High	9	10	14

Table 7: Cluster profiles in terms of demographic variables and frequency of online purchase (%), in the shopping goods category

Table 8 shows the importance scores and part-worth utilities for each cluster. Cluster 1 is the largest segment (54%, 90 cases). *Delivery fee* is rated as the most important attribute, much more important than the other four attributes (importance score: 80%). This cluster will be referred to as “price-sensitives”. Cluster 2 is the smallest segment (12%, 21 cases). Most consumers of Cluster 2 are male (71%, see Table 7). Although *delivery fee* is still the most important attribute, it is far less important (40%) than in the other three segments. In contrast, attributes such as *time slot*, *daytime/evening delivery*, and *delivery date* are more important than in other segments. This segment can be labeled as “non-price-oriented”. Cluster 3, consisting of 57 cases (34%), has an importance pattern somewhat similar to that of Cluster 1. However, *delivery speed*, *time slot*, and *delivery date* are relatively more important, at the expense of *delivery fee*. Because this cluster is most similar to the average consumer (see last column of Table 8), we use the label “average shoppers”.

	Cluster 1 (N=90)	**Cluster 2 (N=21)**	**Cluster 3 (N=57)**	**Overall[b] (N=168)**
Constant	3.627	3.060	3.525	3.522
Delivery speed				
+ Order today and delivery today	0.068[a]	0.095	0.280[a]	0.143[a]
+ Order today and delivery tomorrow	0.052	0.162[a]	0.180	0.109
+ Order today and delivery in 2-5 business days	-0.120	-0.257	-0.459	-0.252
Importance score (%)	5.811	15.934	15.423	10.338
Time slot				
+ No timeslot	-0.071	-0.424	-0.108	-0.128
+ 2 hours	0.058[a]	0.181	0.149[a]	0.104[a]
+ 4 hours	0.013	0.243[a]	-0.041	0.024
Importance score (%)	5.814	18.062	8.600	8.290
Daytime/evening delivery				
+ During daytime	-0.051	-0.156	-0.070	-0.071
+ During daytime and evening	0.051[a]	0.156[a]	0.070[a]	0.071[a]
Importance score (%)	3.033	10.703	4.287	4.417
Delivery date				
+ Monday to Friday	-0.029	0.121	-0.136	-0.047
+ Monday to Friday as well as Saturday	-0.008	0.073[a]	0.063	0.026[a]
+ All days in the week including Sunday	0.037[a]	-0.194	0.073[a]	0.021
Importance score (%)	5.406	15.641	9.554	8.093
Delivery fee				
+ Free	2.720[a]	1.282[a]	2.249[a]	2.381[a]
+ €2.50	0.829	0.587	0.898	0.822
+ €4	-0.053	0.034	0.035	-0.012
+ €7.50	-1.195	-0.766	-1.056	-1.094
+ €17.50	-2.302	-1.137	-2.126	-2.097
Importance score (%)	79.936	39.660	62.137	68.862
Correlations				
Pearson’s R	0.999	0.950	0.991	0.996
Kendall’s tau	0.940	0.809	0.898	0.926

[a]Attribute level with the highest part worth

[b] One outlier was detected and deleted from the overall sample for this product category.

Table 8: Cluster analysis for shopping goods

4.2.3. Cluster analysis results for specialty goods

Three clusters were identified for the specialty goods. Table 9 presents details for the three clusters in terms of demographic characteristics and frequency of online purchase.

Variable		Cluster 1 (N=75)	Cluster 2 (N=28)	Cluster 3 (N=54)
Age (years)	18-20	7	0	0
	21-40	17	18	26
	>40	76	82	74
Gender	Male	36	54	44
	Female	64	46	56
Education	Low	13	22	9
	Middle	57	64	63
	High	30	14	28
Income	Low	39	21	28
	Middle	24	36	26
	High	17	18	15
Purchase frequency/year	Low	37	39	35
	Medium	50	57	57
	High	13	4	8

Table 9: Cluster profiles in terms of demographic variables and frequency of online purchase (%), in the specialty goods category

Table 10 shows importance scores and part-worth utilities for each cluster. Cluster 1 is the largest segment, accounting for half of the consumers (48%, 75 cases). Respondents in this cluster attributed a significantly higher importance to *delivery fee* than to the other attributes (79% versus 21%). This segment mainly consists of female (64%, see Table 9), and low- and middle-income consumers (63%). This cluster will be referred to as "price-sensitives". Cluster 2 is the smallest segment (18%, 28 cases). Although *delivery fee* is still identified as the most important attribute, its importance value is much lower than that of Cluster 1 and Cluster 3. The non-price attributes *delivery speed*, *time slot*, *daytime/evening delivery*, and *delivery date* are more important than *delivery fee* (67% versus 33%). This segment will be labeled as "non-price-oriented". Finally, Cluster 3 has a preference pattern somewhat similar to Cluster 1, although all non-price attributes are considered more important than in Cluster 1. Because the consumers in this cluster are most representative of the overall specialty goods sample (see last column of Table 10), they can be referred to as "average shoppers".

	Cluster 1 (N=75)	Cluster 2 (N=28)	Cluster 3 (N=54)	Overall (N=157)
Constant	3.695	3.294	3.651	3.608
Delivery speed				
+ Order today and delivery today	0.039[a]	0.039	0.249[a]	0.111
+ Order today and delivery tomorrow	0.024	0.279[a]	0.202	0.131[a]
+ Order today and delivery in 2-5 business days	-0.064	-0.318	-0.451	-0.242
Importance score (%)	6.034	18.558	13.896	10.972
Time slot				

	Cluster 1 (N=75)	Cluster 2 (N=28)	Cluster 3 (N=54)	Overall (N=157)
+ No timeslot	-0.076	-0.318	-0.149	-0.144
+ 2 hours	0.071[a]	0.207[a]	0.101[a]	0.105[a]
+ 4 hours	0.005	0.111	0.049	0.039
Importance score (%)	5.506	19.183	9.316	9.255
Daytime/evening delivery				
+ During daytime	-0.019	-0.146	-0.127	-0.079
+ During daytime and evening	0.019[a]	0.146[a]	0.127[a]	0.079[a]
Importance score (%)	3.136	9.427	5.330	5.012
Delivery date				
+ Monday to Friday	-0.027	-0.185	-0.098	-0.080
+ Monday to Friday as well as Saturday	0.013	0.133[a]	0.093[a]	0.062[a]
+ All days in the week including Sunday	0.014[a]	0.051	0.006	0.018
Importance score (%)	6.092	19.626	9.600	9.712
Delivery fee				
+ Free	2.686[a]	0.611[a]	2.188[a]	2.145[a]
+ €2.50	0.902	0.290	0.721	0.731
+ €4	0.001	0.011	0.081	0.030
+ €7.50	-1.196	-0.231	-0.912	-0.926
+ €17.50	-2.394	-0.681	-2.079	-1.980
Importance score (%)	79.233	33.205	61.858	65.048
Correlations				
Pearson's R	1.000	0.954	0.995	0.998
Kendall's tau	0.955	0.828	0.978	0.940
Kendall's tau for Holdouts				

[a]Attribute level with the highest part worth

Table 10: Cluster analysis for specialty goods

4.3. Simulation Analyses

The part-worth utilities from the conjoint analysis can be used to predict preferences in various scenarios by simulating choices and calculating the share of preference for each alternative choice option (Hair et al., 2010; Orme, 2010). Simulation is a useful tool to investigate how preferences change as new services/products are introduced. Based on industry reports and actual delivery offerings on different webshops (Global Webshop Logistics, 2014; MICROS, 2014), we chose three baseline services that reflected the practice at the time of study regarding standard delivery and express delivery (Table 11).

	Delivery speed	Time slot	Daytime/evening delivery	Delivery date	Delivery fee
Baseline Service 1 (BS1)	Order today and delivery in 2-5 business days	No time slot	Daytime	Monday to Friday	Free
Baseline Service 2 (BS2)	Order today and delivery tomorrow	No time slot	Daytime	Monday to Friday	€4.0
Baseline Service 3 (BS3)	Order today and delivery today	4 hours	Daytime and evening	Monday to Friday as well as Sunday	€17.5

Examples: BS1 (standard delivery in UK by Amazon); BS2 (next-day delivery in the Netherlands by Hema); BS3 (same-day delivery in the Netherlands by Coolblue)

Table 11: Baseline scenarios

There are two main models for predicting a consumer's choice of stimulus: the maximum utility model and the preference probability model (Hair et al., 2010). The first model assumes a respondent selects a profile with the highest predicted utility value and determines share of preference by calculating the number of respondents preferring each profile. The second model assumes a respondent has some probability of choosing a profile and determines the overall share of preference by summing up the preference probabilities across all respondents. In our simulation, the former was chosen because the latter presented a few issues: for example, as the probability model deals with negative utilities, negative probabilities are present (Mesías et al., 2005). In each product category, we ran four simulations (A, B, C, and D) by changing the levels of *time slot*, *daytime/evening delivery*, *delivery date*, and *delivery fee* in the baseline services (Table 12). By varying the attribute levels, it is possible to see how consumer preferences for the baseline services changed.

Simulation	New service	Time slot	Daytime/evening delivery	Delivery date	Delivery fee
A	BS1A	4 hours	Unchanged	Unchanged	Unchanged
	BS2A	4 hours	Unchanged	Unchanged	Unchanged
	BS3A	Unchanged	Unchanged	Unchanged	Unchanged
B	BS1B	Unchanged	Daytime and evening	Unchanged	Unchanged
	BS2B	Unchanged	Daytime and evening	Unchanged	Unchanged
	BS3B	Unchanged	Unchanged	Unchanged	Unchanged
C	BS1C	Unchanged	Unchanged	Monday to Friday as well as Sunday	Unchanged
	BS2C	Unchanged	Unchanged	Monday to Friday as well as Sunday	Unchanged
	BS3C	Unchanged	Unchanged	Unchanged	Unchanged
D	BS1D	Unchanged	Unchanged	Unchanged	Unchanged
	BS2D	Unchanged	Unchanged	Unchanged	€2.5
	BS3D	Unchanged	Unchanged	Unchanged	€7.5

Table 12: Simulations for each product category

The results of the simulations are presented in Table 13: in all product categories, BS1A, BS1B, BS1C, and BS1D have the highest preference among the baseline services. This is logical, since this baseline service involves free standard delivery, thus the result agrees with the overall results of the conjoint analysis indicating that *delivery fee* is the most important attribute. In Simulation D, changing the *delivery fee* from €4.0 to €2.5 in BS2D, and from €17.5 to €7.5 in BS3D, significantly increases the preference value for BS2D ('order today delivery tomorrow') across the product categories. The preference value for next-day delivery

(BS2D) is higher than for same-day delivery (BS3D), as the change in delivery fee made the former more attractive. As compared to a change in *time slot* (Simulation A), *daytime/evening delivery* (Simulation B), or *delivery date* (Simulation C), a change in *delivery fee* (Simulation D) has the greatest impact on consumer preferences. Note that the preference for BS3, which has the highest delivery fee, decreases in simulations A, B, and C, implying that consumers are willing to compromise on delivery fees when there are alternative choices with attractive non-price characteristics. Thus, while expensive delivery options may attract a fair share of shoppers if their non-price attributes are sufficiently attractive (see baseline scenario), they quickly lose appeal when the cheaper delivery options entail similarly attractive characteristics (see, in particular, scenario B). For example, Agatz et al. (2011) found that changing the time slot characteristic (e.g., the number of time slots or delivery time windows) influenced consumer time slot choice. Offering narrow delivery time slots is appreciated by consumers, but reduces routing efficiency.

Unlike a change in *delivery fee*, changes in the other attributes (i.e., *time slot*, *daytime/evening delivery*, and *delivery date*) have a minor impact in all three product categories. In the specialty goods category, the fastest delivery service ('order today delivery today', i.e. BS3A, BS3B, BS3C, and BS3D), has a relatively high preference (compared to the other categories), despite its price. Especially in this product category, consumers seem to appreciate fast service.

Simulation (an attribute change)	Maximum Utility Model (%)		
	Convenience goods	Shopping goods	Specialty goods
Baseline scenario			
BS1	87.4	87.6	80.9
BS2	6.7	9.5	9.9
BS3	5.9	3.0	9.2
Simulation A			
BS1A (time slot change)	87.4	87.6	81.2
BS2A (time slot change)	7.5	9.5	11.8
BS3A	5.1	3.0	7.0
Simulation B			
BS1B (daytime/evening delivery)	88.5	87.6	83.1
BS2B (daytime/evening delivery)	8.3	10.1	11.8
BS3B	3.2	2.4	5.1
Simulation C			
BS1C (delivery date)	88.0	87.3	81.2
BS2C (delivery date)	7.0	10.1	11.8
BS3C	5.1	2.7	7.0

Simulation (an attribute change)	Maximum Utility Model (%)		
	Convenience goods	Shopping goods	Specialty goods
Simulation D			
BS1D	74.6	77.5	73.2
BS2D (delivery fee)	16.0	18.3	16.9
BS3D (delivery fee)	9.4	4.1	9.9

Table 13: Simulation results

5. Conclusions

Delivery is an important factor influencing consumers in online retailing, and has recently received significant attention. In practice, online retailers are likely to diversify their delivery service since consumers tend to have heterogeneous preferences. However, there is a lack of research on consumers' preferences for different delivery attributes in online retailing. Prior research only focused on investigating single delivery attributes, for example, impacts of delivery fee on consumer behaviour studied by Lewis (2006) and Lewis et al. (2006); impacts of on-time delivery on repurchase intentions studied by Collier and Bienstock (2006) and Rao et al. (2011b); time-slot management studied by Agatz et al. (2011) and Campbell and Savelsbergh (2006). The current study therefore contributes to the literature by identifying consumer preferences for specific delivery attributes, including *delivery fee*, *delivery speed*, *time slot*, *delivery date*, and *daytime/evening delivery* across three product categories in the Netherlands. Conjoint analysis is used to examine how consumer preferences for delivery services are formed on the basis of the service's attributes and attribute levels. We find that conjoint analysis is an adequate tool to study consumer preferences in logistics and supply chain management, where its application is still limited (Garver et al., 2012).

Our study examines importance values of different delivery attributes. We find that the most important attribute in shaping consumer preferences is *delivery fee*, followed by *delivery speed*, *time slot*, *delivery date*, and *daytime/evening delivery*. The results of the current study are similar to those of Xing et al. (2010) and Garver et al. (2012), who demonstrated that delivery fee, compared with speed of delivery, carrier, convenience, and tracking availability to name just a few, has the greatest impact on consumer behaviour in online retailing. Our study adds to this previous work by focusing on the effects of *delivery fee* in relation to other non-price delivery attributes. The preference structure is similar across three product categories: convenience goods, shopping goods, and specialty goods. This finding illustrates the fact that offering various forms of free delivery (as done by several online retailers; Soper, 2015; Target, 2015) may be a key delivery strategy for attracting consumers. By examining the part-worth utilities of individual attribute levels, the conjoint analysis results shed further light on consumers' preferences in each of the product categories.

Although *delivery fee* is of great importance to consumers, our cluster analysis indicates that, in each of the three product categories, there are consumers who care about non-price attributes. Simulations were used to investigate the extent to which consumers adopt new delivery services, and to examine how they compromise between the different service attributes. Simulations are also useful to assess alternative realities in logistics and supply chain management (Goldsby and Zinn, 2016). The simulation results show that most consumers prefer free delivery with standard delivery speed across product categories. A change in *delivery fee* has the greatest impact on preferences, compared to a change in *time slot*, *daytime/evening delivery*, or *delivery date*. Consumers seem to only slightly adjust their preferences when non-price attributes are changed, regardless of the product category. Consumers still prefer a longer lead time with a lower *delivery fee*. This is consistent with the findings by Xing et al. (2010) and Garver et al. (2012), demonstrating that *delivery fee* is the most important factor to consumers shopping online.

This study makes a contribution to literature at the interface of marketing and logistics by offering a better understanding of consumers' expectations regarding delivery service in online retailing. While previous studies focused on the impact of on-time delivery on such consumer behaviours as purchase and repurchase intentions in online retailing (Nguyen et al., 2018), our study investigates consumer choice in time-based attributes; the results can help online retailers in offering delivery attributes that generate the highest consumer satisfaction. Put differently, our findings help online retailers convert consumers' needs and preferences into concrete delivery services. In addition, by identifying different consumer segments for each product category, this study helps online retailers target distinctive delivery services towards groups of consumers.

Our research has some limitations which offer opportunities for further research. First, as the study is conducted in a specific country, the results may be limited to a particular culture. Future research should account for the fact that cross-border e-commerce is growing in Europe (Nguyen et al., 2018), such that retailers are confronted with very diverse shopping habits and consumer preferences. Second, we acknowledge that this study is unable to capture all aspects of reality. The conjoint profiles in our study consist of five attributes that are mainly time-related. There are other attributes that may also be of great concern to consumers when choosing delivery options, for example, shipment tracking availability and the retailer's reliability. In addition, regarding the attribute levels of *delivery fee*, we examined the unconditional free delivery attribute while ignoring the threshold-based free delivery option. Future research should also address these alternate shipping fee strategies. Finally, our research uses traditional conjoint analyses with an orthogonal design, which enables us to examine the attributes' main effects, but not their interaction effects. Future research could investigate the possible interaction effects between the attributes. Despite these limitations, this study contributes to the currently limited understanding on delivery attributes in both theory and practice, the limited body of literature on consumer response to delivery attributes, and opens up avenues for future research.