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What Is the Right Delivery Option for You? Consumer Preferences for Delivery Attributes in Online Retailing

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Nowadays, online retailers are offering a variety of delivery options consisting of varying combinations of delivery attributes. This study investigates how consumers value these delivery attributes (e.g., delivery speed, time slot, daytime/evening delivery, delivery date, and delivery fee) when selecting a delivery option for their online purchases. Mental accounting theory is used to frame the research and to suggest how mental accounts for money, time, and convenience influence consumer preferences for online delivery options. Specifically, the results of a conjoint analysis show that the most important attribute in shaping consumer preferences is the delivery fee, followed by nonprice delivery attributes. For individual attributes, significant differences are found in consumer preferences between gender and income groups. Cluster analysis reveals three consumer segments that show distinct preference structures: We identify a "price-oriented," a "time- and convenience-oriented," and a "value-for-money-oriented" consumer segment. This study has practical implications for online retailers when implementing suitable delivery strategies and designing effective delivery options to maximize consumer satisfaction.

Keywords: last mile delivery; E-commerce logistics; online retail; conjoint analysis; consumer behavior; mental accounting theory

INTRODUCTION

The Internet has not only attracted a considerable number of consumers who search for, and buy, products online but has also created opportunities for retailers to increase sales. In 2017, online retailing in western Europe grew by 11% to around €255 billion (Euromonitor 2018). In the first three quarters of 2017, the Dutch business-to-consumer (B2C) e-commerce industry was worth €15.7 billion, with the expectation to grow to €22.0 billion in 2017 (Ecommerce News 2017). Though logistics has been recognized as a key activity in e-fulfillment and an important driver of the growth of the e-commerce sector (Maltz et al. 2004; Turban et al. 2015), it brings challenges for online retailers as well. Specifically, last mile delivery is one of the most important success factors in order fulfillment (Esper et al. 2003; Boyer et al. 2009). From a consumer′s perspective, last mile delivery is a crucial aspect in their purchase decision (Xing et al. 2010).

Although a significant number of studies investigated the effects of delivery on online consumer behavior, such as speed of delivery (Bart et al. 2005; Otim and Grover 2006), on-time delivery (Collier and Bienstock 2006), time slot (Campbell and Savelsbergh 2006; Agatz et al. 2011), and delivery fees (Rao et al. 2011a), very little research has examined consumer preferences for delivery attributes in online retailing (Garver et al. 2012). In addition, whether or not consumer preferences for delivery attributes depend on contextual factors (e.g., product categories or consumer characteristics) is virtually unexplored.

Prior work on last mile delivery identified delivery as an important element of logistics consumer service and a significant driver of consumer loyalty (Dadzie et al. 2005). Several studies have since examined a variety of delivery aspects in online retailing. Lewis (2006) and Lewis et al. (2006) showed that shipping fees significantly impact a consumer′s purchase decisions regarding order incidence and order size. Rao et al. (2011b) indicated that delivery delays decrease consumer loyalty levels. Online consumers are quite sensitive to delivery time, and therefore, this factor has a strong impact on consumer satisfaction and repurchase intentions (Collier and Bienstock 2006). Based on exploratory factor analysis using survey data, Xing et al. (2010) found that consumers highly value distribution punctuality in online retailing, including various options for delivery dates, delivery on the first day arranged, or within a specified time slot, and the ability to deliver orders quickly.

Given the lack of prior research on consumer evaluations of delivery attributes in online retailing and the importance of understanding this for online retailers, this paper aims to answer the following main research questions: (1) How do online shoppers value and trade off delivery attributes when selecting a delivery option? and (2) do these evaluations and trade-offs vary across product categories or consumer segments? These research questions are addressed using a middle-range theorizing approach. Mental accounting theory (MAT) was used as a starting point. MAT has been used often in studying consumer behavior (Antonides and Ranyard 2018; Hossain and Bagchi 2018). It predicts that individuals categorize their activities into mental accounts and make purchase decisions based on the allocated resources of their budgets for each of their mental accounts

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(Thaler 1985, 1999). MAT has been applied to a variety of problems in purchasing decisions of retail consumers. This paper intends to study how MAT can help explain consumer preferences for last mile delivery options in online retailing. This research is based on the recent systematic literature review by Nguyen et al. (2018) on order fulfillment in online retailing to systematically investigate prior research in this domain and structure the insights of observations on the topic. Conjoint analysis and cluster analysis, based on data from 692 and 683 respondents, respectively, were used to gain a deeper understanding of the degree to which and conditions under which delivery attributes collectively impact consumer preferences in online retailing. Based on this, propositions have been developed that may be used for future theory testing research. This study offers insights into consumer preferences for logistics services that have not been set forth in the literature yet, thereby further expanding MAT on consumer behavior in online retailing. This may help retailers in implementing suitable delivery strategies and designing effective delivery options to maximize consumer satisfaction.

This paper is structured as follows: in Section Literature review, the extant literature on the effects of delivery on consumer behavior and consumer preferences in online retail is discussed. Additionally, how the theory of mental accounting is adopted as guidance in this study is also discussed. Section Methodology presents the methodology, while Section Findings reports the findings of the study, which leads to a number of propositions. Section Discussion discusses the theoretical and managerial implications. Finally, Section Conclusion concludes with limitations and future research avenues.

LITERATURE REVIEW

Last mile delivery

Middle-range theory is an appropriate approach to understand phenomena in the logistics domain where general theories are often mute due to a lack of domain specificity and starts from well-established relationships in the domain of research (Stank et al. 2017). To this end, one would ideally start with a meta-analysis of empirical papers in the domain considered. Unfortunately, such a meta-analysis is not possible in this relatively nascent field of research due to a dearth of empirically grounded papers. Instead, this research builds on and extends the systematic literature survey of Nguyen et al. (2018) in the domain of order fulfillment in online retailing. Nguyen et al. (2018) adopt the five-step approach by Denyer and Tranfield (2009), which is regularly used for literature reviews in the field of management and organization. Nguyen et al. (2018) (1) formulate research questions (which order fulfillment elements are relevant to online consumer behavior from prepurchase to postpurchase, and what is the relation between order fulfillment performance and consumer behavior); (2) locate studies (drawn from international peer-reviewed journal papers between 2000 and September 2015, by using keywords and search strings to find studies in databases and in journals from journal quality lists, and by using snowballing); (3) select and evaluate studies (based on a list of inclusion and exclusion criteria and quality assessment criteria that assess theory, methodology, analysis, relevance, and contribution of studies), culminating in 52 relevant articles; (4) analyze and synthesize studies; and (5) report and use the results. Using the same approach as described in Nguyen et al. (2018), the coverage is extended to September 2018. Specifically, the same keywords and search strings developed in the Nguyen et al. (2018) study were used to search for papers published in the Web of Science between 2015 and September 2018. We then used snowballing to identify additional articles. Next, the studies were evaluated based on inclusion and exclusion criteria to obtain the final papers. Specifically, an additional four papers were retrieved that are relevant to this study, including Blut (2016), Xu et al. (2017), Duarte et al. (2018), and Gawor and Hoberg (2018).

In the paper of Nguyen et al. (2018), order fulfillment literature has been split into three domains: inventory management, last mile delivery, and returns management. The present paper focuses on last mile delivery since this part of the supply chain, as the final and critical link between retailers and consumers, is an important success factor in online businesses. The cost of last mile delivery can easily account for 50% of the total supply chain cost (Hübner et al. 2016). Any failure or delay in delivery affects customers′ experiences and consequently a consumer′s potential online ordering behavior (Rao et al. 2011b). Last mile delivery is always incorporated as an indispensable factor into models of electronic (logistics) service quality (Collier and Bienstock 2006; Xing et al. 2010; Rao et al. 2011a; Blut 2016).

Nguyen et al. (2018) distinguish four aspects of last mile delivery, which are discussed below: (1) delivery information/options, (2) delivery fees, (3) delivery, and (4) order tracking.

Delivery information/options refer to what consumers want to know prior to placing an order, for example, carriers, shipping dates, and time slots. The online presence of information and options could affect purchase and repurchase intentions. For example, Esper et al. (2003) found that consumers are willing to purchase a product online if they are allowed to choose a carrier that is revealed on the web site. Delivery options are an important component of order fulfillment that helps to develop online trust, which subsequently significantly affects consumer purchase intentions (Bart et al. 2005). A similar result in the study by Rao et al. (2011a) indicated that delivery options contribute to a significant impact of physical distribution service quality on consumer satisfaction, hence leading to consumer repurchase intention. Agatz et al. (2011) found that changing the number of time slots for delivery over spatial areas affects consumer choice of time slots in an online purchase.

Delivery fees are an important means for online retailers to recover logistics costs (Lewis 2006). At the same time, charging low (or no) delivery fees can be an effective marketing tool for influencing a consumer′s purchase decision. Delivery fee structures influence consumer purchase patterns in terms of order incidence and size, thus influencing consumer acquisition and retention (Lewis 2006; Lewis et al. 2006; Becerril-Arreola et al. 2013). According to Schindler et al. (2005), unconditional free shipping (also known as “bundled pricing”) and flat-rate shipping (also known as “unbundled pricing”) result in different consumer preferences for an online offer depending on the degree of consumer shipping fee skepticism and the presence of external reference prices. Koukova et al. (2012) found that online consumers evaluate threshold-based free shipping and flat-rate shipping differently depending on whether the order value is lower or higher than the threshold. For the unconditional free delivery structure, Lantz and Hjort (2013) found that this policy leads to an increase in the total number of online orders and a decrease in the average value of the purchased products. In general, satisfaction with the physical distribution service price (including delivery fees and the online presentation of all fees prior to purchase) positively affects overall consumer purchase satisfaction and consumer retention (Rao et al. 2011a).

The *delivery* aspect is mostly related to timeliness and delivery speed. As online consumers are especially sensitive to on-time delivery, this factor is known to enhance consumer satisfaction significantly (Collier and Bienstock 2006; Xing et al. 2010; Rao et al. 2011a; Koufteros et al. 2014; Blut 2016). The recent study on e-service offerings by Xu et al. (2017) indicated that fast delivery (within 24 hr) increases consumer satisfaction for hedonic products such as toys, wine, and jewelry because online consumers tend to buy these products on impulse and want to possess them quickly. Wilson-Jeanselme and Reynolds (2006) used a choice-based conjoint analysis to analyze the preference structures of consumers for online grocery purchases across three online retailers in the UK. In this study, consumers made purchase decisions on the basis of a combination of different factors including delivery service attributes. The results show that delivery speed and on-time delivery are among the most important decision criteria. Goebel et al. (2012) investigate consumer perception of a time-based home delivery service and how it affects the willingness to pay for this service. The authors indicated that in particular the level of the consumer′s availability at home and working hours per week influence the perceived attractiveness of the service. A recent study by Gawor and Hoberg (2018) examines different drivers of consumers′ valuation of e-fulfillment. They show that, while total price is the most important attribute, delivery speed and delivery method follow directly. Furthermore, the authors uncover four consumer segments, based on the monetary value of time and convenience. Duarte et al. (2018) emphasize the importance of “possession convenience,” that is, the convenience to physically obtain online products (in comparison with, for instance, “transaction convenience”).

Order tracking refers to an online service that helps consumers know the status of their orders. A number of studies have revealed that this factor has a significant impact on consumer repurchase intention (Cao et al. 2003; Otim and Grover 2006; Rao et al. 2011a; Thirumalai and Sinha 2011; Cho 2015). Garver et al. (2012) used adaptive choice modeling to examine how consumers select logistics services for their online purchases. Their findings show that tracking availability is the third most important attribute, after delivery fee and speed of delivery. They also identify five distinct consumer segments with different preference patterns. The availability of an order tracking and tracing system contributes to improving the physical distribution service quality in online retailing (Xing et al. 2010).

Table 1 summarizes the previous studies on the effects of last mile delivery aspects on online consumer behavior. The above review and Table 1 show that prior research has provided an understanding of how specific circumstances affect consumer preferences in online retailing. However, although it is known that, for example, time and convenience are part of consumers′ criteria when selecting a delivery service (Gawor and Hoberg 2018), it is not yet understood how consumers make a choice when they have to consider a variety of delivery attributes or why and how specific delivery attributes may jointly affect consumer preferences. This study aims to contribute to this understanding. As far as can be determined, there is no conceptualization of how consumer preferences relate to delivery attributes in online retailing (Garver et al. 2012), nor of how these preferences depend on contextual factors (e.g., product categories or consumer characteristics). In this empirical study, delivery information/options, delivery fees, and aspects of the actual delivery (i.e., delivery speed) were focused on. We use MAT to further conceptualize how consumer preferences relate to delivery attributes.

Mental accounting and consumer behavior

A significant amount of research has shown that mental accounting matters in studying consumer behavior (Antonides and Ranyard 2018; Hossain and Bagchi 2018). Mental accounting refers to the cognitive processes in which individuals organize and manage their financial decisions (Kahneman and Tversky 1984; Thaler 1985, 1999; Shefrin and Thaler 1988). According to this theory, individuals categorize their activities into mental accounts and make purchase decisions based on the allocated resources of their budgets for each of the mental accounts instead of integrating all the decisions to optimize their consumption. For example, the seminal publication of Kahneman and Tversky (1984) presents how consumers evaluate a multi-attribute option in a transaction by creating a mental account with advantages and disadvantages associated with the option. Consumers consequently make decisions if the value of the advantages exceeds the value of the disadvantages. Kahneman and Tversky propose three mental accounts in an outcome frame: minimal, topical, and comprehensive mental accounts. The minimal account refers to the differences between options, regardless of the features that they share. The topical account relates the consequences of possible choices to a reference level in the context within which the decision is made. The comprehensive account can be interpreted as the savings that are evaluated in the whole context. The authors found that consumers are likely to establish topical accounts incorporating the most relevant aspects of the transaction. Mental accounting was also used to examine how feelings about a sum of money (i.e., “emotional account”) influence consumers′ expenses (Levav and McGraw 2009). Milkman and Beshears (2009) indicated that online grocery consumers redeeming a \$10-off coupon tend to spend more on goods that they normally do not buy. Also, consumers prefer retailer-specific items when they shop with retailer-specific gift cards (Reinholtz et al. 2015). Helion and Gilovich (2014) found that consumers are more likely to purchase hedonic products with their gift cards than with other forms of payment such as cash or credit cards. In general, the studies of mental accounting suggest that consumers tend to create mental accounting systems and evaluate expenses based on resources allocated to specific accounts.

Interestingly, a fair amount of research has indicated that people create mental accounts for time in a similar way as they do for money (Leclerc et al. 1995; Moon et al. 1999; Soman 2001; Duxbury et al. 2005; DeVoe and Pfeffer 2007; Rajagopal and Rha 2009; Rong-Da Liang et al. 2014). As time and money are considered scarce resources that online consumers trade off while

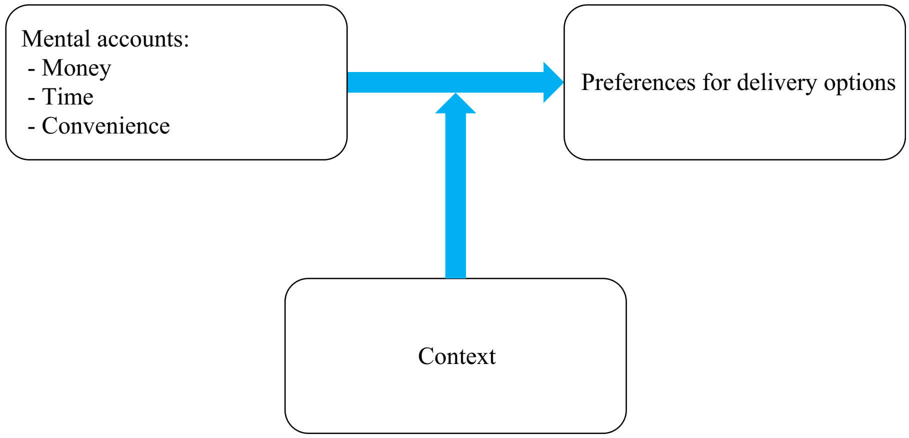
Table 1: Last mile delivery aspects and online consumer behavior in the existing literature

Last mile delivery aspect	Study	Type of research	Last mile delivery variables in focus	Effects on online consumer behavior
Delivery information/ options	Agatz et al. (2011)	Simulation (computational experiments)	Time slots	Change in time slot template affects consumer choice of time slots
	Bart et al. (2005)	Empirical study	Availability of delivery options	Positive effect on consumer willingness to buy
	Esper et al. (2003)	Experiment	Ability to choose a carrier Disclosure of carrier name	Positive effect on consumer willingness to buy
	Rao et al. (2011a)	Empirical study	Variety of delivery options	Increase consumer repurchase intention
Delivery fees	Becerril-Arreola et al. (2013) Lewis (2006) Lewis et al. (2006)	Simulation Empirical study Empirical study	Delivery fee structures	Affect consumer purchase patterns
	Koukova et al. (2012)	Experiment	Delivery fee structures	Affect consumers′ online evaluations and choice
	Lantz and Hjort (2013)	Experiment	Unconditional free delivery	Affect consumer purchase patterns
	Rao et al. (2011a)	Empirical study	Delivery fee	Positive effect on consumer retention
	Schindler et al. (2005)	Experiment	Delivery fee structures	Affect consumer preferences for online offers
Delivery	Blut (2016) Collier and Bienstock (2006) Koufteros et al. (2014) Rao et al. (2011a) Xing et al. (2010)	Empirical study Empirical study Empirical study Empirical study Empirical study	Timeliness Delivery speed	Positive effect on consumer satisfaction
	Duarte et al. (2018)	Empirical study	Delivery time	Increase consumer satisfaction
	Gawor and Hoberg (2018)	Empirical study	Delivery speed Delivery method Delivery fees	Affect consumer preferences for an online purchase
	Goebel et al. (2012)	Empirical study	Delivery time	Affect consumer preferences for time-based delivery services
	Wilson-Jeanselme and Reynolds (2006)	Empirical study	Delivery speed Delivery fees On-time delivery	Affect consumer preferences for online groceries
	Xu et al. (2017)	Empirical study	Delivery speed	Increase consumer satisfaction
Order tracking	Cao et al. (2003) Cho (2015) Rao et al. (2011a) Otim and Grover (2006) Thirumalai and Sinha (2011)	Empirical study Empirical study Empirical study Empirical study Empirical study	Availability of order tracking	Increase consumer repurchase intention
	Garver et al. (2012)	Empirical study	Availability of order tracking	Affect consumer preferences for a delivery service
	Xing et al. (2010)	Empirical study	Availability of order tracking	Increase consumer satisfaction

shopping, for example, "time spent" versus "money spent," consumers form mental accounts for both resources (Punj 2011, 2012; Monga and Zor 2019).

Mental accounting theory thus describes the accounting rules that consumers apply when allocating scarce resources. Studies show that the specific context (e.g., type of product ordered, demographics, or urgency of the need) may have an impact on these accounting rules (Girard et al. 2003; Thirumalai and Sinha 2005; Qureshi et al. 2009). Context may thus influence the relationship between the mental accounts and preferences for delivery options. For example, prior research shows that order fulfillment approaches need to be attuned to product types (Thirumalai and Sinha 2005; Ramanathan 2010, 2011). For very expensive products or products that are needed quickly, consumers may find it less problematic to spend more on delivery fees than for other products. The relationships

Figure 1: A general framework for how preferences for delivery options depend on mental accounts and context



between context, mental accounts for resources, and preferences for delivery options are presented in the framework depicted in Figure 1.

METHODOLOGY

Conjoint analysis is used to obtain an understanding of consumer preferences for delivery options (Rao 2014). Conjoint analysis has gained increasing attention in the logistics and supply chain management literature (Reutterer and Kotzab 2000; Maier et al. 2002; Danielis et al. 2005; Karniouchina et al. 2009; Anderson et al. 2011; Garver et al. 2012). It is a well-known method to identify the heterogeneity of preferences, to design appropriate services or products, and to segment markets (Hauser and Rao 2004).

Delivery attributes

Nowadays, to improve consumer satisfaction and gain competitive advantage, online retailers are offering a variety of delivery options consisting of varying combinations of delivery attributes, for example, combinations of delivery lead times and delivery fees (Barclays 2014; comScore 2014; IMRG 2015). Consumers must base their delivery choices on a trade-off of these attributes. Below, three categories of delivery attributes in online retailing are investigated in line with the structure presented in Table 1: delivery information/options (time slots, daytime/evening delivery choice, and delivery date selection), delivery fees (cost of delivery), and delivery (speed of delivery). The selection of these attributes is based on the literature and inspired by the Global Webshop Logistics Industry Report (2014) that details actual levels of these attributes in the industry as well as changes over time that show where online retailers compete. Below, the five selected attributes are discussed in detail in the order described above.

Firstly, a *delivery time slot* can be defined as the time interval 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). Some authors proposed time slot management to help online retailers maximize profit. 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 retailers can also change the time slot template (e.g., the number of time slots) over spatial areas. Increasing numbers of retailers have adopted time slots as a way to diversify online services (Agatz et al. 2008b, 2013; Ehmke and Campbell 2014). 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 the 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, when customer density reached a certain level, short window lengths could have the same cost as long window lengths. Campbell and Savelsbergh (2006) investigated ways to use discounts in order to affect consumer behavior when choosing time slots and to maximize expected profits. Offering different time slots with corresponding fees can serve as a means of differentiation to maximize revenues since consumers are not homogenous in terms of willingness to pay, time preferences, and flexibility (Agatz et al. 2013).

Secondly, *daytime/evening delivery* allows consumers to choose the part of the day during which the product will be delivered. It is basically a special time slot (daytime: from 9 a.m. to 5 p.m.; evening: 6 to 10 p.m.) that is increasingly offered by online retailers (e.g., amazon.co.uk, bol.com, and blokker.nl). This may be appealing as more and more people choose to work alternate shifts and flexible hours, that is, daytime or evening (Southerton 2003; Van der Lippe 2007). Indeed, households try to balance the time spent at work and at home (Tausig and Fenwick 2001).

Thirdly, being able to select a *delivery date* is an attribute that was found to contribute to consumer satisfaction in online retailing (Xing and Grant 2006; Xing et al. 2010). Offering a choice of delivery during a specific part of the day or on a specific day can help online retailers reduce the risk of failed delivery because it reduces the probability that consumers are not at home.

Fourthly, the *delivery fee* involves a crucial attribute with a clear impact on consumer behavior (Lewis 2006). Typically, online retailers charge higher fees for less flexible delivery options. Often, they offer a premium delivery service in addition to standard ones. The delivery fees can be used as effective marketing parameters influencing a consumer′s final choice of delivery service (Agatz et al. 2013). A substantial amount of research has found that delivery fees influence consumer acquisition and retention (Cao et al. 2003; Lewis 2006; Rao et al. 2011a; Koukova et al. 2012). For example, consumer satisfaction with delivery fees and online presentation of the fees prior to purchase influences consumer retention (Rao et al. 2011a). Specific attention has been paid to consumers′ different evaluations and perceptions of 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 order-size incentives. Becerril-Arreola et al. (2013) also showed that consumer purchase amounts were affected when a threshold was applied to free delivery. Research by Garver et al. (2012) and Wilson-Jeanselme and Reynolds (2006) has emphasized the role of the delivery fee attribute in preference structures of online consumers. In the former study, delivery fees are even found to be the most important attribute.

Finally, *delivery speed* is measured by the lead time between a consumer placing an online order and receiving the order. Online consumers increasingly want shorter lead times such that online retailers face a “last mile” challenge with increasing delivery costs (Collier and Bienstock 2006). Chen and Chang (2003) include speed in their online shopping process model. Garver et al. (2012) showed that delivery speed is the second most important attribute when consumers shop online, after delivery fee. In their study, delivery speed had four levels: next-day, three-day, seven-day, and 10-day delivery lead time. Wilson-Jeanselme and Reynolds (2006) found this attribute to be placed on the 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 shopping online for specialty foods, where short delivery lead times directly contribute to the quality of the food received.

In this paper, conjoint and subsequent cluster analyses were conducted in which the above-mentioned five aspects of an online retailer′s delivery service will be the key attributes. These analyses facilitate the exploration of how consumers evaluate delivery options and how these evaluations differ across consumers and product categories.

Different context, different requirements?

Previous studies have identified the need to customize order fulfillment approaches to product types (Thirumalai and Sinha 2005; Ramanathan 2010, 2011). 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, 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 behavior 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 products representing three different product types in their classification, namely a personal care item (representing convenience goods), a pair of jeans (representing shopping goods), and a digital camera (representing specialty goods). This classification is based on the usual volume and the unit value of the products purchased. For example, consumers tend to buy convenience goods in large volumes and at low unit cost.

Previous research also showed that demographic and behavioral variables (e.g., gender, age, education, income, and frequency of online purchases) influence consumers′ decisions in online retailing (Teo 2001; Girard et al. 2003; Pavlou 2003; Qureshi et al. 2009; Chiu et al. 2014). For example, it was found that males are more likely to engage in online purchasing than females (Teo 2001). Girard et al. (2003) indicate that gender, education, and income are significantly related to a preference for online shopping. In line with this, gender and income were also found to have a significant impact on online consumer repurchase intention (Qureshi et al. 2009; Chiu et al. 2014). Although online purchasing frequency did not have a significant impact on purchase intention in the study by Pavlou (2003), Chiu et al. (2014) identified a significant difference between the group of heavy purchasers (six or more purchases) and the group of light purchasers (less than six purchases) for the relationship between perceived risk and purchase intention. Given the findings from the previous literature, this study argues that consumer preferences for delivery attributes in an online purchase may therefore be different with respect to the discussed demographic and behavioral variables.

By carrying out a segmentation analysis on the basis of the outcomes of the conjoint analysis and linking the segments to demographic and behavioral variables, a more fine-grained understanding of consumer preferences for delivery attributes in an online context can be obtained. Surprisingly, consumer segmentation, a well-established concept in marketing, has only received limited attention in the logistics and supply chain management literature (Godsell et al. 2011). Using segmentation, online retailers can provide better e-fulfillment services and design logistics strategies more effectively (Agatz et al. 2008a) as the “one size fits all” theory becomes obsolete (Hjort et al. 2013). Chen and Bell (2012) propose to segment a market using two consumer return policies (i.e., full-refund and no-returns) to enhance profits in online business. In another approach of segmentation, consumer segments in terms of buying and returning behavior in fashion e-commerce enable online retailers to tailor their service strategies (Hjort et al. 2013).

Conjoint analysis in the current study

Conjoint analysis is a set of methodologies used to study how customers make choices between products or services, and includes traditional, adaptive, and choice-based conjoint analysis (Hair et al. 2010). In all these conjoint methods, the underlying assumption is that an individual′s utility for a certain product or service can be expressed as the sum of the part-worth utilities of the characteristics (the attribute levels) that define the products or services. Respondents evaluate combinations of attributes, and statistical analysis is then used to infer the part-worths.

The current study uses traditional conjoint analysis with a full-profile method: Respondents are presented with combinations (so-called profiles) of the different levels of each attribute and rate these profiles according to their preference. This full-profile method was chosen because it leads to more realistic profiles. A fractional factorial design is used to reduce the number of profiles to be evaluated by respondents (Keen et al. 2004; Hair et al. 2010). The general model underlying a conjoint analysis can be expressed as follows:

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

where U 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 jth level ($j = 1, 2, \ldots, k_i$) of the ith attribute ($i = 1, 2, \ldots, m$), k_i is the number of levels of attribute i, m is the number of attributes, and D_{ij} equals 1 if the jth level of the ith attribute is present (0 otherwise). For identification purposes, the sum of the part-worths β_{ij} for a given attribute i is constrained to be zero.

The part-worths can be used to calculate the relative importance values of each attribute, W_{i}:

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

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

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

Design of the conjoint analysis

The first step of conjoint analysis is the selection of appropriate attributes and their levels. Here, the choice of attributes was based on a review of the literature discussed in the previous section and on industry reports on consumer preferences and expectations. For each attribute, we select levels that reflect the current market situation. Specifically, the three most applicable levels of delivery speed—namely same-day delivery, next-day delivery, and standard delivery (two–five days)—were chosen. Furthermore, we include three time slot levels: "no time slot," "2 hr," and "4 hr." 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, two commonly applied practices were selected: daytime and evening delivery. Next, we distinguish between delivery on weekdays only and delivery on both week and weekend days (i.e., Saturday and/or Sunday). It is common to provide weekday delivery service, but more and more retailers also offer the option to deliver on Saturdays and Sundays. Finally, we also selected different levels for the delivery fee attribute. The majority of online retailers offer free delivery. It was noted that there are two popular structures of free delivery in online retailing: unconditional free shipping and threshold-based free shipping (Global Webshop Logistics 2014). Since it was not an objective of this paper to study customer sensitivity to different threshold levels, it was decided to only adopt free shipping without a threshold (i.e., unconditional free shipping) in the questionnaire. Global Webshop Logistics (2014) was used to select the other delivery fee levels: €2.5, €4, €7.5, and €17.5. Conjoint questions were piloted with eight colleagues experienced with online shopping to ensure the clarity of the questions. Table 2 gives an overview of the selected attributes and their levels.

Given the five attributes and their levels, a total of 270 (3*3*2*3*5) profiles were constructed. To reduce the respondent′s evaluation task, a fractional factorial design was employed by generating an orthogonal design in IBM® SPSS® Statistics version 21. Specifically, each respondent was presented with 29 delivery profiles (25 profiles meant for estimation and four profiles that SPSS included for validation purposes; these four profiles and the corresponding ratings will not be used in the rest of this analysis). Each respondent rated the profiles (on a seven-point scale, 1 = very undesirable and 7 = very desirable); these ratings were used to estimate the part-worth utilities of the following model by means of ordinary least squares:

$$U = \alpha_0 + \sum\nolimits_{j=1}^{3} \beta_{1j} D_{1j} + \sum\nolimits_{j=1}^{3} \beta_{2j} D_{2j} + \sum\nolimits_{j=1}^{2} \beta_{3j} D_{3j} + \sum\nolimits_{j=1}^{3} \beta_{4j} D_{4j} + \sum\nolimits_{j=1}^{5} \beta_{5j} D_{5j}$$

where β_{1j}, β_{2j}, β_{3j}, β_{4j}, β_{5j} are the coefficients (i.e., part-worth utilities) associated with the levels of the attributes (1) delivery

Table 2: Attributes and attribute levels

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 hr
	■ 4 hr
Daytime/evening delivery	■ During daytime
	■ During daytime and evening
Delivery date	
	■ Monday to Friday
	■ Monday to Friday as well as Saturday
	■ All days of the week, including Sunday
Delivery fee	
	■ Free (€ 0)
	■ € 2.5
	■ € 4.0
	■ € 7.5
	■ € 17.5

speed, (2) time slot, (3) daytime/evening delivery, (4) delivery date, and (5) delivery fee, with D_{1j}, D_{2j}, D_{3j}, D_{4j}, D_{5j} being the dummy variables for the attribute levels.

Data collection and sample

A survey was conducted with an online panel of a market research service, Mobiel Centre. Mobiel Centre (http://www.mobielcentre.nl) 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. Respondents were randomly assigned to one of three product categories (personal care item, representing convenience goods; a pair of jeans, representing shopping goods; or a digital camera, representing specialty goods) and asked to complete a questionnaire that consisted of three main parts: (1) questions about online shopping experience and perception, (2) the delivery service profiles for the category to which the respondent was assigned, (3) and questions about demographics. As an example of the delivery service profiles in the second part of the questionnaire, Figure 2 shows a profile in the shopping goods category.

The survey was sent to 6,000 randomly selected panelists of which 1,782 started and 1,294 (21.57%) completed the survey. Of the completed surveys, 282 responses were removed because the respondents had not ordered a product online at least once. The final sample consisted of 1,012 respondents. Table 3 lists the demographic information of the respondents. The sample is by and large representative of the Dutch population (see CBS, 2019), although our focus on people that at least have *some* experience with buying online may have led to some deviations.

A total of 345 responses were collected for convenience goods, 329 for shopping goods, and 338 for specialty goods. Based on the results of the pretest, 7 min 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 respondents that qualified for deletion were the ones that had an extremely high Pearson′s R (.970–1.000), indicating unreasonable preference patterns. Alternatively, respondents that had a Pearson R lower than the calculated minimum correlation of .46[1] were also candidates for deletion (Hair et al. 2010). In the cluster analysis, described later in this paper, outliers were also removed. 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 4 summarizes final sample sizes for the conjoint and cluster analyses.

[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 $R^2_{\text{adjusted}} = 1 - \frac{(1-R^2)(N-1)}{N-p-1}$ where $R^2_{\text{adjusted}} = 0$, $p = 5$ (number of attributes), $N = 25$ (number of profiles/observations per respondent, excluding holdout profiles), $R = .46$ was obtained.

FINDINGS

Conjoint analyses

The survey data were analyzed using IBM® SPSS® Conjoint, which performs conjoint analyses using ordinary least squares. The part-worth utilities of the individual levels of the attributes in the three product categories were estimated. Importance values of these attributes for each product category were calculated using these 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. When all three product categories were examined together, Pearson′s R and Kendall′s tau statistics of .90 ($p < .001$) were found. These results suggest a decent model fit (Cohen 1988; Evans 1996). Aggregate importance values for each sample are shown in Figure 3, and the part-worth utilities per level are reported in Table 5.

The results show that *delivery fee* is by far the most important attribute of the three product categories. Garver et al. (2012) already indicated that delivery fee is an important attribute: These results show that this remains true even when attributes that reflect recent developments in e-tailing (e.g., time slot selection) are added. For the other attributes, the importance value decreases as it moves from *delivery speed* over *time slot* and *delivery date* to *daytime/evening delivery*. *Daytime/evening delivery* is rated as the least important attribute for all three product categories. Overall, the importance values are similar across categories.

Table 5 reveals that the most preferable combination for consumers is to have free delivery, delivery from Monday to Saturday, delivery during daytime and in the evening, delivery within a time slot of 2 hr, and same-day delivery. In line with initial expectations, it was found that a consumer′s preference for a delivery option decreases with an increase in delivery fee. The part-worth utilities 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), which showed that the preference score for 24-hour delivery was higher than that for 48-hour delivery. From the part-worths of the *time slot* attribute, it can be concluded that consumers prefer a specific time slot (2 or 4 hr), instead of an unknown time, for receiving a shipment at home. It was also noted that consumers prefer receiving shipments on weekdays (i.e., from Monday to Friday) and Saturdays, but, interestingly, including Sunday does not lead to higher preferences. *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 home after working hours.

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

Figure 2: Example of a profile

Profile 1:
Suppose you were buying a pair of jeans online and considering using the following delivery attributes offered on a web site:

- *Speed of delivery*
- *Time slot within which you expect to receive your product*
- *Delivery during daytime or in the evening*
- *Delivery date*
- *Delivery fee*

Please indicate your preference on the 7-point scale below (1=very undesirable; 7=very desirable)

- Order today and delivery in 2-5 business days
- Delivery within a two-hour time slot
- Delivery during daytime
- Delivery all days of the week, including Sunday
- Delivery fee of €7.50

Very undesirable 1 2 3 4 5 6 7 Very desirable

option (Hair et al. 2010; Orme 2010). Simulation is a useful tool to investigate how preferences change as new services/products are introduced or existing services/products are modified. It is especially useful to assess alternative realities in logistics and supply chain management (Goldsby and Zinn 2016). Based on industry reports and actual delivery offerings on different web sites (Global Webshop Logistics 2014; MICROS 2014), we chose three baseline services that reflected the practice at the time of study (Table 6).

There are two main models for predicting a consumer′s choice: 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 the simulation used

Table 3: Demographic information of respondents (n = 1,012)

Measures	Items	Frequency	Percent
Gender	Male	481	47.5
	Female	531	52.5
Age	<20 years	43	4.2
	21–40 years	251	24.8
	>40 years	718	71.0
Education	No education/education/training integration/Dutch language course	15	1.5
	LBO/VBO/degree (frame or vocational program)/1 MBO (program assistant)	86	8.5
	MAVO/HAVO or VWO (first three years)/ULO/MULO/degree (theoretical or mixed pathway)/secondary special education	139	13.7
	MBO 2, 3, 4 (basic vocational, professional, middle management, or specialist training) or MBO old structure (before 1998)	332	32.8
	HAVO or VWO (transferred to the 4th class)/HBS/MMS/HBO propaedeutic or university foundation course	152	15.0
	HBO (except HBO master)/WO bachelor or university bachelor	222	21.9
	WO-doctoral or master′s degree program or HBO master/ postgraduate education	66	6.6
Income*	Low (<€20,000)	243	31.9
	Middle (€21,000–€40,000)	326	42.8
	High (>€ 40,000)	192	25.2
Online purchase (times in a year)	1–2	67	6.6
	3–5	280	27.7
	6–10	330	32.6
	11–20	238	23.5
	21–50	80	7.9
	>50	17	1.7

Notes: *Two hundred fifty-one respondents chose “Prefer not to state.”

Table 4: Final sample sizes for conjoint and cluster analyses

	Total subjects	Convenience goods	Shopping goods	Specialty goods
Conjoint analysis	692	242	226	224
Cluster analysis	683	237	224	222

for this research, the former was chosen. In each product category, four simulations (A, B, C, and D) were run by changing the levels of *time slot*, *daytime/evening delivery*, *delivery date*, and *delivery fee* in the baseline scenario (Table 7). We then examined how consumer preferences changed compared to the baseline scenario.

The results of the simulations are presented in Table 8: In all scenarios and for all product categories, Option 1 has the highest preference because this option always involves free delivery, and the conjoint analysis indicated that *delivery fee* is the most important attribute. Similarly, in Simulation D, changing the *delivery fee* of Option 2 (next-day delivery) from €4.0 to €2.5, and that of Option 3 (same-day delivery) from €17.5 to €7.5, increases preferences for both options, in particular for Option 2. Indeed, 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. However, note that consumers are willing to make trade-offs: Especially in the specialty goods category, the fastest delivery service ("order today deliver today," i.e., Option 3) has a sizeable preference share, despite the fact that it has the highest delivery fee. Yet, this share tends to decrease in Simulations A, B, and C (except in Simulations A and C for shopping goods where there is a small increase): While expensive delivery options may attract a fair share of shoppers if their nonprice attributes are sufficiently attractive (see baseline scenario), they lose appeal when the cheaper delivery options entail similarly attractive characteristics (see, in particular, Simulation B).

In summary, this study shows that consumers want to pay the lowest delivery fees but are, to some extent, also willing to accept higher delivery fees in exchange for faster delivery, a shorter time slot, or a more convenient delivery moment (during the day or week). The results of conjoint analysis and the simulations show that consumers evaluate monetary and nonmonetary attributes differently to choose a delivery option. This decision depends on consumers′ trade-offs related to three main mental accounts: money (i.e., delivery fee), time (i.e., delivery speed), and convenience (i.e., selecting a delivery moment). It is therefore proposed that:

Proposition 1a: Consumer preferences for delivery options in online retailing are primarily guided by a consumer′s mental account for money (i.e., delivery fees).

Proposition 1b: Consumers are willing to have their mental accounts for nonmonetary resources prevail over their mental account for money (i.e., delivery fees) if the nonmonetary delivery attribute levels are sufficiently attractive.

Figure 3: Importance scores for different product categories (%)

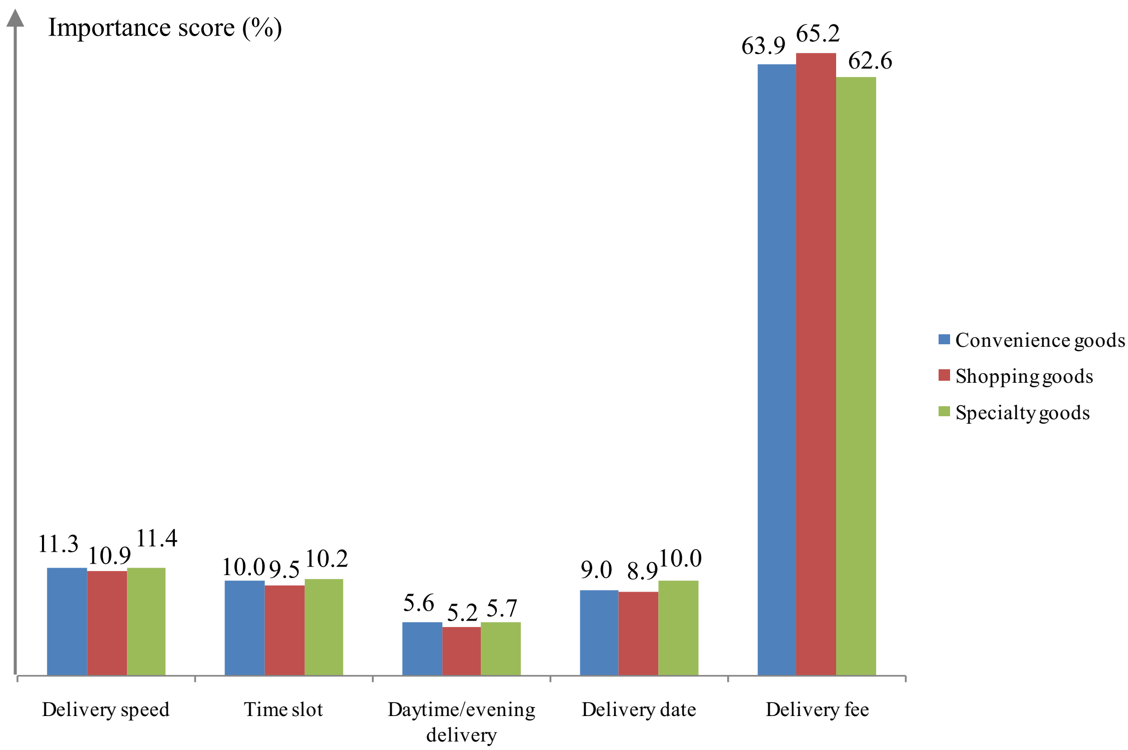


Table 5: Part-worth utilities for the three product categories

Attribute	Attribute level	Part-worth utility (standard error)		
		Convenience goods	**Shopping goods**	**Specialty goods**
Delivery speed	Order today and deliver today	.177 (.050)*	.157 (.050)*	.126 (.040)*
	Order today and deliver tomorrow	.082 (.050)	.103 (.050)	.115 (.040)
	Order today and deliver in 2–5 business days	−.259 (.060)	−.260 (.060)	−.241 (.048)
Time slot	No time slot	−.157 (.050)	−.178 (.050)	−.185 (.040)
	2 hr	.113 (.050)*	.146 (.050)*	.136 (.040)*
	4 hr	.040 (.060)	.032 (.060)	.049 (.048)
Daytime/evening delivery	During daytime	−.090 (.037)	−.095 (.037)	−.087 (.030)
	During daytime and evening	.090 (.037)*	.095 (.037)*	.087 (.030)*
Delivery date	Monday to Friday	−.063 (.050)	−.057 (.050)	−.079 (.040)
	Monday to Friday as well as Saturday	.054 (.050)*	.049 (.050)*	.066 (.040)*
	All days of the week including Sunday	.009 (.060)	.008 (.060)	.012 (.048)
Delivery fee	Free (€ 0)	2.162 (.072)*	2.185 (.072)*	1.964 (.058)*
	€ 2.5	.773 (.072)	.842 (.072)	.812 (.058)
	€ 4.0	−.015 (.072)	.057 (.072)	.075 (.058)
	€ 7.5	−1.009 (.072)	−1.040 (.072)	−.873 (.058)
	€ 17.5	−1.912 (.072)	−2.044 (.072)	−1.978 (.058)

Note: *Level with the highest utility.

Table 6: Options in the baseline scenario

Option*	Delivery speed	Time slot	Daytime/evening delivery	Delivery date	Delivery fee
Option 1	Order today and delivery in two–five business days	No time slot	Daytime	Monday to Friday	Free
Option 2	Order today and delivery tomorrow	No time slot	Daytime	Monday to Friday	€4.0
Option 3	Order today and delivery today	4 hr	Daytime and evening	Monday to Friday as well as Sunday	€17.5

Note: *Options: Option 1 corresponds to standard delivery by Amazon in the UK; Option 2 to next-day delivery by Hema in the Netherlands; and Option 3 to same-day delivery by Coolblue in the Netherlands.

Demographics and purchase frequency

In each of the three product categories, the sample was split on the basis of demographic variables and frequency of online purchase (Table 9). One-way analysis of variance (ANOVA) was then used to compare the importance values of the different attributes across groups. The ANOVA revealed that there were significant differences between certain groups. Subsequent post hoc analyses indicated that, for convenience and shopping goods, some significant differences were found between consumer groups, differing in terms of gender or annual income ($p < .05$). Specifically, in the convenience goods category, *time slot* and *daytime/evening delivery* were more important for men than for women. An interpretation may be that, in the Netherlands, men are less flexible than women because they often work during the day, whereas women often work part-time (see, e.g., a recent study on differences in work life between men and women that shows that women work much more part-time than men[2]). In contrast, *delivery fee* was more important for women than for men in both the convenience and shopping goods categories. For convenience goods, the low-income group had lower importance values than the middle-income group for *time slot*. Similarly, for shopping goods, the low-income group had lower importance values for *time slot* than the high-income group; however, it had higher importance values for *delivery fee*. No significant differences in importance values were found for the different age,

[2]Source: https://www.scp.nl/Nieuws/Nederlandse_vrouwen_werken_al_op_jonge_leeftijd_in_deeltijd (In Dutch, accessed on 14 February 2017). This study shows among others that 62% of the women aged 18–25 years and 28% of the men in this age category work part-time. Under women and men aged 26–30 and 31–35, the differences are even larger.

Table 7: Simulations for each product category

Simulation	Option	Time slot	Daytime/evening delivery	Delivery date	Delivery fee
A	Option 1	4 hr	Unchanged	Unchanged	Unchanged
	Option 2	4 hr	Unchanged	Unchanged	Unchanged
	Option 3	Unchanged	Unchanged	Unchanged	Unchanged
B	Option 1	Unchanged	Daytime and evening	Unchanged	Unchanged
	Option 2	Unchanged	Daytime and evening	Unchanged	Unchanged
	Option 3	Unchanged	Unchanged	Unchanged	Unchanged
C	Option 1	Unchanged	Unchanged	Monday to Friday as well as Sunday	Unchanged
	Option 2	Unchanged	Unchanged	Monday to Friday as well as Sunday	Unchanged
	Option 3	Unchanged	Unchanged	Unchanged	Unchanged
D	Option 1	Unchanged	Unchanged	Unchanged	Unchanged
	Option 2	Unchanged	Unchanged	Unchanged	€2.5
	Option 3	Unchanged	Unchanged	Unchanged	€7.5

Table 8: Simulation results on the basis of maximum utility model

	% of respondents choosing the option		
Simulation (attribute changed)	Convenience goods	Shopping goods	Specialty goods
Baseline scenario			
Option 1	83.5	84.5	78.1
Option 2	7.6	10.6	12.7
Option 3	8.9	4.9	9.2
Simulation A			
Option 1 (time slot)	84.3	83.6	78.3
Option 2 (time slot)	9.3	10.6	15.0
Option 3	6.4	5.8	6.7
Simulation B			
Option 1 (daytime/evening delivery)	85.3	85.0	79.7
Option 2 (daytime/evening delivery)	9.1	11.9	14.1
Option 3	5.6	3.1	6.3
Simulation C			
Option 1 (delivery date)	85.1	83.8	78.8
Option 2 (delivery date)	7.9	11.1	14.1
Option 3	7.0	5.1	7.1
Simulation D			
Option 1	69.6	71.0	66.5
Option 2 (delivery fee)	18.4	18.4	19.6
Option 3 (delivery fee)	12.0	10.6	13.8

education, and purchase frequency groups ($p > .05$). Furthermore, for specialty goods, there were no significant differences in importance values across consumer groups ($p > .05$). Table 9 shows the results of the post hoc comparisons.

Punj (2011, 2012) indicated that demographic characteristics moderate the effects of mental accounts on online purchase behavior. We find that gender and income influence consumers′ evaluations of delivery attributes for convenience and shopping goods, while education, purchase frequency, and age do not affect preferences for delivery attributes across all three categories. This paper argues that the specific context (in particular, the consumer characteristics gender and income) may influence how consumers allocate their resources including money, time, and convenience in making decisions for a delivery service. It is therefore posited that:

> *Proposition 2a: Female consumers tend to assign a lower importance to their mental account of convenience and a higher importance to their mental account of money than men when selecting multi-attribute delivery options.*

> *Proposition 2b: Lower income consumers tend to assign a lower importance to their mental account of convenience than middle/higher income consumers when selecting multi-attribute delivery options.*

Segmentation

A cluster analysis was performed based on the consumer-level importance values in order to identify homogenous 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 nonhierarchical methods) was adopted, because of its advantages over either purely hierarchical or purely nonhierarchical methods (Keen et al. 2004; Hair et al. 2010). The cluster analysis was performed with IBM® SPSS® Statistics version 21. First, hierarchical clustering was used to determine the appropriate number of clusters. Specifically, Ward′s method was used and the sum of squared Euclidean distances between individuals and the centroids of their clusters was minimized. Since all importance values are expressed as percentages, they were not standardized first. Based on the agglomeration schedules and scree plots produced by the hierarchical clustering results, a three- and four-cluster solution for convenience goods, and a three-cluster

Table 9: Importance values by demographic variables and frequency of online purchase (%)

		Attributes				
Variable	***N***	**Delivery speed**	**Time slot**	**Daytime/evening delivery**	**Delivery date**	**Delivery fee**
Convenience goods						
Age (years)						
18–20	4	18.233	6.871	4.269	8.872	61.755
21–40	22	11.966	8.662	4.806	8.299	66.267
>40	74	10.851	10.627	5.898	9.268	63.356
Gender						
Male	49	11.541	**11.213**	**6.447**	9.405	**61.394**
Female	51	11.257	**8.943**	**4.786**	8.699	**66.315**
Education						
Low	7	10.082	6.605	4.744	7.832	70.737
Middle	66	11.575	10.516	5.682	9.507	62.720
High	27	11.280	9.754	5.594	8.214	65.159
Income						
Low	29	11.448	**7.613**	5.383	9.165	66.392
Middle	46	11.393	**10.881**	5.827	8.917	62.982
High	25	11.787	10.570	5.602	9.385	62.655
Purchase frequency/year						
Low	34	11.629	10.611	5.498	8.871	63.392
Medium	61	11.406	9.838	5.716	9.319	63.721
High	5	9.822	8.958	4.850	6.983	69.386
Shopping goods						
Age (years)						
18–20	6	11.969	7.907	7.997	6.385	65.742
21–40	24	12.816	10.293	4.709	9.220	62.962
>40	70	10.218	9.462	5.168	9.129	66.023
Gender						
Male	45	11.432	10.544	5.672	9.614	**62.738**
Female	55	10.549	8.758	4.873	8.460	**67.361**
Education						
Low	12	10.292	9.965	5.044	8.860	65.838
Middle	60	11.081	9.224	5.185	8.684	65.825
High	28	10.954	10.100	5.417	9.654	63.875
Income						
Low	32	10.488	**7.567**	5.019	7.622	**69.305**
Middle	44	10.172	10.014	5.227	9.460	65.128
High	24	13.593	**11.665**	5.505	10.332	**58.905**
Purchase frequency/year						
Low	36	9.807	10.469	5.292	9.687	64.746
Medium	53	11.003	9.180	5.117	8.411	66.290
High	11	14.513	8.449	5.626	9.471	61.940
Specialty goods						
Age (years)						
18–20	4	7.746	10.269	6.555	6.871	68.559
21–40	22	11.681	10.851	5.081	9.493	62.895
>40	74	11.561	10.103	5.823	10.328	62.184
Gender						
Male	46	11.827	11.112	6.101	10.592	60.396
Female	54	11.093	9.547	5.334	9.499	64.526
Education						
Low	12	9.366	10.796	6.508	10.968	62.362

Continued.

Table 9: (Continued)

Variable	N	Attributes: Delivery speed	Time slot	Daytime/evening delivery	Delivery date	Delivery fee
Middle	64	12.101	10.805	5.846	10.307	60.940
High	24	10.702	8.605	4.867	8.729	67.096
Income						
Low	42	10.374	9.278	5.544	9.450	65.355
Middle	36	10.263	11.389	5.883	10.906	61.559
High	22	12.700	8.711	5.000	9.954	63.635
Purchase frequency/year						
Low	39	11.013	10.804	6.043	10.252	61.888
Medium	51	11.963	10.085	5.319	10.131	62.500
High	10	10.403	9.202	6.193	8.458	65.745

Notes: Remark: For a given consumer characteristic (e.g., gender), values in bold significantly differ from one another ($p < .05$).

Table 10: Cluster analysis for convenience goods

	Cluster 1 (N = 86)	Cluster 2 (N = 53)	Cluster 3 (N = 98)	Overall* (N = 237)
Delivery speed				
+ Order today and delivery today	.082†	.240†	.232†	.179†
+ Order today and delivery tomorrow	.043	.077	.127	.085
+ Order today and delivery in 2–5 business days	−.125	−.317	−.360	−.265
Importance score (%)	6.471	17.580	12.152	11.304
Time slot				
+ No time slot	−.032	−.255	−.177	−.142
+ 2 hr	.033†	.109	.160†	.103†
+ 4 hr	−.001	.145†	.016	.039
Importance score (%)	5.189	16.455	9.741	9.590
Daytime/evening delivery				
+ During daytime	−.51	−142	−.085	−.085
+ During daytime and evening	.051†	.142†	.085†	.085†
Importance score (%)	3.266	9.246	5.067	5.348
Delivery date				
+ Monday to Friday	−.026	−.006	−.127	−.063
+ Monday to Friday as well as Saturday	.011	.096†	.056	.049†
+ All days of the week including Sunday	.015†	−.091	.071†	.014
Importance score (%)	4.895	15.635	9.069	9.023
Delivery fee				
+ Free	2.797†	.955†	2.352†	2.201†
+ €2.50	.892	.386	.895	.780
+ €4	−.108	.076	.003	−.021
+ €7.50	−1.243	−.482	−1.121	−1.022
+ €17.50	−2.338	−.935	−2.129	−1.938
Importance score (%)	80.180	41.084	63.972	64.735
Correlations				
Pearson′s R	.999	.959	.995	.996
Kendall′s tau	.903	.838	.953	.953

Notes: *Five outliers were detected and deleted from the overall sample for this product category.
†Attribute level with the highest part-worth.

solution for shopping and specialty goods were found. The cluster solutions in this stage were then used for nonhierarchical 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 four-cluster solution led to relatively comparable clusters in terms of attribute importance patterns. In the three-cluster solution, in contrast, each cluster had more distinct features. Thus, the three-cluster solution was chosen for convenience goods.

Cluster analysis results for convenience goods

Three clusters were identified for this product category. Table 10 shows the importance scores and part-worth utilities for each cluster.

In Cluster 1, consisting of 86 cases (36%), *delivery fee* is by far the most important delivery attribute and is much more important than in the other clusters (importance score: 80%). This cluster can thus be referred to as "price-oriented." In Cluster 2, the smallest segment (22%, 53 cases), *delivery fee*, is still the most important attribute but it is far less important (41%) than in the other two segments. The nonprice attributes, *delivery speed*, *time slot*, *daytime/evening delivery*, and *delivery date*, collectively are more important than *delivery fee* (59% vs. 41%). This segment can be labeled as "time- and convenience-oriented." Finally, in Cluster 3, the largest segment (42%, 98 cases), the importance values are situated between those of Cluster 1 and Cluster 2: Consumers in this segment care more about price than those in Cluster 2 but also care more about speed, time slot, and moment of delivery than those in Cluster 1. This cluster is described as "value-for-money-oriented."

Table 11 presents details of the three clusters in terms of demographic characteristics and frequency of online purchase. One striking observation is that in Cluster 1, female and low-income consumers are better represented than in the other clusters. The percentages of male and middle- to high-income consumers are greater in Clusters 2 and 3.

Cluster analysis results for shopping goods

Also, in the shopping goods category three clusters were identified. Table 12 shows the importance scores and part-worth utilities for each cluster.

A cluster composition that is comparable to that in the convenience goods category was found. Consumers in Cluster 1, consisting of 77 cases (35%), mainly care about *delivery fee* (importance score: 82%) and will therefore be referred to as "price-oriented." In contrast, for consumers in Cluster 2, the smallest segment (23%, 52 cases), *delivery speed*, *time slot*, *daytime/evening delivery*, and *delivery date* collectively are more important than *delivery fee* (58% vs. 42%). This segment can be labeled as "time- and convenience-oriented." Finally, Cluster 3, the largest segment (42%, 95 cases), is situated somewhere in between Clusters 1 and 2 in that its members care about price yet also about convenience. This cluster will be referred to as "value-for-money-oriented."

Table 13 presents details of the three clusters in terms of demographic characteristics and frequency of online purchasing. In line with the observations in the convenience goods category, the percentage of male and middle-to high-income consumers is highest in Cluster 2, the convenience-oriented segment. Clusters 1 and 3 skew female and low-income consumers. Finally, consumers in Cluster 1 appear to be slightly older.

Cluster analysis results for specialty goods

Finally, three clusters were also identified in the specialty goods category. Table 14 shows the importance scores and part-worth utilities for each cluster.

Again, Cluster 1, the largest segment (48%, 107 cases), consists of "price-oriented" consumers who care more about *delivery fee* than consumers in the other clusters do (importance score: 77%). Like before, Cluster 2, the smallest segment (19%, 43 cases), represents the "time- and convenience-oriented" consumers: *Delivery fee* is far less important (35%) in favor of the other delivery attributes. Finally, Cluster 3 consists of "value-for-money" consumers, who to some extent care about price as well as convenience attributes. Note that in contrast with the convenience and shopping goods categories where most consumers were value-for-money-oriented, most consumers in the specialty goods category are price-oriented.

Table 15 reports the demographic characteristics and purchase frequencies for the three clusters. Like before, the proportion of female consumers is highest in Cluster 1, the price-sensitive segment. Furthermore, the percentages of male and middle-to high-income consumers are greatest in Cluster 2, the convenience-oriented segment. Finally, Cluster 2 also has the highest percentage of consumers with an intermediate education level.

The results of the cluster analyses lead to the following propositions:

Table 11: Cluster profiles in terms of demographic variables and frequency of online purchase (%) in the convenience goods category

Variable	Cluster 1 (N = 86)	Cluster 2 (N = 53)	Cluster 3 (N = 98)
Age (years)			
18–20	5	6	3
21–40	22	15	25
>40	73	79	72
Gender			
Male	41	51	53
Female	59	49	47
Education			
Low	9	2	7
Middle	65	72	63
High	26	26	30
Income			
Low	35	27	25
Middle	40	46	54
High	25	27	21
Purchase frequency/year			
Low	31	41	32
Medium	61	57	64
High	8	2	4

Table 12: Cluster analysis for shopping goods

	Cluster 1 (N = 77)	Cluster 2 (N = 52)	Cluster 3 (N = 95)	Overall* (N = 224)
Delivery speed				
+ Order today and delivery today	.065†	.253†	.183†	.159†
+ Order today and delivery tomorrow	.033	.201	.112	.105
+ Order today and delivery in 2–5 business days	−.098	−.454	−.295	−.264
Importance score (%)	5.194	16.956	12.082	10.847
Time slot				
+ No time slot	−.047	−.372	−.172	−.176
+ 2 hr	.024†	.285†	.169†	.146†
+ 4 hr	.023	.087	.004	.030
Importance score (%)	5.194	15.621	9.451	9.420
Daytime/evening delivery				
+ During daytime	−.052	−.220	−.061	−.095
+ During daytime and evening	.052†	.220†	.061†	.095†
Importance score (%)	2.926	9.710	4.599	5.210
Delivery date				
+ Monday to Friday	−.012	−.068	−.079	−.053
+ Monday to Friday as well as Saturday	−.011	.109†	.063†	.048†
+ All days of the week including Sunday	.023†	−.041	.016	.005
Importance score (%)	4.819	15.392	8.462	8.819
Delivery fee				
+ Free	2.703†	1.324†	2.280†	2.203†
+ €2.50	.866	.612	.962	.848
+ €4	.002	.112	.072	.057
+ €7.50	−1.206	−.684	−1.120	−1.048
+ €17.50	−2.365	−1.365	−2.194	−2.060
Importance score (%)	81.862	42.321	65.406	65.704
Correlations				
Pearson′s R	.999	.973	.996	.996
Kendall′s tau	.901	.843	.925	.945

Notes: *Two outliers were detected and deleted from the overall sample for this product category.
†Attribute level with the highest part-worth.

Proposition 3a: There exists a segment of consumers, namely price-oriented consumers, prioritizing their mental account for money (delivery fees) when choosing a multi-attribute delivery option.

Proposition 3b: There exists a segment of consumers, namely time- and convenience-oriented consumers, prioritizing mental accounts for time and convenience (delivery speed and delivery information/option) when choosing a multi-attribute delivery option.

Proposition 3c: There exists a segment of consumers, namely value-for-money-oriented consumers, tending to find options that jointly satisfy mental accounts for money, time, and convenience.

Proposition 4: Consumers exhibit different profiles of delivery attribute preferences dependent on the product category that they shop for; consumers shopping for convenience and shopping goods are more likely to exhibit characteristics of the value-for-money consumer segment; consumers shopping for specialty goods show similarity with the price-oriented consumer segment.

Figure 4 summarizes how the propositions relate to the conceptual model.

DISCUSSION

Delivery is an important factor influencing consumers in online retailing. In practice, online retailers are likely to offer a variety of delivery services in an attempt to cater for heterogeneous preferences of consumers. However, only few studies have addressed how consumers evaluate these delivery attributes. This study detailed how consumer preferences are guided by mental accounts for money, time, and convenience, depending on the context. Below the theoretical and managerial implications of this study are discussed.

Table 13: Cluster profiles in terms of demographic variables and frequency of online purchase (%) in the shopping goods category

Variable	Cluster 1 (N = 77)	Cluster 2 (N = 52)	Cluster 3 (N = 95)
Age (years)			
18–20	7	8	5
21–40	19	25	26
>40	74	67	69
Gender			
Male	43	50	43
Female	57	50	57
Education			
Low	15	15	8
Middle	60	56	61
High	25	29	31
Income			
Low	39	24	31
Middle	46	46	42
High	15	30	27
Purchase frequency/year			
Low	35	36	36
Medium	55	52	55
High	10	12	9

Theoretical implications

This research is based on MAT to offer insights into consumer preferences for logistics services that have not been set forth in the literature yet. According to MAT, consumers make a purchase decision based on established mental accounts for their resources. Based on the results of the conjoint analysis and simulation, it is suggested in this paper that consumers form mental accounts for convenience (i.e., time slot, delivery date, and daytime/evening delivery), next to mental accounts for time (i.e., delivery speed) and money (i.e., delivery fee) when they choose between delivery options. Traditional mental accounting predicts that mental accounts are money-dominated (Duxbury et al. 2005). The results in this study show that the mental account for the resource “money” is also dominant when consumers make delivery choices for online orders, followed by the time account. The mental account for convenience appears to be least important when it comes to trade-offs. However, these results show that domination of one mental account is affected by how the other mental accounts are formed. For example, this study shows that consumers adjust their preferences when nonprice attributes are changed regardless of the product category. For example, consumers prefer a longer lead time to a short lead time when the long lead time comes with a lower *delivery fee*. The more expensive delivery fee options in this study may attract a fair share of shoppers if their nonprice (i.e., convenience-related) attributes are sufficiently attractive, though these options lose appeal if the cheaper delivery options entail similarly attractive characteristics.

It was also observed that there are differences in the relative importance of mental accounts dependent on contextual factors, in particular, gender and income. It was found, for example, that in the convenience goods category, *time slot* and *daytime/evening delivery* were more important for men than for women. For shopping goods, the low-income group rated the importance of delivery in a small *time slot* lower than the high-income group.

Relative importance of delivery fees

This research found that the most important attribute in shaping consumer preferences is *delivery fee*, followed by *delivery speed*, *time slot*, *delivery date*, and *daytime/evening delivery*. This implies that consumers pay the least attention to delivery information/options when making delivery choices. Although Xing et al. (2010) reported that a low price of a product is most important for online consumers to select a retailer, they also found that the cost of obtaining products is relatively unimportant to consumers when *selecting an online retailer* to buy from (much less important than speed of delivery). Our results show the opposite: The cost of obtaining a product (i.e., delivery fees) is a crucial aspect of a delivery service, much more important than speed of delivery, thus strongly affecting consumer behavior. The results of the current study are in line with the conjoint study of Garver et al. (2012). Their study demonstrated that price, speed of delivery, and tracking are the three most important variables in the selection decision of consumers in online retailing. However, in the Garver et al. (2012) study, only two price points were used in the conjoint analysis. These prices were relatively far apart (the two levels for delivery fee were free delivery vs. US$29.90) so that a strong preference for free delivery may not be surprising. The highest delivery fee is hardly realistic in today′s markets with delivery fees in northern European countries ranging between free and a few euros per shipment for the most common delivery options. This study (which contained five different price levels) shows that when modeling scenarios with a diversity of realistic delivery fee options, *delivery fee* dominates nonprice delivery attributes when consumers choose between delivery options.

Different products, different requirements?

The results of the research by Thirumalai and Sinha (2005) suggest that different order fulfillment strategies should be designed for different product types. In this study, the role of product category characteristics remains rather limited. In all three studied categories, it was found that the different delivery attributes were similarly important. Yet, some differences were found across categories in how consumer characteristics drive preferences for delivery attributes. For example, while consumer characteristics did not seem to matter for specialty goods, such effects were found for shopping and convenience goods. Specifically, for convenience and shopping goods women worry more about the delivery fee while men may care more about time slots and daytime/evening delivery. Also, in the convenience and shopping goods categories, middle- to high-income consumers care more about time slots, while low-income consumers may be more concerned about the delivery fee. The results in this paper are in line with the finding by Girard et al. (2003) that the relationship between demographic variables and preferences for online purchase significantly differs across product categories. It is thus

Table 14: Cluster analysis for specialty goods

	Cluster 1 (N = 107)	Cluster 2 (N = 43)	Cluster 3 (N = 72)	Overall* (N = 222)
Delivery speed				
+ Order today and delivery today	.078†	.140	.199†	.129†
+ Order today and delivery tomorrow	.032	.172†	.196	.112
+ Order today and delivery in 2–5 business days	−.111	−.312	−.394	−.242
Importance score (%)	6.896	19.578	13.075	11.356
Time slot				
+ No time slot	−.077	−.343	−.241	−.181
+ 2 hr	.072†	.139	.216†	.132†
+ 4 hr	.005	.204†	.025	.050
Importance score (%)	6.147	18.219	11.298	10.156
Daytime/evening delivery				
+ During daytime	−.047	−.084	−.145	−.086
+ During daytime and evening	.047†	.084†	.145†	.086†
Importance score (%)	3.360	9.555	6.756	5.661
Delivery date				
+ Monday to Friday	−.030	−.089	−.121	−.071
+ Monday to Friday as well as Saturday	.012	.141†	.118†	.071†
+ All days of the week including Sunday	.017†	−.052	.004	−.001
Importance score (%)	6.234	17.418	10.564	9.805
Delivery fee				
+ Free	2.572†	0.705†	1.871†	1.983†
+ €2.50	.968	.445	.824	.820
+ €4	.110	.031	.057	.078
+ €7.50	−1.204	−.304	−.754	−.884
+ €17.50	−2.447	−.876	−1.998	−1.997
Importance score (%)	77.363	35.230	58.307	63.022
Correlations				
Pearson′s R	.999	.947	.994	.997
Kendall′s tau	.953	.859	.945	.957

Notes *Two outliers were detected and deleted from the overall sample for this product category.
†Attribute level with the highest part-worth.

suggested that, depending on the product category, delivery services in online retailing should be customized taking into account gender and income of the targeted consumers.

Segments of consumers
Consumer segmentation, a well-established concept in marketing, has only received relatively limited attention in the logistics and supply chain management literature (Godsell et al. 2011). Cluster analysis was used to identify segments of consumers. Although *delivery fee* is of great importance to consumers, this analysis indicates that there are segments of consumers who also value other aspects. The results of this study reveal three segments: a segment that is focused on the lowest price (which is labeled price-oriented consumers). Irrespective of other attributes, they tend to select the option with the lowest price. The second segment, labeled convenience-oriented consumers, considers convenience aspects such as time slot choice or the ability to get delivery in the evening or during the weekend. The third segment, consisting of value-for-money-oriented consumers, considers both delivery fee and convenience-related aspects. The results indicate that these segments share demographic characteristics, including gender and income. More specifically, the "price-oriented" segment mainly consists of female and low- to middle-income consumers. The "time- and convenience-oriented" segment mainly consists of male and middle- to high-income consumers. The "value-for-money-oriented" segment has a less outspoken profile that hovers between that of the price-oriented and that of the convenience-oriented segment. Our analyses thus show that consumer preferences for delivery options depend, to a certain extent, on demographics. This is in contrast with findings by Bellman et al. (1999) that demographics do not influence consumer buying behavior in online retailing. There are only a few segmentation studies that also focus on an online retail setting. Chen and Bell (2012), for example, propose to segment a market using two consumer return policies (i.e., full-refund and no-returns), and Hjort et al. (2013) form consumer segments in terms of buying and returning behavior in fashion e-commerce. This study adds to the literature on segmentation in logistics and supply chain management by identifying segments of consumers based on the importance values of delivery attributes in online

retail. It also finds that not all demographic characteristics are relevant. Differences in education, age, and purchase frequency do not lead to different consumer segments in this study; in this paper, these characteristics do not affect preferences for delivery attributes any differently across consumers.

Managerial implications

Our results also have important managerial implications, which we checked for validity and relevance in an interview with the e-commerce operations manager of Navabi, a German online retailer of designer plus-size fashion.

Table 15: Cluster profiles in terms of demographic variables and frequency of online purchase (%), in the specialty goods category

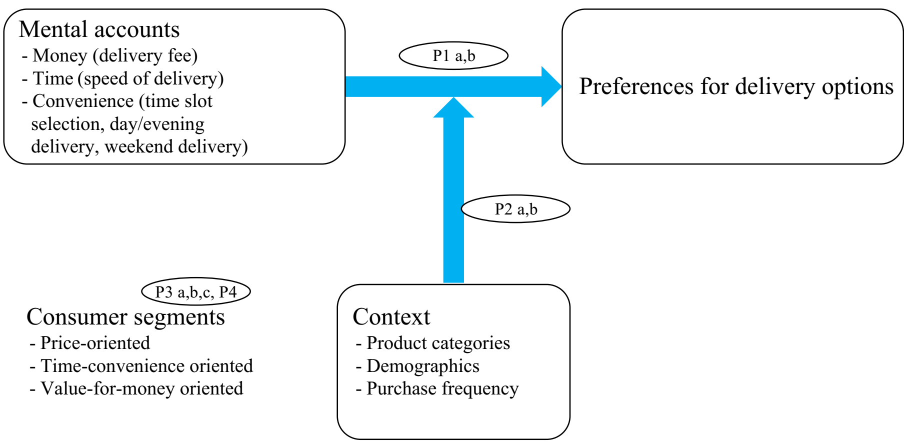
Variable	**Cluster 1 (*N* = 107)**	**Cluster 2 (*N* = 43)**	**Cluster 3 (*N* = 72)**
Age (years)			
18–20	5	0	6
21–40	22	23	21
>40	73	77	73
Gender			
Male	42	56	47
Female	58	44	53
Education			
Low	10	14	14
Middle	61	72	62
High	29	14	24
Income			
Low	42	30	51
Middle	34	52	31
High	24	18	18
Purchase frequency/year			
Low	37	40	43
Medium	52	53	46
High	11	7	11

Our study shows that consumers place most importance on low delivery fees when making decisions about delivery options for their online orders. With this in mind, offering free delivery (with or without threshold, as done by Navabi) seems a key strategy to attract and satisfy online consumers. It is important to note, however, that this research also shows that not all consumers are equally sensitive to delivery fees. While the operations manager of Navabi indicated that individual retailers may have a relatively homogenous customer base due their specific positioning, offering free delivery together with different types of paid deliveries (e.g., for speedy delivery or time slot delivery) may be a key delivery strategy. This enables the retailer to attract not only those online consumers who are sensitive to low delivery fees but also those consumers who, for example, prefer more convenient options. In fact, as the interviewed manager pointed out, even a single consumer′s preferences may not be constant: For example, a customer′s willingness to pay for home delivery of a party dress may depend on how urgently she needs it. Thus, retailers should design a reasonably wide mix of delivery options to cater for individual requirements. However, because consumers are overall very price-sensitive, retailers should ensure that the more expensive delivery options involve a substantially better service than free delivery. To avoid the typically high express delivery fees charged by international couriers, Navabi itself created a relatively cheap premium delivery service in which delivery speed is increased merely by prioritizing order processing.

CONCLUSION

This study investigates consumer preferences for delivery attributes in online retailing across product categories. The study set out to investigate literature on consumer preferences for delivery options. Conjoint analysis and cluster analysis were used to examine how online consumers value and trade off delivery attributes when selecting a delivery option. While most previous studies focused on the impact of on-time delivery on such consumer behaviors as purchase and repurchase intentions in online retailing, this study investigates consumer evaluations of delivery attributes derived from the actual delivery options provided by

Figure 4: Conceptual model and propositions (P1–P4)



online retailers. It was found that mental accounts for money, time, and convenience influence consumer preferences for a multi-attribute delivery option, and in that order. Specifically, when evaluating a delivery service, consumers attribute the greatest weight to *delivery fee*, followed by *delivery speed*, *time slot*, *delivery date*, and *daytime/evening delivery*. However, the preferences of different consumers are sufficiently distinct to form three segments across the product categories, namely a price-oriented, a time- and convenience-oriented, and a value-for-money-oriented segment. This segmentation appears to be related to differences in gender and income.

This research has some limitations which offer opportunities for further research. Firstly, as the study is conducted in a specific country the results are limited to a particular culture. Future research should account for the fact that cross-border e-commerce is growing in Europe, such that retailers are confronted with very diverse shopping habits and consumer preferences. Secondly, it is acknowledged that this study is unable to capture all aspects of reality. The conjoint profiles in this study consist of five attributes. There are other attributes that may also be of great concern to consumers when choosing delivery options, for example, published information on retailer′s delivery reliability. Incorporating a variety of product price levels may also enable capturing the role of product price in these decisions. The simulation results may also be used to develop an optimization model for a retailer who wants to select delivery options that provide maximum utility to consumers. In addition, regarding the attribute levels of *delivery fee*, unconditional free delivery was examined but the threshold-based free delivery option was ignored. Future research should also address these alternative shipping fee strategies. Thirdly, this 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. Finally, meta-analysis is considered an important method to develop theory and identify phenomena in the logistics domain (Goldsby and Autry 2011; Rabinovich and Cheon 2011). However, in the studied domain, meta-analysis was not an option due to a lack of enough observations: Once sufficient empirically grounded papers become available, a meta-analysis of the field would be a good addition to integrate the existing insights.

REFERENCES

Agatz, N., Campbell, A.M., Fleischmann, M., and Savels, M. 2008b. "Challenges and Opportunities in Attended Home Delivery." In *The Vehicle Routing Problem: Latest Advances and New Challenges*, edited by Bruce L. Golden, S. Raghavan, S. and Edward A. Wasil, 379–96. New York, NY: Springer.

Agatz, N., Campbell, A., Fleischmann, M., and Savelsbergh, M. 2011. "Time Slot Management in Attended Home Delivery." *Transportation Science* 45(3):435–49.

Agatz, N., Campbell, A.M., Fleischmann, M., Van Nunen, J., and Savelsbergh, M. 2013. "Revenue Management Opportunities for Internet Retailers." *Journal of Revenue and Pricing Management* 12(2):128–38.

Agatz, N.A.H., Fleischmann, M., and van Nunen, J.A.E.E. 2008a. "E-Fulfillment and Multi-Channel Distribution - A Review." *European Journal of Operational Research* 187 (2):339–56.

Anderson, E.J., Coltman, T., Devinney, T.M., and Keating, B. 2011. "What Drives the Choice of a Third-Party Logistics Provider?" *Journal of Supply Chain Management* 47(2):97–115.

Antonides, G., and Ranyard, R. 2018. "Mental Accounting and Economic Behaviour." In *Economic Psychology*, edited by Rob Ranyard, 123–38. Hoboken, NJ: John Wiley & Sons.

Barclays 2014. The Last Mile: Exploring the Online Purchasing and Delivery Journey. https://www-uatgem.barclayscorporate.com/content/dam/corppublic/corporate/Documents/research/The-last-ilereport.pdf

Bart, Y., Shankar, V., Sultan, F., and Urban, G.L. 2005. "Are the Drivers and Role of Online Trust the Same for All Web Sites and Consumers? A Large-Scale Exploratory Empirical Study." *Journal of Marketing* 69(4):133–52.

Becerril-Arreola, R., Leng, M., and Parlar, M. 2013. "Online Retailers' Promotional Pricing, Free-Shipping Threshold, and Inventory Decisions: A Simulation-Based Analysis." *European Journal of Operational Research* 230(2):272–83.

Bellman, S., Lohse, G.L., and Johnson, E.J. 1999. "Predictors of Online Buying Behavior." *Communications of the ACM* 42 (12):32–8.

Blut, M. 2016. "E-Service Quality: Development of a Hierarchical Model." *Journal of Retailing* 92(4):500–17.

Boyer, K.K., Prud'homme, A.M., and Chung, W.. 2009. "The Last Mile Challenge: Evaluating the Effects of Customer Density and Delivery Window Patterns." *Journal of Business Logistics* 30(1):185–201.

Campbell, A.M., and Savelsbergh, M. 2005. "Decision Support for Consumer Direct Grocery Initiatives." *Transportation Science* 39(3):313–27.

Campbell, A.M., and Savelsbergh, M. 2006. "Incentive Schemes for Attended Home Delivery Services." *Transportation Science* 40(3):327–41.

Cao, Y., Gruca, T.S., and Klemz, B.R. 2003. "Internet Pricing, Price Satisfaction, and Customer Satisfaction." *International Journal of Electronic Commerce* 8(2):31–50.

CBS. 2019. https://www.cbs.nl/, accessed on 22 February 2019.

Chen, J., and Bell, P.C. 2012. "Implementing Market Segmentation Using Full-Refund and No-Refund Customer Returns Policies in a Dual-Channel Supply Chain Structure." *International Journal of Production Economics* 136(1):56–66.

Chen, S.-J., and Chang, T.-Z. 2003. "A Descriptive Model of Online Shopping Process: Some Empirical Results." *International Journal of Service Industry Management* 14 (5):556–69.

Chen, M.-C., Hsu, C.-L., Hsu, C.-M., and Lee, Y.-Y. 2014. "Ensuring the Quality of E-Shopping Specialty Foods through Efficient Logistics Service." *Trends in Food Science and Technology* 35(1):69–82.

Chiu, C.-M., Wang, E.T.G., Fang, Y.-H., and Huang, H.-Y. 2014. "Understanding Customers' Repeat Purchase Intentions in B2C e-Commerce: The Roles of Utilitarian Value, Hedonic Value and Perceived Risk." *Information Systems Journal* 24 (1):85–114.

Cho, Y.K. 2015. "Creating Customer Repurchase Intention in Internet Retailing: The Effects of Multiple Service Events and Product Type." *Journal of Retailing and Consumer Services* 22:213–22.

Cohen, J. 1988. *Statistical Power Analysis for the Behavioral Sciences*, 2nd ed. New York: Academic Press.

Collier, J.E., and Bienstock, C.C. 2006. "Measuring Service Quality in E-Retailing." *Journal of Service Research* 8 (3):260–75.

Dadzie, K.Q., Chelariu, C., and Winston, E. 2005. "Customer Service in the Internet-Enabled Logistics Supply Chain: Website Design Antecedents and Loyalty Effects." *Journal of Business Logistics* 26(1):53–78.

Danielis, R., Marcucci, E., and Rotaris, L. 2005. "Logistics Managers' Stated Preferences for Freight Service Attributes." *Transportation Research Part E: Logistics and Transportation Review* 41(3):201–15.

Denyer, D., and Tranfield, D. 2009. "Producing a Systematic Review." In *The Sage Handbook of Organizational Research Methods*, edited by David Buchanan, and Alan Bryman, 671–89. Thousand Oaks, CA: Sage Publications.

DeVoe, S.E., and Pfeffer, J. 2007. "When Time Is Money: The Effect of Hourly Payment on the Evaluation of Time." *Organizational Behavior and Human Decision Processes* 104 (1):1–13.

Duarte, P., e Silva, S.C., and Ferreira, M.B.. 2018. "How Convenient Is It? Delivering Online Shopping Convenience to Enhance Customer Satisfaction and Encourage e-WOM." *Journal of Retailing and Consumer Services* 44:161–69.

Duxbury, D., Keasey, K., Zhang, H., and Chow, S.L. 2005. "Mental Accounting and Decision Making: Evidence under Reverse Conditions Where Money Is Spent for Time Saved." *Journal of Economic Psychology* 26(4):567–80.

Ecommerce News. 2017. "Ecommerce in the Netherlands Will Be Worth €22 Billion in 2017." https://ecommercenews.eu/ecommerce-netherlands-will-worth-e22-billion-2017/

Ehmke, J.F., and Campbell, A.M. 2014. "Customer Acceptance Mechanisms for Home Deliveries in Metropolitan Areas." *European Journal of Operational Research* 233(1):193–207.

Esper, T.L., Jensen, T.D., Turnipseed, F.L., and Burton, S. 2003. "The Last Mile: An Examination of Effects of Online Retail Delivery Strategies on Consumers." *Journal of Business Logistics* 24(2):177–203.

Euromonitor. 2018. Statistics. Retrieved February 15, 2018, from Euromonitor Passport Database.

Evans, J.D. 1996. *Straightforward Statistics for the Behavioral Sciences*. Pacific Grove, CA: Brooks/Cole.

Garver, M.S., Williams, Z., Taylor, G.S., and Wynne, W.R. 2012. "Modelling Choice in Logistics: A Managerial Guide and Application." *International Journal of Physical Distribution and Logistics Management* 42(2):128–51.

Gawor, T., and Hoberg, K. 2018. "Customers' Valuation of Time and Convenience in e-Fulfillment." *International Journal of Physical Distribution and Logistics Management* 49:75–98.

Girard, T., Korgaonkar, P., and Silverblatt, R. 2003. "Relationship of Type of Product, Shopping Orientations, and Demographics with Preference for Shopping on the Internet." *Journal of Business and Psychology* 18(1):101–20.

Global Webshop Logistics. 2014. Global Webshop Logistics: 2014 Research.

Godsell, J., Diefenbach, T., Clemmow, C., Towill, D., and Christopher, M. 2011. "Enabling Supply Chain Segmentation through Demand Profiling." *International Journal of Physical Distribution and Logistics Management* 41(3):296–314.

Goebel, P., Moeller, S., and Pibernik, R. 2012. "Paying for Convenience: Attractiveness and Revenue Potential of Time-Based Delivery Services." *International Journal of Physical Distribution and Logistics Management* 42(6):584–606.

Goldsby, T.J., and Autry, C.W. 2011. "Toward Greater Validation of Supply Chain Management Theory and Concepts: The Roles of Research Replication and Meta-Analysis." *Journal of Business Logistics* 32(4):324–31.

Goldsby, T.J., and Zinn, W. 2016. "Technology Innovation and New Business Models: Can Logistics and Supply Chain Research Accelerate the Evolution?" *Journal of Business Logistics* 37(2):80–1.

Hair, J.F., Black, W.C., Babin, B.J., and Anderson, R.E. 2010. *Multivariate Data Analysis*, 7th ed. New York, NY: Pearson Education Limited.

Hauser, J.R., and Rao, V.R. 2004. "Conjoint Analysis, Related Modeling, and Applications." In *Marketing Research and Modeling: Progress and Prospects*, edited by Yoram Wind, and Paul E. Green, 141–68. Berlin: Springer.

Helion, C., and Gilovich, T. 2014. "Gift Cards and Mental Accounting: Green-Lighting Hedonic Spending." *Journal of Behavioral Decision Making* 27(4):386–93.

Hjort, K., Lantz, B., Ericsson, D., and Gattorna, J. 2013. "Customer Segmentation Based on Buying and Returning Behaviour." *International Journal of Physical Distribution and Logistics Management* 43(10):852–65.

Hossain, M.T., and Bagchi, R. 2018. "How Cognitive Style Influences the Mental Accounting System: Role of Analytic versus Holistic Thinking." *Journal of Consumer Research* 45 (3):615–32.

Hübner, A., Kuhn, H., and Wollenburg, J. 2016. "Last Mile Fulfilment and Distribution in Omni-Channel Grocery Retailing: A Strategic Planning Framework." *International Journal of Retail and Distribution Management* 44(3):228–47.

IMRG. 2015. Consumer Home Delivery Survey 2015. https://www.imrg.org/res/files/D079A1FD568.pdf

Kahneman, D., and Tversky, A. 1984. "Choices, Values, and Frames." *American Psychologist* 39(4):341–50.

Karniouchina, E.V., Moore, W.L., van der Rhee, B., and Verma, R. 2009. "Issues in the Use of Ratings-Based versus Choice-Based Conjoint Analysis in Operations Management Research." *European Journal of Operational Research* 197 (1):340–48.

Keen, C., Wetzels, M., De Ruyter, K., and Feinberg, R. 2004. "E-Tailers versus Retailers: Which Factors Determine Consumer Preferences." *Journal of Business Research* 57 (7):685–95.

Kim, M., and Lennon, S.J. 2011. "Consumer Response to Online Apparel Stockouts." *Psychology and Marketing* 28 (2):115–44.

Koufteros, X., Droge, C., Heim, G., Massad, N., and Vickery, S.K. 2014. "Encounter Satisfaction in E-Tailing: Are the Relationships of Order Fulfillment Service Quality with Its

Antecedents and Consequences Moderated by Historical Satisfaction?" *Decision Sciences* 45(1):5–48.

Koukova, N., Srivastava, J., and Steul-Fischer, M. 2012. "The Effect of Shipping Fee Structure on Consumers' Online Evaluations and Choice." *Journal of the Academy of Marketing Science* 40(6):759–70.

Lantz, B., and Hjort, K. 2013. "Real E-Customer Behavioural Responses to Free Delivery and Free Returns." *Electronic Commerce Research* 13(2):183–98.

Leclerc, F., Schmitt, B.H., and Dube, L. 1995. "Waiting Time and Decision Making: Is Time like Money?" *Journal of Consumer Research* 22(1):110–19.

de, Leeuw, S., and Spiliotopoulou, E. 2017. Assessing Logistical Service Offerings of Online Retailers in Europe and the USA. Working Paper. VU University Amsterdam.

Levav, J., and McGraw, A.P. 2009. "Emotional Accounting: How Feelings about Money Influence Consumer Choice." *Journal of Marketing Research* 46(1):66–80.

Lewis, M. 2006. "The Effect of Shipping Fees on Customer Acquisition, Customer Retention, and Purchase Quantities." *Journal of Retailing* 82(1):13–23.

Lewis, M., Singh, V., and Fay, S. 2006. "An Empirical Study of the Impact of Nonlinear Shipping and Handling Fees on Purchase Incidence and Expenditure Decisions." *Marketing Science* 25(1):51–64.

Maier, G., Bergman, E.M., and Lehner, P. 2002. "Modelling Preferences and Stability among Transport Alternatives." *Transportation Research Part E: Logistics and Transportation Review* 38(5):319–34.

Maltz, A.B., Rabinovich, E., and Sinha, R. 2004. "Logistics: The Key to e-Retail Success." *Supply Chain Management Review* 8(3):48–54.

MICROS. 2014. Multi-Channel Retail Delivery Report 2014. London.

Milkman, K.L., and Beshears, J. 2009. "Mental Accounting and Small Windfalls: Evidence from an Online Grocer." *Journal of Economic Behavior & Organization* 71(2):384–94.

Monga, A., and Zor, O. 2019. "Time Versus Money." *Current Opinion in Psychology* 26:28–31.

Moon, P., Keasey, K., and Duxbury, D. 1999. "Mental Accounting and Decision Making: The Relationship between Relative and Absolute Savings." *Journal of Economic Behavior & Organization* 38(2):145–53.

Nguyen, D.H., de Leeuw, S., and Dullaert, W.E.H. 2018. "Consumer Behaviour and Order Fulfilment in Online Retailing: A Systematic Review." *International Journal of Management Reviews* 20(2):255–76.

Orme, B.K. 2010. *Getting Started with Conjoint Analysis: Strategies for Product Design and Pricing Research*, 3rd ed. Glendale, CA: Research Publishers.

Otim, S., and Grover, V. 2006. "An Empirical Study on Web-Based Services and Customer Loyalty." *European Journal of Information Systems* 15(6):527–42.

Pavlou, P. 2003. "Consumer Acceptance of Electronic Commerce: Integrating Trust and Risk with the Technology Acceptance Model." *International Journal of Electronic Commerce* 7(3):101–34.

Punakivi, M., Yrjola, H., and Holmstrom, J. 2001. "Solving the Last Mile Issue: Reception Box or Delivery Box?" *International Journal of Physical Distribution and Logistics Management* 31(6):427–39.

Punj, G. 2011. "Effect of Consumer Beliefs on Online Purchase Behavior: The Influence of Demographic Characteristics and Consumption Values." *Journal of Interactive Marketing* 25 (3):134–44.

Punj, G. 2012. "Income Effects on Relative Importance of Two Online Purchase Goals: Saving Time versus Saving Money?" *Journal of Business Research* 65(5):634–40.

Qureshi, I., Fang, Y., Ramsey, E., McCole, P., Ibbotson, P., and Compeau, D. 2009. "Understanding Online Customer Repurchasing Intention and the Mediating Role of Trust: An Empirical Investigation in Two Developed Countries." *European Journal of Information Systems* 18(3):205–22.

Rabinovich, E., and Cheon, S. 2011. "Expanding Horizons and Deepening Understanding via the Use of Secondary Data Sources." *Journal of Business Logistics* 32(4):303–16.

Rajagopal, P., and Rha, J.-Y. 2009. "The Mental Accounting of Time." *Journal of Economic Psychology* 30(5):772–81.

Ramanathan, R. 2010. "The Moderating Roles of Risk and Efficiency on the Relationship between Logistics Performance and Customer Loyalty in E-Commerce." *Transportation Research Part E: Logistics and Transportation Review* 46 (6):950–62.

Ramanathan, R. 2011. "An Empirical Analysis on the Influence of Risk on Relationships between Handling of Product Returns and Customer Loyalty in E-Commerce." *International Journal of Production Economics* 130(2):255–61.

Rao, V.R. 2014. *Applied Conjoint Analysis*. New York: Springer.

Rao, S., Goldsby, T.J., Griffis, S.E., and Iyenga, D. 2011a. "Electronic Logistics Service Quality (e-LSQ): Its Impact on the Customer's Purchase Satisfaction and Retention." *Journal of Business Logistics* 32(2):167–79.

Rao, S., Griffis, S.E., and Goldsby, T.J. 2011b. "Failure to Deliver? Linking Online Order Fulfillment Glitches with Future Purchase Behavior." *Journal of Operations Management* 29(7–8):692–703.

Reinholtz, N., Bartels, D.M., and Parker, J.R. 2015. "On the Mental Accounting of Restricted-Use Funds: How Gift Cards Change What People Purchase." *Journal of Consumer Research* 42(4):596–614.

Reutterer, T., and Kotzab, H.W. 2000. "The Use of Conjoint-Analysis for Measuring Preferences in Supply Chain Design." *Industrial Marketing Management* 29(1):27–35.

Rong-Da Liang, A., Lee, C.-L., and Tung, W. 2014. "The Role of Sunk Costs in Online Consumer Decision-Making." *Electronic Commerce Research and Applications* 13(1):56–68.

Schindler, R.M., Morrin, M., and Bechwati, N.N. 2005. "Shipping Charges and Shipping-Charge Skepticism: Implications for Direct Marketers' Pricing Formats." *Journal of Interactive Marketing* 19(1):41–53.

comScore. 2014. UPS Pulse of the Online Shopper^{TM}: A Customer Experience Study. https://www.ups.com/media/en/2014-UPS-Pulse-of-the-Online-Shopper.pdf.

Shefrin, H.M., and Thaler, R.H. 1988. "The Behavioral Life-Cycle Hypothesis." *Economic Inquiry* 26(4):609–43.

Soman, D. 2001. "The Mental Accounting of Sunk Time Costs: Why Time Is Not like Money." *Journal of Behavioral Decision Making* 14(3):169–85.

Southerton, D. 2003. "'Squeezing Time' Allocating Practices, Coordinating Networks and Scheduling Society." *Time and Society* 12(1):5–25.

Stank, T.P., Pellathy, D.A., In, J., Mollenkopf, D.A., and Bell, J.E. 2017. "New Frontiers in Logistics Research: Theorizing at the Middle Range." *Journal of Business Logistics* 38(1):6–17.

Tausig, M., and Fenwick, R. 2001. "Unbinding Time: Alternate Work Schedules and Work-Life Balance." *Journal of Family and Economic Issues* 22(2):101–19.

Teo, T.S.H. 2001. "Demographic and Motivation Variables Associated with Internet Usage Activities." *Internet Research* 11(2):125–37.

Thaler, R. 1985. "Mental Accounting and Consumer Choice." *Marketing Science* 4(3):199–214.

Thaler, R.H. 1999. "Mental Accounting Matters." *Journal of Behavioral Decision Making* 12(3):183–206.

Thirumalai, S., and Sinha, K.K. 2005. "Customer Satisfaction with Order Fulfillment in Retail Supply Chains: Implications of Product Type in Electronic B2C Transactions." *Journal of Operations Management* 23(3):291–303.

Thirumalai, S., and Sinha, K.K. 2011. "Customization of the Online Purchase Process in Electronic Retailing and Customer Satisfaction: An Online Field Study." *Journal of Operations Management* 29(5):477–87.

Turban, E., King, D., Lee, J.K., Liang, T.-P., and Turban, D.C. 2015. Electronic Commerce: A Managerial and Social Networks Perspective. 8th ed. Cham: Springer.

Van der Lippe, T. 2007. "Dutch Workers and Time Pressure: Household and Workplace Characteristics." *Work, Employment and Society* 21(4):693–711.

Wilson-Jeanselme, M., and Reynolds, J. 2006. "Understanding Shoppers' Expectations of Online Grocery Retailing." *International Journal of Retail and Distribution Management* 34(7):529–40.

Xing, Y., and Grant, D.B. 2006. "Developing a Framework for Measuring Physical Distribution Service Quality of Multi-Channel and 'Pure Player' Internet Retailers." *International Journal of Retail and Distribution Management* 34(4/5):278–89.

Xing, Y., Grant, D.B., McKinnon, A.C., and Fernie, J. 2010. "Physical Distribution Service Quality in Online Retailing." *International Journal of Physical Distribution and Logistics Management* 40(5):415–32.

Xu, X., Munson, C.L., and Zeng, S. 2017. "The Impact of E-Service Offerings on the Demand of Online Customers." *International Journal of Production Economics* 184:231–44.

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