# UNIVERSITY OF GOTHENBURG 

SCHOOL OF BUSINESS, ECONOMICS AND LAW

## Utility and Weight Importance of Product Delivery Attributes in a Collection and Delivery Point Dominated Marketplace

[^0]
#### Abstract

When purchasing a product from an e-commerce retailer, consumers often gets to choose among different delivery options, consisting of multiple attributes that are evaluated to choose the most preferred one. Information integration theory (IIT) was used as the model to know how consumers integrate and evaluate a multi-attribute problem such as last mile delivery choice. The aim of this research paper was to find which attributes that had the highest impact on delivery option choice in a marketplace were collection and delivery points (CDPs) dominated the delivery method. This was done by calculating the importance weights of different attributes through consumers' part-worth utility for different attribute levels. Based on a conjoint analysis survey study based on responses from 90 individuals, delivery cost was found to be the most important attribute for consumer choice, with delivery method and delivery lead time having lower similar importance ratings. Consumers found much more part-worth utility in a CDP offering where the pick-up location could be chosen rather than getting their product to a default CDP. This research paper gives academia a framework and method combination to solve future multi-attribute problems and help e-commerce retailers in a CDP dominant marketplace to know what attributes to focus on when implementing delivery options in the future.

\subsection*{1.0 Introduction}

E-commerce retailing has seen a steadily increased revenue growth during the last years. In Sweden, the e-commerce revenue grew by $13 \%$ to 87 billion SEK in 2019 (Postnord, 2020a). Consumers find utility in many aspects of online shopping, like the convenience of easily evaluating multiple retailers to find the best products for the lowest prices (Gawor \& Hoberg, 2019). An important aspect for e-commerce consumers is of course how the delivery of the purchased product is handled. Delivery aspects plays a part in the perceived service quality of a website, with better service quality greatly increasing the odds of the consumer selecting the website for a purchase (Zo \& Ramamurthy, 2009). Consumers are concerned how, when and where products are delivered and has been shown to have effect on both overall purchase intention and customer retention (Nguyen et. al., 2019; Collier \& Bienstock, 2006).

Knowing which delivery attribute levels to include in the delivery options are therefore a key for e-commerce retailing success. Attributes are different characteristics that makes up an overall option, having different levels that can be both quantitative and qualitative (Scholl et. al., 2005). Product delivery can be seen as a multi-attribute problem, with each attribute level being assigned a part-worth utility that makes up the overall utility of the delivery option. The utility is an individual perception of measuring value, with a higher utility leading to a higher chance of choice (Hair et. al., 2014). There have been previous studies done of finding attribute importance and part-worth utility of attribute levels for product deliveries, but these have been set with consumers that are infrequent users of collection and delivery points (CDPs). These CDPs are external locations where consumers collect products bought online. In some countries, consumers only think of CDPs as a place to pick up unsuccessful home deliveries (Kedia et. al., 2017). This was confirmed by Rai et. al. (2019) and Gawor \& Hoberg (2019) where the CDP delivery method had less utility than any of the home delivery


options. In countries such as the Nordics, most products are delivered to CDPs (Postnord, 2020b) and these countries therefore have a marketplace with CDP as the dominant delivery method. In many other comparable European countries such as Germany or the UK less than $5 \%$ of products are delivered to a CDP (Postnord, 2018). Neither retailers nor academia can be sure what attributes that have high importance weights and which attribute levels consumers find utility in for e-commerce retailers in countries with a CDP dominant marketplace. Furthermore, whether getting to choose your preferred CDP location over a default one brings higher part-worth utility for consumers or not are virtually unexplored.

More than a fourth of consumers in Sweden, a country with CDPs as the majority delivery method cancelled a purchase the last year due to unwanted delivery options at the checkout (Postnord, 2019). The delivery option consumers choose is defined as the last mile delivery of the product, meaning the shipping from the last distribution point to where the consumer receives the package (Olsson et. al., 2019). Retailers can often not offer levels that has highest perceived utility in all attributes, due to last mile delivery being up to half of the overall supply chain cost of a delivered package (Hübner et. al., 2016). Therefore, one problem this report wishes to solve is what delivery attributes e-commerce retailers in a CDP dominant marketplace should focus on in their delivery offering. In last mile delivery consumers would like to have all benefits and no downsides. Almost half of the consumers in Sweden, a CDP dominated marketplace stated that 11 out of 12 last mile delivery attributes were important (Postnord, 2020a). This does not say much about what the consumer really values when choosing how to get their product delivered and in turn what delivery attributes e-commerce retailers should focus on.

The purpose of this research paper is to investigate what last mile delivery attributes that consumers in a CDP dominated marketplace find most important and therefore bases their choice of delivery option on when ordering an e-commerce product. This will be done by applying how consumers solve multi-attribute problems with the help of informational integration theory (IIT). IIT states that individuals use separate attribute utilities to form an overall preference of an option (Degeratu et. al., 2000). Through three stages attributes are evaluated and based on the part-worth utility of each attribute an overall utility preference is formed. Through these part-worth utilities, the importance weights can be calculated as a percentage of overall delivery option choice importance. This research paper aims to answer the following research questions:
"What last mile delivery attribute levels does consumers in a CDP dominant marketplace find most part-worth utility in?"
"What last mile delivery attributes does consumers in a CDP dominant marketplace find the most important for their overall delivery option choice?"

It is important to point out that the e-commerce retailers often contract external logistic service providers (Punakivi \& Saranen, 2001). Since the research paper is focused on the ecommerce retailers and their consumers more than the logistic actors, delivery options are said to be offered and fulfilled by the e-commerce retailers. The reason for not focusing on the logistic service providers is that these were found to have the lowest importance score of
different delivery attributes in a similar research paper (Garver et. al., 2012). This means consumers put less importance on logistic service providers, and more on what the ecommerce retailers offer with the help of these companies in terms of delivery. Some data regarding attribute importance from consumers in Sweden, a CDP dominated country, are taken from the Swedish e-barometer, distributed by HUI research and Postnord (Postnord, 2020a). Since Postnord is a logistic service provider there are risks of bias in data found in these reports. However, the data is representative for the Swedish population with thousands of respondents for each e-barometer (Postnord, 2020a). Since Sweden is the largest country in Europe with a CDP dominated delivery marketplace, these statistics are deemed to be applicable for the whole population of the research question.

In the literature review the IIT framework on how overall utility is formed from different attributes in an option is presented. Then previous research on which last mile delivery attributes that have high importance weights for delivery option choice and aspects of these attributes will follow. In the method chapter different methods of finding the part-worth utility and importance weights of multi-attribute problems will be presented, followed by how the data was collected. Afterwards the results will be presented which are followed by an analysis and discussion of the results in line with theory. Lastly a conclusion and contribution part will finish this research paper.

### 2.0 Literature review

### 2.1 Information integration theory

When the consumer is in the stage of choosing a delivery option the individual is faced with a multi-attribute decision problem. Decision makers faces multi-attribute problems in many fields of research such as marketing, management, and logistics (Scholl et. al., 2005). Here, the decision maker is faced with choosing one option out of a larger number of alternatives, with each alternative consisting of multiple attributes (Wallenius, et. al., 2008). Like a matrix, a multi-attribute problem has rows with levels, columns with attributes and cells with measurement of these combinations (Hopkins, 2001). Keeney \& Raiffaa (1993), states that attributes should first be measurable, meaning that the decision maker can evaluate different levels of the attribute. It should also be comprehensive, meaning that it is understood how attributes affect the overall choice.

A theoretical framework that deals with multi-attribute problems is known as information integration theory (IIT). IIT describes how individuals use separate available attribute information to form an overall choice preference (Degeratu et. al., 2000). Multi-attribute problems are therefore explained by IIT by studying information processing of several attributes (Louviere \& Hout, 1988). Here attributes utilities and their weights can be combined to form an overall value of a product or service. Anderson (2014) states that IIT provides a focus of how decision takes place for basic issues with multiple values. Since choosing a product delivery method is quite a basic issue, this theoretical framework is deemed suitable. IIT has seen use in both marketing and communication research (eg. Bettman et. al., 1975) as well as logistics and transportation research (eg. Louviere \& Levin, 1978) furthermore solidifying the theoretical framework in this report. One criticism could be that many academic papers discussing this theoretical framework is quite old. Much of the
work done are set to the 70s and 80s. However, due to its usage in both marketing and logistic research and its proof of external validity explained later, it is deemed suitable.

The IIT model states that an evaluation of a multi-attribute problem is done as follows by a subject. The individual starts at a valuation stage where different stimuli or different attribute levels are evaluated separately from each other (Lynch, 1985). The subject then uses previous memory and external information to assign a part-worth utility to each attribute level. To know exactly which processes in the brain that takes place to assign these partworth utility values are very complex, but the IIT states that it can be exactly summarized in these values (Anderson, 2014). The next part of the model is the integration stage. Here the part-worth utilities of the attribute levels are integrated and added together into an overall evaluation of the option (Lynch, 1985). The last part is the output stage. The subject transforms its internal evaluation into a tangible assessment of the option. Most common is a rating response (for example $0-10$ ) which means that the option can be compared to other decisions (Anderson, 2014). The model is shown below in figure 1.

Figure 1. Information integration model


Where $\mathrm{S}_{1 \mathrm{j}}$ is a stimuli or attribute level that is transformed to a subjective part-worth utility at $\mathrm{V}_{1}$. Together with the other attribute part-worth levels $\mathrm{V}_{2}$ and $\mathrm{V}_{3}$ these are combined into an overall internal utility value $\mathrm{U}_{1 \mathrm{j}}$ that are then rated by the individual on a scale as R . This additive model which reveals overall utility from an IIT standpoint is calculated with the following equation:

$$
U_{1 j}=V\left(S_{1 j}\right)+V\left(S_{2 j)}+V\left(S_{3 j}\right)\right.
$$

Where $\mathrm{V}\left(\mathrm{S}_{1 \mathrm{j}}\right)$ to $\mathrm{V}\left(\mathrm{S}_{3 \mathrm{j}}\right)$ are the part-worth utilities of three different attributes for a product or service (Louviere \& Hoult, 1988). Utility is a subjective preference judgement that measures value for an individual (Hair et. al., 2014). Classical utility theory states that individuals receive the highest utility when personal satisfaction of a choice is maximized (Lagoudis et. al., 2006). What attributes that is deemed to have a high utility is unique to every consumer, but with surveys a general valuation of different attribute levels can be estimated. When combining utility of multiple attributes like in the IIT model above the product or service with the highest overall utility value has a higher chance of being chosen (Hair et. al., 2014).

Looking back at the research questions, the part-worth utilities V in the above IIT model will be able to answer the research question regarding which levels that have the highest utility. Importance weights can be calculated based on the part-worth attribute level utilities. These are on a common scale and can therefore be computed based on the difference of the lowest
and highest attribute level utility value (Hair et. al., 2014). Attributes with larger part-worth utility level difference have larger impact weight on overall utility $\left(\mathrm{U}_{1 \mathrm{j}}\right)$ and is calculated as a percentage of total importance. Higher importance weight of an attribute means that the consumer will on average base the choice more on this attribute. Attributes with higher importance weights have utility part-worth levels that differ greatly in the IIT model. Options with attribute levels $\left(\mathrm{S}_{1 \mathrm{j}}\right)$ that are perceived as beneficial and has a high importance weigh lead to higher overall utility $\left(\mathrm{U}_{1 \mathrm{j}}\right)$. Therefore, such delivery options will be rated with a higher R by consumers.

There have been studies made to test external validity of IIT which have shown that the model does a good job of predicting actual choice behaviour by consumers facing multiattribute problems (Lynch, 1985). Examples of part-worth utility showing overall option preference with an IIT model is choice of shopping location based on type of purchase and location attributes, as well as likelihood of choosing a bus ride based on cost and time attributes (Levin et. al., 1983).

### 2.2 Attributes that affect last mile delivery option choice

With last mile delivery being a multi-attribute problem, previous research has been done to examine the importance weights of different attributes. These have been done in countries were home delivery is the major delivery method but can still give information on what attributes consumers base their delivery option choice on. Delivery cost has been deemed the most important delivery attribute in several research papers (Nguyen et. al., 2019; Gawor \& Hoberg, 2019; Rai et. al., 2019; Garver et. al., 2019). In three of these research papers the delivery fee had over half of the delivery option weight contribution, meaning it was more important than all other aspects combined. Consumers are therefore willing to deal with less convenience if the shipping is cheap or even free. Free shipping has been the largest partworth utility off all attribute levels in all four of these delivery studies, suggesting very high importance for consumers.

For the delivery method attribute Rai et. al. (2019) and Gawor \& Hoberg (2019) concluded that this attribute made up $12.6 \%$ and $10.8 \%$ respectively of the delivery option choice. Nguyen et. al. (2019) included time slot and daytime/evening delivery as separate attributes, which in total made up $15.4 \%$ of delivery choice. Moving on to another attribute of the multi-attribute problem, respondents of Nguyen et. al. (2019) and Rai et. al. (2019) evaluated lead time as making up $11,2 \%$ and $13,7 \%$ respectively of the overall delivery option choice. In the other two articles from Garver et. al. (2012) and Gawor \& Hoberg (2019), respondents found lead time more important, making up $19,1 \%$ and $24,2 \%$ of the attribute importance weight. Logically, all four studies found that on average shorter delivery lead times levels have higher perceived utility by consumers.

Other attributes that has been studied in previous last mile delivery research papers have been weekend delivery (Nguyen et. al., 2019), different return possibilities (Rai et. al., 2019), as well as guaranteed delivery and which logistic service provider that is used (Garver et. al., 2012). To be able to receive packages on not only weekdays but also weekends had some importance weight, with this making up $9,3 \%$ of the delivery option choice in the study by Nguyen et. al. (2019). However, after examination of e-commerce retailers in the Swedish

CDP dominant market, almost no retailers offered weekend delivery. Different return possibilities had a 20.2 \% attribute importance weight in the research by Rai et. al. (2019), higher than delivery method or delivery lead time. However, this could be somewhat biased due to some return attribute levels having a fee which is not very common, which consumers are sensible to as shown in the importance weight of delivery cost. For pure e-commerce retailers in a CDP dominant marketplace such as Sweden, returns are also likely to be offered at CDPs no matter the delivery option and with only $6 \%$ being unhappy with product returns it furthermore means a low pain point for consumers (Postnord, 2020a). In research by Garver et. al. (2012) guaranteed delivery made up $7.7 \%$ of attribute weight and will be discussed in the lead time part of the literature review. Which logistic service provider that delivers the product had the lowest delivery attribute importance weight of only $6.7 \%$ (Garver et. al., 2012). Due to not being suitable as attributes in a CDP dominant marketplace or having low importance weights in previous research, these four mentioned attributes will not be included in this research paper. What will follow is a focus on what aspects of delivery method, delivery lead time and delivery cost consumers find utility in.

### 2.2.1 Delivery methods

If given a choice on delivery method, the consumer will choose the alternative that provides the most utility compared to the fewest constraints, such as having to be home for a home delivery or traveling to a CDP (Collins, 2015). The CDPs are divided in two different types. There is the employer attended CDP, often within an external store (Tiwapat et. al., 2018). The most common example in the Swedish market is Postnord packages handed out in grocery stores. There is also the unattended CDP concept, with products being placed in storage boxes and the consumer receiving a PIN-code to collect the package (Xu et. al., 2011). In Sweden with a CDP dominant marketplace the latter technique is less popular with only one percent receiving their last product with this method (Postnord, 2019). Due to its low usage, attended CDPs will be the focus of this research paper and when CDPs are mentioned in this article it will refer to attended ones.

Of the previous conjoint analysis studies, two evaluated the consumer utility of a CDP method attribute level. In research from Rai et. al. (2019), consumer saw less utility from receiving the package at a CDP than all options of home delivery, it was however more preferred than a store pick-up or an unattended CDP. Gawor \& Hoberg (2019) had CDP or in-store pick up as one delivery method level and this alternative also had lower utility compared to any home delivery alternative. One reason for this low utility found in CDP attributes is that some consumers only think of it as an option for picking up failed deliveries and needs incentives to use it over home delivery (Kedia et. al., 2017). Examining some of the larger European countries, less than $5 \%$ of consumers from Germany, Italy or the UK had CDPs as their preferred delivery method (Postnord, 2018).

According to the Postnord (2019) study, $41 \%$ did not get to choose their CDP location when ordering a product online in Sweden, a country with a CDP dominant marketplace, and instead got it delivered to their default CDP. This default CDP is based on the consumer's postal code and many e-commerce retailers only offer delivery to this default CDP point. A key success for CDPs to be a delivery method consumers find utility in is that they are
accessible by the consumers near their home and in Europe it is estimated that $95 \%$ of the population can access a CDPs within 15 minutes by foot or car (Kedia et. al., 2017). This is in line with research from Weltevreden (2008) that found that the more people living within five minutes of a CDP, the more parcels where collected from this service point. Interestingly, the Nordic countries where CDPs are popular are quite scarcely populated and still use CDPs the most. Another benefit of being able to choose which CDP the product should be delivered to, is the opportunity for trip chaining. Here the consumer can pick up packages when doing other tasks, such as shopping groceries or going back home from work (Collins, 2015; Weltevreden, 2008). For this consumer group, utility will be found in being able to choose a CDP that is in line with the daily commute. CDP product delivery also reduces the amount of vehicle kilometres by e-commerce retailers being able to deliver many packages to one location at the same time, leading to lower environmental impact of the last mile delivery (Rai et. al., 2019). Mangiaracina et. al. (2015) also recognizes that CDPs eliminates unnecessary missed delivery trips when the customer is not at home. Therefore, individuals that has environmental impact as a large weight importance might find higher utility in CDP delivery options.

Home delivery is seen by some consumers as the delivery method with highest utility due to the convenience of getting the product straight to their house (Campbell \& Savelsbergh, 2005). These home deliveries have different service levels, either being scheduled to come during the whole day, or a during specific time slot (Punakivi \& Saranen, 2001). A time slot is a specific time frame spanning a few hours when people must be home to receive a delivery (Nguyen et. al., 2019). These time slots can either be fixed times set by the retailers or requested by consumers from where it is determined by the retailers if the product can be delivered at that time slot (Bent \& Van Hentenryck, 2004). For the Swedish e-commerce retailers examined the time slots are generally fixed during the evening. Time slots are often seen by consumers as a higher utility offer than home deliveries without a time frame as these can lead to fewer missed deliveries (Agatz et. al., 2011). Han et. al. (2017), found that consumers prefer time slots and that consumers will not get too dissatisfied if the delivery arrives slightly before or after the stated time slot.

For the retailers, these delivery time slots are harder for providers to serve efficiently. Boyer et. al. (2009) found that a three-hour window compared to whole day delivery increased last mile transportation costs for the company by almost $50 \%$. Utility is provided by time slots due to reducing failed deliveries, with products being delivered when consumers are at work being the largest reason for delivery failures (Rai et. al., 2019). Interestingly, previous attribute level utility studies have not reached a similar conclusion whether home delivery time slot is preferable. Nguyen et. al. (2019) did find that a two-hour time slot had the highest part-worth utility for consumers. Individuals in both Rai et. al. (2019) and Gawor \& Hoberg (2019) however, perceived highest utility with whole day delivery and preferred that over time slots. Some criticism is reasonable for these findings due to contrary findings in other research papers focusing on time slots such as Han et. al. (2017) and (Agatz et. al., 2011).

### 2.2.2 Delivery lead times

The delivery lead time is defined as the time passed between the consumer placing an order and being able to pick up or receiving the item (Gawor \& Hoberg, 2019). This means a oneday delivery lead time equals a product ordered today and arriving either at home or at a CDP the next day. Previous conjoint analysis last mile delivery studies all had lead time as an attribute factor for examination.

For consumers in Sweden, a CDP preferred delivery country, the respondents in the Postnord (2019) survey stated that most wanted their delivery within two days of lead time, with a large drop of having to wait four days or more. One reason for the weight importance of lead times that exists is that the saving of time compared to traditional shopping is one of the largest points of e-commerce shopping (Gupta et. al., 2004). Time saved from not having to travel to physical retail locations is deemed a utility factor by consumers and Duarte et. al. (2018) found that having your order delivered in a timely fashion was one of the foremost drivers of online shopping convenience and utility. Time spent waiting for orders to be processed and delivered is seen as a non-monetary cost associated with online shopping (Bednarz \& Ponder, 2010). Gawor \& Hoberg (2019) examined this non-monetary cost and concluded that each reduced delivery day was worth on average $\$ 3.61$ for consumers. For the book industry Hsiao (2009) states that this value was only $\$ 0.53$ per day, a significantly lower sum. The difference is substantial and an exact measurement on lead time value is hard to specify. A value of $\$ 3.61$ per day seems a bit too high of a cost for consumers to pay for one less day of lead time. One reason for this sum could be that they used expensive electronic equipment in their study, meaning that the delivery cost would be a lower percentage of the overall cost.

Lead times are generally not guaranteed, and consumers are not compensated if the product arrives later than the lead time stated at purchase. It is nonetheless important for retailers to deliver the product within the lead time stated and that the product arrives in the promised timeframe is a large service quality factor of perceived e-commerce utility by consumers (Collier \& Bienstock, 2006; Rao et. al., 2011). It has also been found to increase consumer satisfaction and that a product arrives in time has a large impact on customer retention (Gupta et. al., 2004); Rao et. al., 2011). Longer delivery lead time than stated will therefore affect both the consumer evaluation of the current order, but also whether to order from the ecommerce retailer in the future. Many of the examined e-commerce retailers has set a span of days that the product can arrive, protecting themselves from an incorrect lead time. One negative aspect of shorter delivery lead times could be increased environmental impact due to trucks going out with unfilled cargo space, leading to more total kilometres and $\mathrm{CO}_{2}$ production (Rai et. al., 2019). Consumers with environmental concerns might therefore be willing to wait longer for a product if they knew it was more sustainably shipped.

### 2.2.3 Delivery cost

Understanding the connection between consumer behaviour and shipping costs should be a goal for e-commerce retailers (Lewis, et. al., 2006a). Especially since the shipping cost is not consumed in the total price of a product like other characteristics but tagged on at the end of
the purchase (Dinlersoz et. al., 2006). This means that the cost of last mile delivery is extra clear for the consumer. Research by Rao et. al. (2011) found that the delivery cost had a higher impact for consumer retention than distribution quality, meaning people are more likely to return to e-commerce retailers that offer lower cost shipping even if they were not completely satisfied. Lower shipping fees makes consumers willing to change delivery method and delivery time to get lower costs, showing the high utility of low shipping costs. For example, IMRG (2018) stated that the main reason that consumers choose CDP delivery was due to being cheaper than home delivery. This was however in the UK where CDP is seen as a worse alternative than home delivery.

That the shipping cost is completely free can preferably be used as a marketing tool to bring in new customers (Frischmann et. al., 2012). That a service or product is free has been shown in other marketing research to be much more attractive for consumers, compared even to very low costs (Shampanier et. al., 2007). Having one set fee independent of the order size leads to larger orders, due to consumers wanting the shipping to be a lower percentage of the total cost (Lewis, 2006b). However, it is likely that this higher fee leads to fewer overall orders from consumers. Many e-commerce retailers do not have unconditional free shipping, but rather demands a certain price threshold to be reached. Research from Lewis (2006b) has shown that a threshold based free pricing structure leads to larger average valued order sizes and gross margin than unconditional free shipping. However, it also led to fewer orders in total, both from new and repeat customers.

### 3.0 Methodology

### 3.1 Different methods to solve multi-attribute problems

Answering the research questions about consumers part-worth utility of different attribute levels and their importance weights, a method to find both are needed. A quantitative survey method has been chosen over a qualitative interview method, in large part due to the of the utility concept being unique and subjective for every individual (Hair et. al., 2014). It is therefore reasonable with a quantitative method with more respondents to get a closer truth to the preferences and importance values of the overall population. Another important factor when choosing the method is that it is not too complicated for individuals to answer. If respondents feel that it is too large of a task, many will drop out and choose to not be part of the study.

To solve a multi-attribute problem, Scholl et. al. (2005), mentions four methods that measures an individuals' perceived preference of an option which will now be briefly evaluated to choose a method for this research paper. In the multi-attribute value theory method, a value function explaining utility from different attributes is calculated by respondents directly assigning utility scores to attribute levels, and afterwards importance weights can be computed (Scholl et. al., 2005). However, the data collection procedures to calculate these functions are time-consuming and this method is therefore not used in many marketing studies (Rao, 2014). The outranking method is based on pairwise comparison of two options with multiple attributes where the individual chooses their preferred option (Greco et. al., 2016). By examining which options with which attribute levels are being chosen more often, utility for attribute levels can be calculated. Here, the decision maker
must set their own acceptable threshold values of all attribute levels, which is demanding and therefore leads to many approximations from the respondent (Scholl et. al., 2005). It is therefore deemed unsuitable for this report.

The analytic hierarchy process also makes individuals compare two multi-attribute options at the same time, where the judgement of experts can help the respondent when facing difficult attribute level evaluation (Greco et. al., 2016). The importance weights of attributes and part-worth utility of levels are computed by measuring inconsistencies between option choices (Scholl et. al., 2005). This also requires many evaluations by the respondent. Lastly, conjoint analysis makes subjects evaluate overall options with varying attribute levels and this method is suitable for multi-attribute problems due to being originally created to deal with these issues (Scholl et. al., 2005). An attribute level utility part-worth is calculated via multiple regression analysis and weight importance is formed by the range from the highest and lowest part-worth utility level for each attribute (Hair et. al., 2014). Since all attribute weights are on a common scale, it can be transformed into a percentage of overall attribute importance. One reason to choose the conjoint analysis method is that it has seen frequent use in marketing research to evaluate consumer attribute preference (Silayoi \& Speece, 2007).

Another reason for the choice of conjoint analysis in this research paper is its close relation to the information integration theory (IIT) (Rao, 2014). Just like according to IIT, an individual's total utility of an option is calculated by adding utility part-worth's together (Hair et. al., 2014). The conjoint analysis and IIT are both helpful to investigate the integration when part-worth utilities are formed and then transformed to an overall perception (Louviere \& Hoult, 1988). This is done by performing a traditional, rating-based conjoint analysis. Traditional, meaning all examined attributes are part of the options at the same time and rating-based meaning that consumers give each delivery option a rating. The rating-based conjoint analysis is relatively simple to understand compared to other multi-attribute problem methods and are deemed easy enough to be distributed via e-mail (Hair et. al., 2014). Orme (2014) suggests that the traditional approach is suitable for up to six attributes without being confusing for respondents.

Looking back at figure 1 describing how utility is formed from a multi-attribute problem via the IIT model the respondent is given three attribute levels $S_{1 \mathrm{j}}$ to $\mathrm{S}_{3 \mathrm{j}}$ that makes up the delivery option. Based on these three attribute levels, the respondent of the conjoint analysis survey gives a preference rating $R$ between $0-10$ for each delivery option. This rating process are repeated several times by each individual meaning different options with different attribute levels receives a rating R. Based on which attribute levels $\mathrm{S}_{\mathrm{j}}$ gets higher ratings R , the preference can be decomposed backwards with the help of regression-methods to find the individuals' part-worth utility for each attribute level (Rao, 2014). This is denoted with $\mathrm{V}_{\mathrm{j}}$ in the IIT model and the aim of this research paper to find. Based on the different part-worth utilities the additive equation allows the calculation of an overall utility $\mathrm{U}_{\mathrm{j}}$ for different delivery options. The importance weights are then calculated by the difference of part-worth utility between the highest and lowest level of each attribute (Hair et. al., 2014). Larger difference in part-worth utility means more impact on overall utility $\mathrm{U}_{\mathrm{j}}$ and are therefore associated with higher importance weight. Compared to other rating-based survey methods trade-offs are measured in conjoint analysis, meaning that respondents cannot choose all attributes as being important (Garver et. al., 2012).

As with the other methods, conjoint analysis does have its limitations. One problem with conjoint analysis is that utility might be changed during the conjoint analysis survey. There are many reasons for this, such as change of preference, fatigue, or simplification (Liechty et. al., 2005). Especially when many options are needed to be rated by the respondent. The more attributes and levels examined; the more profiles are needed to be evaluated to receive reliable results. As an example, the conjoint analysis survey by Nguyen et. al. (2019) required respondents to rate 25 profiles, plus answering demographic questions. Another drawback with the rating-based conjoint analysis is that same preference ratings can be stated for slightly different alternatives if the respondent is unengaged or finds just one attribute to be the ultimate choice factor (Hair et. al., 2014; Orme, 2014). However, due to its similar theoretical framework as the IIT and relative simplicity of finding the part-worth utility it was chosen for this research paper.

Conjoint analysis is validated externally by other traditional concept tests matching the findings of this method when it comes to consumer preference (Tumbusch, 1991). Findings from conjoint analysis has shown to be reliable indicators on how the consumer will evaluate part-worth attribute levels and attribute importance (Orme, 2014). An internal validation of the method is the Pearson's R rating, which is recommended when doing rating based conjoint analysis (Hair et. al, 2014). This measurement estimates the correlation between model prediction and actual preference for each respondent.

### 3.2 Delivery attributes and their levels

To evaluate what delivery attributes and levels that should be examined, real delivery profiles of Sweden, a CDP dominant delivery marketplace was examined. Retailers from three different industries was investigated to get as generalized delivery option attribute levels as possible. These industries are home electronics, often distributing larger more expensive products, clothes and shoes shipping medium sized and prized products and pharmaceuticals distributing smaller sized and lower cost products. For each industry, the ten largest pure ecommerce retailers with more than $50 \%$ of their revenue from their e-commerce were selected (Andersen, 2019). This choice was made due to the hypothesis of pure e-commerce retailers offering more delivery options. For pharmaceuticals, Apotea is the only pure ecommerce retailer on this list, which has therefore been filled out with smaller online actors and the five largest omnichannel pharmacies (Swedish Pharmacy Association, 2019).

In line with the literature review, delivery method, delivery lead time and delivery cost attribute levels offered by the thiry e-comerce retailers were examined. The most common attribute levels and how frequently these were available can be seen in Table 1. A hypothetical delivery address was needed to find the delivery options available. The address chosen was set in the urban city of Gothenburg in order to get more delivery options offered by the retailers. An address on the countryside would likely have both less home delivery and CDP location options due to fewer delivery trucks going there. Other conjoint analysis research papers has divided the home delivery method in different aspects. For example Nguyen et. al. (2019) has time slot options, which time of the day it will arrive and whether the product will arrive on weekdays or weekends. Since the examined e-commerce retailers in a CDP dominant country offers mainly whole day or evening time-slot home delivery,
these were combined into delivery method attribute levels. That not all attributes that makes up a delivery option choice is examined is a methodological weakness since as many attributes as possible, even those with lesser importance should be included in the conjoint analysis for the highest truth to reality (Hair et. al., 2014). However, due to wanting a simple and understandable survey for respondents, the three attributes of delivery method, delivery lead time and delivery cost were chosen for examination.

Table 1. Delivery attributes and their levels

|  | Method | N | Max lead time | N | Cost (SEK) | N |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| Level 1 | CDP with location choice | x20 | 1 weekday | x18 | $0-9(\mathbf{0})$ | x41 |
| Level 2 | CDP without location choice | x12 | 2 weekdays | x22 | $10-29(\mathbf{1 9})$ | x9 |
| Level 3 | Home delivery with a time slot | x18 | 3 weekdays | x15 | $30-49(\mathbf{3 9})$ | x8 |
| Level 4 | Home delivery the whole day | x14 | 4 weekdays | x11 | $50-69(\mathbf{5 9})$ | x8 |
| Level 5 | CDP parcel box | x9 | 5 weekdays | x4 | $70-89$ | x5 |
| Level 6 | Pick up in-store | x7 | 6+ weekdays | x5 | $90-109$ | x3 |
| Level 7 | Mailbox | x7 | 0 weekdays | x1 |  |  |

Note: $\mathrm{N}=$ number of alternatives offered by thirty leading Swedish e-commerce retailers. Bold indicate it is used as delivery attribute levels

Four different delivery methods where common offers by e-commerce retailers in a CDP dominant country. First off, delivery to the CDP of the consumer's choice means that at the checkout the preferred pick-up location can be chosen, for example a Postnord service point in a grocery store. Secondly, delivery to the default CDP means the pick-up location cannot be chosen but instead are delivered to a location based on the consumer's postal code. For home delivery with a time slot the large majority offered were evening delivery between 5 to 10 pm which is therefore chosen as a delivery method attribute level. Home delivery at any time of the day means the package will be delivered to the consumer that must be home to receive it at an unknown time of the day. CDP delivery to a parcel box would be interesting to include in this research paper. However, five attribute levels would require far more delivery option profile evaluations from respondents, and in the spirit of keeping the survey simple these where not included due to Sweden, a CDP dominant marketplace seeing lower usage of these parcel boxes (Postnord, 2019). The delivery lead time is how many days it takes for the order to arrive at either the CDP or at home, meaning one day of lead time results in the product arriving the next day. Lastly, the cost is the extra sum in SEK added to the order at checkout, resulting in the fee for the last mile delivery.

### 3.3 Research design

Garver et. al. (2012) states that it is important to have a realistic scenario that respondents can relate to. Having a set product, price and size of the order will help to achieve a sense of tangibility of how the respondents would like a product delivered. However, it might also affect the results of the part-worth utilities and attribute importance weights depending on the choices. The chosen product was a sweater costing 600 SEK. This is considered a mid-size mid-cost neutral item that does not usually fit in a mailbox and therefore needs to be picked up at a CDP or received at home. However, some respondents might find this item valuable
to receive with shorter lead time than other products if they would want to wear it to a special occasion. The cost might also lead to people being willing to pay for a higher delivery cost due to this being a lower percentage of the overall cost compared to a lower priced product. Nguyen et. al. (2019) researched whether products with different sizes and prices had different attribute importance weights, but three different product types was within $3 \%$ importance of each other for all attributes examined. Therefore, only one product will be examined for this research paper and the results will be general findings, rather than focusing on specific product categories.

The survey was sent through e-mail to 902 bachelor and master students at the School of Business and Economics at the University of Gothenburg. In total 98 responses were collected with a response rate of $10.9 \%$. College students is chosen to represent online consumers in this report due to being the most active internet users (Collier \& Bienstock, 2006). Most respondents will also live in the urban city of Gothenburg and are more used to these different delivery options. Respondents living urbanely could find higher utility in the delivery method choice, due to generally having more different methods available to choose from than individuals on the countryside. To be part of the study respondents would have to have engaged in online shopping the last year and college students have been found to give reliable results in topics they have familiarity with (Shuptrine, 1975). On the other hand, other research has found that student subjects differentiate in answer compared to other consumer groups (Burnett \& Dune, 1986). Students are a price sensitive group, meaning higher part-worth utility could be found in low cost delivery than a more general respondent base.

A response basis of 50 is enough for conjoint analysis to show how preferences differ due to the multiple profile ratings from each respondent leading to high reliability with lower number of respondents (Voss et. al., 2009). More respondents to use for results and analysis purposes would have been optimal but quality and reliability of responses was prioritized and therefore a choice was made to not share the survey outside the original base of 902 students. Data cleaning was done to find the final sample from the 98 respondents. Three respondents were removed from the analysis due to answering the survey unreasonable quick, resulting in doubts about answer quality. The sample was then examined for reversals, which are signs of illogical preference patterns (Hair et. al., 2014). Shorter lead time and lower cost attribute levels should most of the times have higher part-worth utility than higher levels. Five subjects had reversed part-worth utility of more than $10 \%$ for the lead time and cost attributes and was therefore removed from the sample. Furthermore, two of these five subjects had the lowest Pearson's R rating in the sample showing low levels of model fit (Hair et. al., 2014). In total 90 answers were therefore used to evaluate utilities and attribute importance. Homoscedasticity, normality, and independence tests are not needed for conjoint analysis due to the quite unique survey method (Hair et. al., 2014).

With $4 * 4 * 4$ attribute levels, this led to 64 different profiles which would be too many for respondents to evaluate. Therefore, a fractional factorial design was generated allowing estimation of part-worth utilities without needing respondents to answer all profile combinations (Orme, 2014). The design was also orthogonal and balanced, meaning that the
attribute level part-worth utilities was able to be calculated independent from change of other attribute levels and that each attribute level was in an equal amount of rated profiles (Hair et. al., 2014). In total 16 profiles were used to assess utility and rated from 0 to 10 by the respondents. Examining the demographics of respondents in Table 2, the median age was 25 years old and respondents were almost equally split between male and female. Buying a product online a few times every semester was the most frequent, with respondents purchasing something a few times every week being very scarce. Respondents were also asked a multiple-choice question on what product category they had purchased from the previous year. Clothes and shoes were the most popular category, with books and pharmacy goods filling out the top three most purchased categories.

The question is if these respondents can represent the whole population in CDP delivery dominant countries and if the results will be valid for the research questions. There are some issues discussed in this method chapter, like the respondents being students from Sweden most likely to live in an urban town. On the other hand, Sweden is the largest country in the Nordics, with the Nordic countries unlike other western European countries all having CDPs as their main delivery method (Postnord, 2020b). Students have proven to be reliable in familiar topics and all respondents stated that they had engaged in online shopping the previous year. Therefore, these respondents should be able to give validity of generalizing the result for the larger population of the research question.

## Table 2. Demographic table

| Demographics | Items | $\mathbf{N}$ | $\boldsymbol{\%}$ |
| :--- | :--- | :--- | :--- |
| All respondents |  | 90 | 100 |
| Age | 25 years or younger | 48 | 53.3 |
|  | 26 years or older | 42 | 47.7 |
| Gender | Male | 43 | 48.8 |
|  | Female | 47 | 52.2 |
| Purchase frequency | A few times every year | 24 | 26.7 |
|  | A few times every semester | 38 | 42.2 |
|  | A few times every month | 24 | 26.6 |
|  | A few times every week | 4 | 4.4 |
| Products purchased | Clothes and shoes | 71 | 78.9 |
| at least once within | Pharmacy goods | 34 | 37.7 |
| the last year | Home electronics | 24 | 26.6 |
|  | Books | 51 | 56.7 |
|  | Furniture and interior decoration | 18 | 20 |
|  | Sporting goods | 31 | 34.4 |
|  | Groceries | 14 | 15.6 |
|  | None of these | 4 | 4.4 |

### 4.0 Results

### 4.1 Part-worth utility of different attribute levels

Shown in Table 3 are the utility part-worth assigned to each attribute level. These can be added together with the additive IIT model equation to receive values of optimal and suboptimal delivery options:

$$
U_{j}=V\left(S_{1 j}\right)+V\left(S_{2 j)}+V\left(S_{3 j}\right)\right.
$$

A delivery option that let the consumer choose the CDP, arrives the day after ordering and is free of charge would be the optimal delivery option for consumers. This optimal delivery option would be given $0.825+0.922+2.608=4.355$ overall utility score for the average consumer with part-worth utility numbers taken from table 3 . On the reverse end, a delivery option with home delivery during the whole day, taking 4 weekdays to reach the individual and costing 59 SEK was deemed the worst option, with an overall utility score of $-0.694-$ 0.789-1.969=-3.452.

For the delivery method, the option of retrieving the product to a CDP of your choice was the clearly preferred option. Home delivery between 5 to 10 pm had the second most utility, being slightly preferred over getting the product delivered to the non-chosen default CDP location. These two options were similarly rated and were the levels within an attribute that had the closest part-worth utilities. Home delivery at any time of the day was not seen as a good alternative and had the lowest part-worth utility score of the different delivery methods.

Continuing with the delivery lead time, the respondents perceived lower lead time as something positive. However, the lead time preference was not linear with one day delivery lead time having a much higher part-worth utility than two days. The utility gap was smaller between waiting two or three weekdays, meaning the difference between these two levels are less important for consumers. Having to wait for four days has clearly the lowest part-worth utility score and this option should be avoided from e-commerce retailers.

That the delivery was free had the highest part-worth utility score of all attribute levels, with the difference between 0 and 19 SEK also being the largest gap in perceived utility between any levels within an attribute. Just as for delivery lead time, the part-worth utility for different attribute levels was not linear. The part-worth utility difference between 39 and 59 SEK was not as large as the other adjacent delivery cost levels, but still differentiated more than any adjacent level difference in the other attributes.

Table 3. Part-worth utility table

| Attribute name | Attribute level | Part-worth Utility |
| :--- | :--- | :--- |
| Delivery method | CDP with location choice | $\mathbf{0 . 8 2 5}$ |
|  | CDP without location choice | $\mathbf{- 0 . 1 8 3}$ |
|  | Home delivery with time slot | $\mathbf{0 . 0 5 3}$ |
|  | Home delivery the whole day | $\mathbf{- 0 . 6 9 4}$ |


| Delivery lead time | 1 weekday | $\mathbf{0 . 9 2 2}$ |
| :--- | :--- | :--- |
|  | 2 weekdays | $\mathbf{0 . 0 8 3}$ |
|  | 3 weekdays | $\mathbf{- 0 . 2 1 7}$ |
|  | 4 weekdays | $\mathbf{- 0 . 7 8 9}$ |
| Delivery cost | 0 SEK | $\mathbf{2 . 6 0 8}$ |
|  | 19 SEK | $\mathbf{0 . 4 7 8}$ |
|  | 39 SEK | $\mathbf{- 1 . 1 1 7}$ |
|  | 59 SEK | $\mathbf{- 1 . 9 6 9}$ |

Since the conjoint analysis was rating-based the Pearson's R correlation between the model prediction and actual preferences were calculated for the utility levels. The Pearson's R rating was significant ( $p<0.001$ ) above 0.95 indicating reliable results and a good model fit (Nguyen et. al., 2019).

### 4.2 Importance weights of the different attributes

The importance values seen are seen in Table 4 and are a reflection in difference between the highest and lowest level of part-worth utility. Delivery method had a difference of 0.825-($0.694)=1.519$, delivery lead time had a difference of $0.922-(-0.789)=1.711$ and delivery cost had a difference of $2.608-(-1.969)=4.577$. The overall utility gap was therefore $1.519+1.711+4.577=7.807$. Dividing the individual attribute level differences with the overall difference gives the importance weights. Delivery method had an importance weight of 19.5 $\%$, delivery lead time had an importance weight of $21.9 \%$ and delivery cost had an importance weight of $58.6 \%$.

Combining the conjoint analysis results with the demographic questions resulted in the ability to examine if there were any different importance weights for different consumer groups. The full importance value table for different demographic groups can be found in Table 4 below the overall importance weights. The demographic characteristics examined was age, gender, online purchase frequency and type of products purchased online. To find out whether the attribute difference was significant, an ANOVA measurement was conducted. The result of these was that none of the different demographic groups showed significant differences with a $95 \%$ confidence ( $p<0.05$ ). There was however a $90 \%$ significant importance weight difference of the method and cost attributes between genders and online purchase frequencies.

The respondents were also asked to give their own importance rating for delivery method, lead time and cost from a 0 to 10 scale. This was made to examine if the respondents' own importance estimation matched that of the conjoint analysis. Just like for the conjoint analysis the delivery method and delivery lead time importance were rated very similar, with a 6.36 respectively 6.19 average importance rating. On the other hand, the delivery cost aspect was
deemed much more important with an average rating of 8.58. This means consumers are aware of cost having a larger importance weight for their choice of delivery option. These consumers were grouped into equally sized groups depending on their rating. Between these groups significant $(p<0.05)$ differences were seen after ANOVA testing. For method and lead time ratings, only their respective attribute was significantly different. For cost, all three attributes differentiated.

Table 4. Importance weight table

| Importance weight values | $\mathbf{N}$ | Method | Time | Cost |
| :--- | :--- | :--- | :--- | :--- |
| All respondents | 90 | 19.5 | 21.9 | 58.6 |
| Age |  |  |  |  |
| $18-25$ | 48 | 18.1 | 21.9 | 60 |
| $26+$ | 42 | 21 | 21.9 | 57.1 |
| Gender |  |  |  |  |
| Male | 43 | $23.8^{*}$ | 23.8 | $52.4^{*}$ |
| Female | 47 | $15.6^{*}$ | 20.2 | $64.1^{*}$ |
| Purchase frequency |  |  |  |  |
| A few times every year | 24 | $31.2^{*}$ | 21 | $47.8^{*}$ |
| A few times every semester | 38 | $11.3^{*}$ | 19.7 | $69^{*}$ |
| A few times every month | 24 | $23.5^{*}$ | 23.9 | $52.6^{*}$ |
| A few times every week | 4 | $7.8^{*}$ | 36.9 | $55.3^{*}$ |
| Products purchased |  |  |  |  |
| (multiple choice) | 71 | 17.2 | 22.5 | 60.3 |
| Clothes and shoes | 71 | 19.1 | 19.3 | 61.6 |
| Pharmacy goods | 34 | 20.4 | 23.3 | 56.3 |
| Home electronics | 24 |  |  |  |
| Own stated importance |  | $31.67^{* *}$ | 16.79 | $51.53^{*}$ |
| Method 8-10 | 36 | $13.15^{* *}$ | 28.23 | $58.6^{*}$ |
| Method 5-7 | 33 | $9.54^{* *}$ | 20.71 | $69.75^{*}$ |
| Method 0-4 | 21 |  |  |  |
|  |  | 15.61 | $30.08^{* *}$ | 54.31 |
| Lead time 8-10 | 31 | 20.78 | $19.51^{* *}$ | 59.72 |
| Lead time 5-7 | 39 | 23.09 | $13.37^{* *}$ | 63.54 |
| Lead time 0-4 | 20 |  |  |  |
|  |  | $12.99^{* *}$ | $14.84^{* *}$ | $72.17^{* *}$ |
| Cost 10 | $21.65^{* *}$ | $22.59^{* *}$ | $55.75^{* *}$ |  |
| Cost 8-9 | 23 | $34.32^{* *}$ | $34.11^{* *}$ | $38.57^{* *}$ |
| Cost 1-7 | 39 |  |  |  |
| Difference between demographic groups $p<0.05$ indicated by **.p<0.10 indicated by *. |  |  |  |  |

### 5.0 Analysis and discussion

When the consumer is ready to order a product from an e-commerce retailer, the individual will face a multi-attribute problem. In line with the IIT framework by Lynch (1985) and

Anderson (2014) the consumer starts at the validation stage where levels from different attributes are evaluated based on previous experiences and knowledge to form a part-worth utility for each attribute level. Three attributes with four levels each where examined, with each delivery option consisting of three attributes with varying levels. Delivery method was the first attribute used in the IIT model, given an importance weight of 19,5 \% by respondents. This was higher than any of the previous research papers examining attribute importance weights in a home delivery dominated marketplace (Nguyen et. al., 2019; Rai et. al., 2019; Gawor \& Hoberg, 2019). The reason for this could be that combination of delivery location, delivery time slot and evening delivery was combined into one attribute of delivery method, leading to larger differentiation of preference. A delivery method to the CDP location of the consumers choice had the most part-worth utility. Respondents does not see CDPs as a method for picking up a failed home delivery like previous research done in other counties dominated by home delivery (Kedia et. al., 2017).

Interesting is the large gap between preference of getting the product to your chosen CDP location versus the default CDP location. Especially since almost half of the consumers in Sweden, a CDP dominated country did not get to choose their preferred location for their last purchase (Postnord, 2019). That location choice was deemed so important in this study could be one of two main reasons in line with theory. The first reason is a great willingness of trip chaining and picking up packages when doing for example grocery shopping (Collins, 2015). The second reason would be that the default location is known to be far away, with respondents may having bad experiences in the past when having to travel to an inconvenient CDP. This led to the CDP attribute level that did not allow for location choice had a lower part-worth utility than home delivery between 5-10 pm. With Weltevreden (2008) concluding that more parcels were collected from a CDP the more people living close to it, the urban living respondents with more choice of nearby CDPs might have increased the part-worth utility of choosing a CDP location nearby. Both CDP options could also be more popular as it generally is seen as a more environmentally friendly last mile delivery option than home delivery (Rai et. al., 2019; Mangiaracina et. al., 2015). The response sample consisted of students and students might be more sustainably minded and aware of less environmental impact for CDP delivery versus home delivery. Home delivery with a time slot between 5-10 pm had a much higher part-worth utility than home delivery with no time slot, in line with research from Nguyen et. al. (2019). The logical reason would be that consumers do not want to stay at home the whole day to wait for a product delivery and rather know the time slot when they should be ready to receive it. Especially due to the pain point of missing a home delivery due to not being at home (Agatz et. al., 2011).

The second attribute that makes up a delivery choice option in accordance with the IIT model was the delivery lead time. The importance weight was $21,9 \%$ meaning that delivery lead time contributed to overall choice with a weight between that found by Garver et. al. (2012) and Gawor \& Hoberg (2019). A lead time of two or three days were given similar part-worth utility values, with one-day lead time being much more preferred and four-day having by far the lowest lead time attribute utility. This means that e-commerce retailers should try to offer one day shipping which consumers find high utility in. A calculation of what consumers would be willing to pay for one less day of delivery time as done by Gawor \& Hoberg (2019)
and Hsiao (2009) would be interesting but was out of the scope for this research paper. If one day shipping is not possible, retailers might want to skip offering two-day shipping and instead focusing on three days, since difference in perceived consumer value between these two options are low. For the retailers, three-day shipping can help the retailer consolidate orders which would be both beneficial from a cost perspective, but also from an environmental perspective with less unfilled cargo space in shipping trucks (Rai et. al, 2019). In line with research by Gupta et. al. (2004) and Rao et. al. (2011) e-commerce retailers should make sure to deliver in the time frame promised due to having a large effect on consumer satisfaction and retention, making a difference whether consumers will return to the retailer or not.

The attribute of delivery cost was the most important attribute with an importance weight of $58,6 \%$. This means that when consumers integrate information from different attributes according to the IIT model, this will affect the overall utility of an option the most. This could be amplified due to students that responded to the conjoint analysis survey being price sensitive. But that the delivery cost is the most important attribute in last mile delivery was also found by other research papers examining attribute importance in markets dominated by home delivery (Nguyen et. al., 2019; Gawor \& Hoberg, 2019; Rai et. al., 2019; Garver et. al., 2019). This study confirms that consumers in a CDP dominated country are also willing to deal with less convenience to get low cost shipping. That the largest utility gap of all attributes was between free and 19 SEK shipping indicates the large preference of free shipping for consumers of a CDP dominant market. As argued by Frischmann et. al (2012) free shipping can be used as a good tool to bring in new customers, which this large partworth utility of the free delivery attribute level shows. With delivery cost being an extra fee tagged on at the end of the purchase (Dinlersoz et. al., 2006), it is therefore important to not scare both new and old customers away that are very close to completing the purchase. Since the utility part-worth for the delivery cost attribute levels differ greatly and consumers are reluctant to pay more for other methods or shorter lead times, e-commerce retailers should offer free shipping or at least last mile delivery options around the same low price point. Otherwise the consumer will most likely only be interested in the cheapest one. This research paper did not analyse different free delivery pricing thresholds, but e-commerce retailers should examine using this to increase the value of order sizes (Lewis, 2006b).

When the consumer has valued all delivery attribute levels in the IIT model to form partworth utilities, the individual moves on the integration stage. When integrating the part-worth utilities in line with Louviere \& Hoult (1988), with an additive IIT equation to form an overall utility value, the importance of delivery cost becomes very clear. As an example, a delivery option consisting of CDP delivery to your chosen location with a one-day delivery but costing 19 SEK would give an overall utility $\left(\mathrm{U}_{1 \mathrm{j}}\right)$ of $0.825+0.922+0.478=2.225$. A delivery option with a delivery to the default CDP with a three-day delivery lead time that is free gives a utility ( $\mathrm{U}_{2 \mathrm{j}}$ ) of $-0.183-0.217+2.608=2.208$. These overall utility ratings are very close, and the first option has a slightly higher chance of getting picked by the average consumer (Hair et. al., 2014). With free shipping having such a large part-worth utility, it does not matter that both the delivery method and lead time is two attribute levels worse, but
the utility found in the second option is almost as high as the first one. This was therefore shown in the final output stage of the IIT model, where options with low cost were generally given high ratings (R). The part-worth utility difference of CDP with location choice versus delivery to a default CDP was $0.825-(-0.183)=1.008$. This difference is larger than any partworth difference of lead time attribute levels. This means that if the cost is the same, the lead time would have to be two weekdays less for consumers to find more overall utility $U_{j}$ for an option with default CDP delivery than location choice CDP delivery according to the IIT model. E-commerce retailers should therefore offer delivery options were the CDP location can be chosen by the consumer at checkout.

Regarding different demographics, delivery method and cost had tendencies ( $p<0.10$ ) of differentiation between consumers with different shopping frequencies. Infrequent shoppers put the highest importance on method and lowest on price. This is reasonable since these consumers are the most inexperienced in online shopping and want as smooth of an experience as possible. Interestingly, consumers that purchased online goods a few times every semester was the most price sensitive, not those who purchased online every week. Males and females also had differences ( $p<0.10$ ) with higher importance in delivery method for males and delivery cost for females. Respondents where good at predicting their own importance weights, in large part because all respondents had experience in online shopping. Significant $(p<0.05)$ differences of attribute weights were found in groups that was divided by their own stated attribute importance. Perhaps this could be used by e-commerce retailers by asking individual consumers on their website what attribute they find most important and offer personalized delivery options based on this answer.

Finally, the importance weights found by studies done in product home delivery dominant marketplaces (Nguyen et. al., 2019; Gawor \& Hoberg, 2019; Rai et. al., 2019; Garver et. al., 2019), had the same trends as importance weighs found in this research paper done in a CDP dominated marketplace. Delivery cost dominated the choice of delivery option in all marketplaces and consumers are generally price sensitive when it comes to delivery of products. Facing a multi-attribute problem, individuals quickly examine the delivery fee to make sure that this attribute level has high part-worth utility, which it will if it is low or even free. The delivery method had a higher importance weight in a CDP dominated marketplace than where home delivery is seen as the only preferred option. This is reasonable since consumers in the CDP dominated marketplace has more delivery method attributes to choose from that are deemed viable.

### 6.0 Conclusions and contributions

Consumers in a CDP dominated marketplace find the highest part-worth attribute level utility for their delivery method only if they can choose their preferred CDP location to receive their package. If they get their product delivered to their home, they want it during a time slot in the evening, not as a whole day option. Part-worth utility is found in one day shipping with two- or three-day shipping being rated lower but similarly. This implicates that e-commerce retailers should offer either one day or three-day shipping. Pricing was by far the most important last mile delivery attribute for consumers. Since pricing was deemed more
important than both delivery method and delivery lead time, e-commerce retailers in a CDP dominated marketplace should try to offer at least one option that has free shipping, which consumers find the most part-worth utility in of any attribute levels. Otherwise, low-priced options are preferred by consumers. Delivery method and delivery lead time was seen with similar, lower importance values, meaning that both attributes contribute equally to the overall utility according to the IIT model. However, the delivery method was found to have higher importance weight in this research paper conducted in a CDP dominated marketplace than precious research done where home delivery dominated the delivery method.

This research paper contributes with a clear theoretical framework and methodology to solve a multi-attribute problem. Academia can use a similar combination of IIT and conjoint analysis to solve problems where part-worth utility of attribute levels and attribute weights are unclear. Both in last mile delivery, but also in marketing research to find how consumers use the IIT model of valuation, integration, and output to evaluate and rate products or services. For e-commerce retailers in a marketplace with CDP as the dominant delivery method this research paper can contribute with knowledge of which attribute levels that has more part-worth utility for consumers and which attributes that have higher importance weight, something that was previous not known in a CDP dominated marketplace. This can help both new and experienced e-commerce retailers to know what attributes to focus on when creating delivery options that consumers can choose from.

For future research, other attributes such as delivery reliability or return policy could also be examined, but then the risk of overly complicated conjoint analysis surveys would be an issue to deal with. Having parcel boxes as a delivery method attribute level in the CDP dominated countries would be beneficial, to see if part-worth utility for this method is larger than previously known. Future research could also examine differences in attribute utility for varying product categories further. Another recommendation would be getting a larger sample with a more general population. If wanting to examine a CDP dominated marketplace, this could be consumers from multiple Nordic countries.

## Sources

Agatz, N., Campbell, A., Fleischmann, M., \& Savelsbergh, M. (2011). Time slot management in attended home delivery. Transportation Science, 45(3), 435-449.

Andersen, J., (2019). Lista: Topp 100 största e-handlarna. Available online: https://www.ehandel.se/topp-100-storsta-e-handlarna [Retrieved 2020-02-24]

Anderson, N. H. (2014). Contributions to information integration theory: Volume 1: Cognition. Psychology Press.

Bent, R. W., \& Van Hentenryck, P. (2004). Scenario-based planning for partially dynamic vehicle routing with stochastic customers. Operations Research, 52(6), 977-987.

Bettman, J. R., Capon, N., \& Lutz, R. J. (1975). Information processing in attitude formation and change. Communication Research, 2(3), 267-278.

Boyer, K. K., Prud'homme, A. M., \& 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.

Burnett, J., \& Dune, P. (1986). An appraisal of the use of student subjects in marketing research. Journal of Business Research, 14(4), 329-343.

Campbell, A. M., \& Savelsbergh, M. W. (2005). Decision support for consumer direct grocery initiatives. Transportation Science, 39(3), 313-327.

Collier, J. E., \& Bienstock, C. C. (2006). Measuring service quality in e-retailing. Journal of service research, 8(3), 260-275.

Collins, A. T. (2015). Behavioural influences on the environmental impact of collection/delivery points. In Green logistics and transportation (pp. 15-34). Springer, Cham.

Degeratu, A. M., Rangaswamy, A., \& Wu, J. (2000). Consumer choice behavior in online and traditional supermarkets: The effects of brand name, price, and other search attributes. International Journal of research in Marketing, 17(1), 55-78.

Frischmann, T., Hinz, O., \& Skiera, B. (2012). Retailers' use of shipping cost strategies: Free shipping or partitioned prices?. International Journal of Electronic Commerce, 16(3), 65-88.

Garver, M., Williams, Z., Stephen Taylor, G., \& Wynne, W. (2012). Modelling choice in logistics: A managerial guide and application. International Journal of Physical Distribution \& Logistics Management, 42(2), 128-151.

Gawor, T., \& Hoberg, K. (2019). Customers' valuation of time and convenience in efulfillment. International Journal of Physical Distribution \& Logistics Management.

Gupta, A., Su, B. C., \& Walter, Z. (2004). An empirical study of consumer switching from traditional to electronic channels: A purchase-decision process perspective. International Journal of Electronic Commerce, 8(3), 131-161.

Greco, S., Figueira, J., \& Ehrgott, M. (2016). Multiple criteria decision analysis. New York: Springer.

Hair, J., Black, W., Babin, B., \& Anderson, R. (2014). Multivariate data analysis (Seventh edition, Pearson new international ed.).

Han, S., Zhao, L., Chen, K., Luo, Z. W., \& Mishra, D. (2017). Appointment scheduling and routing optimization of attended home delivery system with random customer behavior. European Journal of Operational Research, 262(3), 966-980.

Hopkins, L. (2001). Multi-attribute Decision Making in Urban Studies. In International Encyclopedia of Social \& Behavioral Sciences (pp. 10157-10160). Elsevier.

Hübner, A., Kuhn, H., \& Wollenburg, J. (2018). Last mile fulfilment and distribution in omni-channel grocery retailing: A strategic planning framework. International Journal of Physical Distribution \& Logistics Management, 48(4), 415-438.

IMRG, 2018, IMRG UK Click \& Collect Review 2018. Available online https://www.imrg.org/uploads/media/default/0001/07/IMRG\ UK\ Click\ and\ C ollect\%20Report\%202018\%20Executive\%20Summary.pdf?st [Retrieved 2020-02-04]

Kedia, A., Kusumastuti, D., \& Nicholson, A. (2017). Acceptability of collection and delivery points from consumers' perspective: A qualitative case study of Christchurch city. Case Studies on Transport Policy, 5(4), 587-595.

Keeney, R. L., \& Raiffa, H. (1993). Decisions with multiple objectives: preferences and value trade-offs. Cambridge university press.

Lagoudis, I. N., Lalwani, C. S., \& Naim, M. M. (2006). Ranking of factors contributing to higher performance in the ocean transportation industry: a multi-attribute utility theory approach. Maritime Policy \& Management, 33(4), 345-369.

Levin, I. P., Louviere, J. J., Schepanski, A. A., \& Norman, K. L. (1983). External validity tests of laboratory studies of information integration. Organizational Behavior and Human Performance, 31(2), 173-193.

Lewis, M., Singh, V., \& Fay, S. (2006a). An empirical study of the impact of nonlinear shipping and handling fees on purchase incidence and expenditure decisions. Marketing Science, 25(1), 51-64.

Lewis, M. (2006b). The effect of shipping fees on customer acquisition, customer retention, and purchase quantities. Journal of Retailing, 82(1), 13-23.

Liechty, J. C., Fong, D. K., \& DeSarbo, W. S. (2005). Dynamic models incorporating individual heterogeneity: Utility evolution in conjoint analysis. Marketing Science, 24(2), 285-293.

Louviere, J. J., \& Hout, M. (1988). Analyzing decision making: Metric conjoint analysis (No. 67). Sage.

Louviere, J. J., \& Levin, I. P. (1978). Functional measurement analysis of spatial and travel behavior. ACR North American Advances.
Lynch Jr, J. G. (1985). Uniqueness issues in the decompositional modeling of multiattribute overall evaluations: An information integration perspective. Journal of Marketing Research, 22(1), 1-19.

Mangiaracina, Riccardo, et al. "A review of the environmental implications of B2C ecommerce: a logistics perspective." International Journal of Physical Distribution \& Logistics Management (2015).

Nguyen, D. H., de Leeuw, S., Dullaert, W., \& Foubert, B. P. (2019). What is the right delivery option for you? Consumer preferences for delivery attributes in online retailing. Journal of Business Logistics, 40(4), 299-321.

Olsson, J., Hellström, D., \& Pålsson, H. (2019). Framework of Last Mile Logistics Research: A Systematic Review of the Literature. Sustainability, 11(24), 7131.

Orme, B. (2014). Getting started with conjoint analysis : Strategies for product design and pricing research (Third ed.).

Postnord (2018). E-handeln i Europa.
Postnord (2019). E-barometern Q2 2019.
Postnord (2020a). E-barometern 2019 årsraport.
Postnord (2020b). E-handeln i Norden, summering 2019.
Punakivi, M., \& Saranen, J. (2001). Identifying the success factors in e-grocery home delivery. International Journal of Retail \& Distribution Management.

Rai, H. B., Verlinde, S., \& Macharis, C. (2019). The" next day, free delivery" myth unravelled Possibilities for sustainable last mile transport in an omnichannel environment. International Journal of Retail \& Distribution Management, 47(1), 39-54.

Rao, S., Goldsby, T. J., Griffis, S. E., \& Iyengar, D. (2011). Electronic logistics service quality (e-LSQ): its impact on the customer's purchase satisfaction and retention. Journal of Business Logistics, 32(2), 167-179.

Rao, V. R. (2014). Applied conjoint analysis. New York: Springer.
Silayoi, P., \& Speece, M. (2007). The importance of packaging attributes: a conjoint analysis approach. European journal of marketing.

Scholl, A., Manthey, L., Helm, R., \& Steiner, M. (2005). Solving multiattribute design problems with analytic hierarchy process and conjoint analysis: An empirical comparison. European Journal of Operational Research, 164(3), 760-777.

Shampanier, K., Mazar, N., \& Ariely, D. (2007). Zero as a special price: The true value of free products. Marketing science, 26(6), 742-757.

Shuptrine, F. K. (1975). On the validity of using students as subjects in consumer behavior investigations. The Journal of Business, 48(3), 383-390.

Swedish Pharmacy Association (2019). Branchrapport 2019. Available online:
http://www.sverigesapoteksforening.se/wp-
content/uploads/2019/04/A\%CC\%8Arsrapport_Apoteksfo\%CC\%88reningen_2019_webbkopia.pdf [Retrieved 2020-02-24]

Tiwapat, N., Pomsing, C., \& Jomthong, P. (2018, September). Last mile delivery: Modes, efficiencies, sustainability, and trends. In 2018 3rd IEEE International Conference on Intelligent Transportation Engineering (ICITE) (pp. 313-317). IEEE.

Tumbusch, J. J. (1991). Validation of adaptive conjoint analysis (ACA) versus standard concept testing. In Sawtooth software conference proceedings (pp. 177-184). Ketchum, Idaho: Sawtooth Software.

Voss, M. D., Closs, D. J., Calantone, R. J., Helferich, O. K., \& Speier, C. (2009). The role of security in the food supplier selection decision. Journal of Business Logistics, 30(1), 127-155.

Wallenius, J., Dyer, J. S., Fishburn, P. C., Steuer, R. E., Zionts, S., \& Deb, K. (2008). Multiple criteria decision making, multiattribute utility theory: Recent accomplishments and what lies ahead. Management science, 54(7), 1336-1349.

Weltevreden, J. W. (2008). B2c e-commerce logistics: the rise of collection-and-delivery points in The Netherlands. International journal of retail \& distribution management.

Xu, J., Hong, L., \& Li, Y. (2011, September). Designing of collection and delivery point for e-commerce logistics. In 2011 International Conference of Information Technology, Computer Engineering and Management Sciences (Vol. 3, pp. 349-352). IEEE.

Zo, H., \& Ramamurthy, K. (2009). Consumer selection of e-commerce websites in a B2C environment: a discrete decision choice model. IEEE transactions on systems, man, and cybernetics-Part A: Systems and Humans, 39(4), 819-839.


[^0]:    Master Degree Project in Marketing and Consumption, Graduate School Author: Axel Angberg
    Supervisor: Jonas Nilsson
    Date: June 2020

