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The Effect of Time Preference and Company Specific Attributes on Willingness to Pay
for Flash Delivery Services in the Netherlands

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The views stated in this thesis are those of the author and not necessarily those of the supervisor, the second assessor, Erasmus School of Economics or Erasmus University Rotterdam.

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Executive Summary

The effects of several company-specific attributes as well as time preference (measured by a time discounting task) and environmental awareness on willingness to pay for flash delivery offerings are studied in this research. To the best of my knowledge there has not been done any academic research on this topic, which means this research adds to the academic understanding of this subject. Flash deliverers are a topic of discussion, causing disturbances for a lot of people. This research helps guiding that discussion and can improve societal understanding on this topic. Next to this, flash delivery companies will be able to use this research to enhance their marketing and better their strategy.

The main research question “To what extent do time preference and company-specific attributes affect willingness to pay for flash delivery services?” will be supported by the following sub questions:

- To what extent do price, delivery time, freshness and delivery method affect the willingness to pay for flash delivery services?
- Does being environmentally conscious affect willingness to pay?
- Is there a significant difference in willingness to pay for faster delivery for patient consumers compared to impatient consumers?

The literature review found that freshness, price, delivery time and delivery method all influence the customers’ decision to order groceries online or not. Next to this it was highlighted that e-grocery could possibly emit less greenhouse gasses than traditional grocery shopping, yet there is a concern whether this also applies for flash delivery services. Diving deeper into academic theories, delay discounting was explained. Two methods for delay discounting were described, namely exponential discounting and hyperbolic discounting. The latter of those was found to have better fit and a higher explanatory value in general.

The hypotheses for the first sub question are that price, delivery time, freshness and delivery method all affect willingness to pay for flash delivery services. For the second sub question, the hypothesis is that environmentally more conscious people have a lower willingness to pay if delivery method is by scooter instead of e-bike, and the third hypothesis is that impatient consumers have a higher willingness to pay for faster delivery than patient consumers.

The data used in this research was gathered by sending out surveys to the target group, which is Dutch people who would ever consider using flash delivery services. The research consists of quantitative descriptive research, with some exploratory parts as well. In the survey a conjoint task and discounting task for financial gains is performed by the respondents. The data is analysed by a conjoint analysis as well as (clustered) logistic regressions.

The key findings of this research are that price and freshness have an effect on the willingness to pay for flash delivery services, and delivery time and delivery method do not. Next to this, it is found that environmentally more conscious people have lower willingness to pay for delivery method by scooter instead of e-bike, and impatient consumers have higher willingness to pay for faster delivery than patient consumers. Because of these conclusions, hypotheses 1b and 1d are rejected, and hypotheses 1a, 1d, 2 and 3 are accepted. For the main research question, it can be concluded that some company-specific attributes (price and freshness) and time preference have an effect on the willingness to pay for flash delivery services.

Recommendations for this branch are to focus on being a heterogeneous company in a homogenic market. Emphasize on a niche aspect of your offering (for instance freshness), target a group of people who value freshness highly and specialize on that part of the market.

For future research, recommendations are to dive deeper in the exploratory results of this research to validate those. Also studying why people use flash delivery services is needed.

1. Introduction

Grocery shopping is evolving. We have already made a switch from employees scanning our products to doing it ourselves, but the latest trend is more radical, shaking up the grocery shopping sector in the Netherlands. Flash delivery services promise they will get your groceries delivered at your doorstep within approximately 20 minutes, which is their competitive advantage over traditional, physical grocery stores. Delivering groceries is nothing new: it has been done by lots of supermarkets like Albert Heijn and Jumbo. These deliverers require a consumer to place the order a day in advance and have a delivery frame of two hours. This means consumers have to stay at home for two or more hours, until the order has been delivered. The flash deliverers solve the problem for impatient consumers: you can order any moment you like, and the delivery time frame is usually less than half an hour.

Flash deliverers offer a solution for people who rather stay at home and are impatient. The service is most popular among the younger generations, ageing from 18 to 34 years and is currently being offered only in big cities (Baij, 2022). The COVID-19 pandemic accelerated the growth of this service, since people became afraid of visiting the supermarket. They rather stay at home and order groceries online.

1.1 Research Relevance

The flash deliverers have big growth potential, with society demanding more and more convenience in everyday tasks. The Dutch market grew 30% in the first 5 months of 2022 (Wiemer, 2022). This now primarily European business phenomena could spread all over the world. Although the flash deliverer market is growing, more research is needed.

This research aims to add to the academic, social and practical understanding of this subject. Starting with academic relevance, no academic research into flash delivery services has been done since it is a rather new phenomenon. By researching what are the important attributes, calculating the willingness to pay for several of those attributes and also segmenting the market, the academic knowledge on flash deliverers and their typical customers grows. This research elaborates on the work of Yeo et al. (2017) and Webber et al. (2010), examining their findings in the flash delivery market. In addition, the works on delay discounting of Samuelson (1937) and Mazur (1987) are combined with delays under 30 minutes and are applied to grocery delivery.

For the social relevance, we look at how society benefits of this research. Flash delivery services are a topic of discussion, since the so-called "dark stores" (the small distribution centra of the deliverers) need to be close to the customers, to ensure delivery time below 30 minutes. Because of this, dark

stores are often located in living areas, causing nuisance for the residents. There are so many complaints about noise disturbance and couriers waiting for their next ride, that Amsterdam and Rotterdam already banned establishing new dark stores (Businessinsider, 2022). To help guide this debate and show that there is a demand for flash delivery services, this research can enhance the societal understanding of this topic.

Lastly, the practical relevance of this research shows the practical solutions it offers to real world problems. This research mostly has an impact on the flash delivery companies like Flink, Getir or Gorillas. They are able to segment their customers on for instance environmental consciousness and patience, and could differentiate their marketing strategies for different segments and be able to target people with more precision. For instance, a difference in willingness to pay for e-bike delivery instead of scooter delivery has been found for environmentally more conscious people compared to environmentally less conscious people. The companies which use e-bikes can use this to promote their delivery method to people which are environmentally conscious and enhance their chances of being chosen by those people. With insights regarding the willingness to pay for several attributes, flash deliverers can improve their pricing strategies to match their offering and create a competitive advantage over their competitors.

1.2 Research Questions

Having stated the relevance of this research, the following main research question has been formulated:

To what extent do time preference and company-specific attributes affect willingness to pay for flash delivery services?

The main research question itself is too broad to answer at once. Therefore, three empirical sub-questions have been formulated to help answer the central research question. There are no theoretical sub-questions in this research, because it is highly focussed on the empirical analysis of self-gathered data on this subject. Next to this, there is zero to none academic research done on flash delivery services, which makes it hard to answer theoretical questions specific for this subject.

The first sub question is "To what extent do price, delivery time, freshness and delivery method affect the willingness to pay for flash delivery services?". The answer to this question helps to determine what company-specific attributes of flash delivery services are important for consumers when choosing between the different offerings. This is analysed by the means of a conjoint analysis.

The second sub question is “Does being environmentally conscious affect willingness to pay?”. This question relates to one of the social demographics, namely the extent that respondents show environmentally friendly behaviour. The answer of this sub question shows whether environmental consciousness is a predictor for willingness to pay for flash delivery services. This question is analysed by logistic regressions.

The third and last sub question goes as follows: “Is there a significant difference in willingness to pay for faster delivery for patient consumers compared to impatient consumers?”. This question uses the time discounting task to determine whether someone is considered as patient or impatient, and shows whether that (im)patience can be a predictor for willingness to pay for flash delivery services. This question is also analysed by logistic regressions.

1.3 Possible Research Limitations & Ethical Issues

Some possible research limitations should be mentioned. The data gathering of this research is performed by distributing surveys by social media and personal contacts of the researcher. This may lead to a sample which does not represent the typical clientele of flash delivery services. Therefore the research findings could become biased. Another possible limitation could be overfitting of some of the regression models, which could lead to unrealistic significant effects.

There are six types of typical ethical issues in research: voluntary participation, informed consent, anonymity, confidentiality, potential for harm and results communication. These issues are all taken into account when design the data collection, and all of them have been avoided. Participation is voluntary, a consent form which ensures anonymity and confidentiality was added to the survey. There is no potential for harm when filling in the survey and the results are communicated as accurately and clear as the researcher is able to.

1.4 Research Structure

This research is structured as follows: First, we review literature about online grocery shopping to examine common trends in the grocery shopping sector as well as e-grocery delivery. Secondly, we examine the literature on delay discounting, where two equations for delay discounting are introduced and compared. The hypotheses of the sub-questions are also introduced. After that, the research methodology is presented, where we show why we made the choices we have made and how the research has been designed. Also, we show how the analyses of the data will be done. Then we report on the results, starting with the descriptive research, showing relevant tables and graphics. After that, some exploratory research results are showed as well.

The main findings of the descriptive research are:

1. Freshness has the highest effect on willingness to pay compared to price, delivery time and delivery method.
2. Environmentally more conscious people seem to be willing to pay more for e-bike delivery instead of delivery by scooter compared to environmentally less conscious people, which could be interesting for the flash delivery firms.
3. Impatient people are willing to pay more for faster delivery than patient people.

Finally, conclusions of this research are shown and a short discussion about the research is presented as well.

2. Literature Review

Flash delivery services are a recent phenomenon. Out of the current largest flash delivery firms currently active in the Netherlands (Gorillas, Flink and Getir), Gorillas has been active for the longest period of time, namely since May 2020, making their introduction in the Dutch market in December of the same year (RTLNieuws, 2021). Since this is such a new subject, no scientific research has yet been done on the topic to the best of my knowledge. Most scientific articles in this literature review are more about the underlying theories used in this research, rather than about the services itself.

2.1 E-grocery Shopping

When buying groceries online, faster delivery has a positive effect on the attitude towards ordering products online (Yeo et al., 2017). Unannounced reduction of delivery time has a positive effect on profits for online retailers, and it is believed the effect will be even greater if faster delivery would be advertised (Fisher et al., 2019). Consumers are conscious of and value the quality of the products when buying fresh products (Webber et al., 2010). Delivering fresh products with good quality is important for the flash delivery services, since delivering inferior products might cause consumers to switch. Price has a negative significant effect on customer satisfaction (Magalhães, 2021). This implies that having a price which is too high might cost the company's market share. To the best of my knowledge, no research on flash deliverers which takes these three variables into account has yet been done.

Grocery delivery services bring different challenges than other e-commerce. An issue that differentiates delivering groceries is that the grocery home delivery operation has to deal with specific preservation temperatures requirements (Punakivi & Saranen, 2001). Flash deliverers do not face this problem, since temperatures will not be too high for a long enough time for the food to suffer damage (UNL Food, 2020).

A concern about e-grocery (or all B2C e-commerce in general) is about its environmental sustainability, and with the growing e-commerce and growing environmental consciousness, this is something flash deliverers should take into account. E-grocery can potentially emit 10-30% less greenhouse gases than traditional, physical grocery shopping, and this resulted from models using cars to deliver the groceries (Siragusa & Tumino, 2021). Since flash deliverers use e-bikes for delivering groceries, the difference compared to physical grocery shopping might even be bigger, especially if the bikes are charged with green energy. However, for e-grocery to emit less greenhouse gasses than traditional grocery shopping, it has to be used by a large portion of society (Siragusa & Tumino, 2021).

Flash delivery services are all about delivering groceries as fast as they can. They promise to deliver your order within 20 minutes of you confirming the order. These short delivery times could be “artificial anchors created to exploit present bias” (Nair & Ananth, 2021). Present bias can be explained as the behavioural bias that people tend to give stronger weight to payoffs that are closer in time when considering trade-offs between two future moments (O’Donoghue & Rabin, 1999). Because of this bias, people prefer having delivery sooner rather than later, and this is exactly what the flash deliverers play into.

2.2 Delay Discounting

Going deeper into this present bias, delay discounting plays a big factor. Delay discounting is often used as a measure for impatience and impulsivity, and can be defined as the cognitive process that allows the individual to compare values between the immediate and delayed consumption of a determined commodity (Da Matta et al., 2012). Thus, high rates of delay discounting are found in subjects who decide on having a smaller, immediate reward as opposed to a larger, delayed reward (Tesch & Sanfey, 2008). This research focusses on whether people that show high rates of delay discounting are willing to pay more for faster delivery.

In general, two equations which are fit to describe delay discounting are used. These two equations are most popular among academic researchers. The first equation was introduced by Samuelson (1937), and describes delay discounting as an exponential function. This equation expresses a personal value V at the present of an amount A , which is received in the future with a delay D . Factor k is a personal discount factor that shows your discount value for time. For each unit D that is added to the delay, a fixed portion of value V will be lost.

$$1) V = Ae^{-kD}$$

Mazur (1987) described and evaluated several different equations to find the equation that fits the hyperbolic form of delay-of-reinforcement functions. His research concluded that the most optimal formula to describe a hyperbolic delay-of-reinforcement function is:

$$2) V = A / (1+kD)$$

The variables are the same as in equation 1, as described above. In the denominator 1 is added to k to ensure that V is well defined when the delay D equals 0. Delay D is multiplied with factor k , which determines how much the personal value is affected by the delay. As k grows, value V gets smaller, which shows a larger discounting effect as k gets larger (Odum, 2011).

Many studies have compared these two equations. The hyperbolic equation has in general a higher explanatory value (Table 1, Odum, 2011; Da Matta et al., 2012), is more applicable when people decide to reverse their preferences as time continues and is more widely used (Odum, 2011). A different approach to measure the discounting of delayed rewards is measuring the area under the curve. This method calculates the area under the empirical discounting function and avoids problems created by the lack of consensus on whether to use a hyperbolic, an exponential or another mathematical form of the discount function (Myerson et al., 2001).

A question could be raised about large versus small amounts of money used in the delay discounting task. Small amounts of money are discounted at a steeper rate (so with a larger k) than large amounts of money (Odum et al., 2006). This research uses a small amount of money (€20) for the discounting task, so that it is representative for ordering some groceries. Therefore, the results might not be applicable for larger amounts of money.

2.3 Hypotheses

Taking the presented literature review into account, hypotheses for all sub-questions have been formulated. The hypotheses for the first sub-question are as follows:

- H1a: Price affects willingness to pay
- H1b: Delivery time affects willingness to pay
- H1c: Freshness affects willingness to pay
- H1d: Delivery method affects willingness to pay

It is expected that all company-specific attributed have a significant effect on the willingness to pay for flash delivery offerings. For the second sub-question, there is one hypothesis:

- H2: Environmentally more conscious people will have a lower willingness to pay if the delivery method is by scooter instead of e-bike.

For the third sub question, the following hypothesis has been formulated:

- H3: Impatient consumers will have a higher willingness to pay for faster delivery compared to patient consumers.

3. Methodology

3.1 Research Category & Data Gathering

In academic research, a distinction between qualitative and quantitative research has to be made. Qualitative research is research based on studying things as they are (in their natural setting) and trying to make sense of phenomena in terms of the meaning people bring to them (Aspers & Corte, 2019). Qualitative research is often paired with interviews or focus groups. Quantitative research can be described as a way to learn about a sample population, relying on observed or measured data to study questions about the population (Coghlan & Brydon-Miller, 2014). Quantitative research relies on data and numbers, whilst qualitative research is more reliant on words. This research consists of quantitative research only. Quantitative research allows researchers to indicate statistically significant effects of variable A on variable B. Since this research is about indicating effects of variables on decision making, using quantitative research is the right choice. This research contains both descriptive and exploratory findings.

The target group of this research are all people living in the Netherlands, either Dutch or non-Dutch, who already have or would ever consider using flash delivery services. Data of the target group is gathered via surveys, which were sent out through social media. The reason surveys are used is because they have the power to gather information from a large group of people, since they often do not take a lot of time to fill in and can be spread using internet. Surveys can be created for free and can be designed very much in the way the researcher sees fit. Other ways of data gathering used in quantitative research are for instance experiments or databanks. Experiments are an expensive way of gathering data and take time to conduct, especially compared to surveys. Databanks provide huge amounts of datapoints which can be very useful. For this research there is no suitable databank available, which is often the case when researching companies in the private sector.

The data was collected in the period between the 17th of May and the 31st of May. The surveys were distributed by WhatsApp and email. In total, 178 responses on the survey were collected. After dropping a part of this because they did not provide useful data (see Appendix 1.1) a sample of 104 respondents was used for the data analysis. The reason why many respondents were dropped is because they showed no intention to ever use flash delivery services. Because of this, they do not belong to the target group, and their survey ended after just two questions.

In the survey, two tasks were fulfilled: a discounting task and a conjoint choice experiment. Next to this, some standard demographic questions are asked, plus three questions about environmental conscious behaviour (see Appendix 2 – Survey).

3.2 Sample Characteristics

Table 1 shows the social demographics of the obtained sample (see Appendix 1) and of the Netherlands (CBS, OCWincijfers). Because respondents who did not consider to ever use flash deliverers are not taken into consideration and therefore did not influence the demographics of the sample, the demographics of the sample should be interpreted as demographics of the target group.

	Sample (N=104)	The Netherlands
Male	52,88%	49,68%
Female	47,12%	50,32%
18-40 years	92,31%	46%
40+ years	7,69%	54%
Secondary school	25,96%	25,8%
Vocational education (MBO, HBO)	30,77%	37,9%
University bachelors	22,12%	22,1%
Graduate degree (PhD, Masters)	20,19%	13,4%
Other	0,96%	0,8%
Working full-time	41,35%	50,64%
Working part-time	21,15%	45,26%
Student	35,58%	2,97%
Other	1,92%	1,13%
<i>Household gross income</i>		
Less than €20,000	35,58%	36,88%
€20,000-€40,000	20,19%	32,74%
€40,000-€70,000	14,42%	18,97%
€70,000 or more	22,11%	11,28%
Prefer not to say	7,69%	x

Table 1: Demographics of the sample and the Netherlands

The sample contains 92,31% 18-40 year olds, which is a higher percentage than overall in the Netherlands (46%). This result was expected, since flash delivery services are more popular among young people, and only 2% of people over 55 have ever used it (Isminstituut, 2021). Older people use it less frequently, and might be unfamiliar with the subject. Therefore this age division is not considered biased for flash delivery services.

Another result that shows a high difference with the Netherlands is that 35,58% of the sample are students compared to 2,97% nationwide. The survey was spread via the social circles of the researcher, which has led to a high percentage of students. However, flash deliverers are popular among students. 50% of students use flash delivery services, and since most students live in the large cities where flash deliverers operate, they are an important customer group for flash delivery companies (Twinkle, 2022). Therefore, students are not considered to be overrepresented in this sample.

3.3 Survey Tasks

The first task to be completed was the choice based discounting task, used in this research to measure time preference for financial gains. The choice based method measures are frequently used for predicting real-world outcomes, which is relevant for this research (Hardisty et al., 2013). For the discounting task, respondents have to choose between two options: having 10 euros immediately, or 20 euros with a three week delay. These amounts were chosen to match a typical amount spent per flash delivery order. If the immediate option is chosen, the delay is shortened and the same question is asked. If the delayed option is chosen, the delay is extended and the respondent has to choose again. This is repeated five times, and after that the indifference point of the respondent is estimated. The indifference point is the point where the respondent is indifferent between the two options; the respondent has no preference for any of the options, they are considered to have the same value. In other words, the subjective value of the delayed reward is equal to the value of the immediate reward in the indifference point.

With the gathered data, the k value can be calculated via equation 2. The discounting task estimates the indifference point where the respondent is indifferent between having 10 euros now or having 20 euros with a delay of x^* days. Because delay x^* is found via the discounting task, the discount factor k can be calculated by using personal value $V = 10$, amount $A = 20$ and delay $D = x^*$ days in equation 2.

As mentioned in the literature review, equation 2 has in general a better fit and a higher explanatory value compared to equation 1. Nevertheless, to check whether calculating the k value with exponential discounting fits the data better, equation 1 is also used in this research. The results both k values yield are compared later in this study.

Next to the discounting task, a conjoint choice experiment is also completed by the respondents. This experiment has a fractional factorial design consisting of an orthogonal subset of all possible combinations of all attributes will be used. The respondents have to choose between two profiles, varying in:

- Delivery time (with levels: 10, 20 or 30 minutes)
- Price for groceries which cost 10 euros in the supermarket (with levels: 12, 13 or 14 euros)
- Freshness regarding fresh products (with levels: 1 day, 1 week or 2 weeks until the expiration date)
- Delivery method (with levels: e-bike, scooter)

Figure 1 shows an example of the choice tasks used in this research. An opt-out option is not used in this research since this might reduce the amount of usable data (if neither option A or B is chosen, a comparison between the two is impossible). The choice sets are fixed, but the order of presentation of choice sets is randomised.

Option A	Option B
Delivery time: 10 minutes	Delivery time: 20 minutes
Price: 14 euros	Price: 12 euros
Freshness: 1 week until you need to throw it away	Freshness: 1 day until you need to throw it away
Delivered by: e-bike	Delivered by: Scooter

Figure 1: Choice set used in this research, varying in four factors.

For online grocery shoppers delivery time, price and freshness are regarded as important characteristics when choosing where to place an order (Zheng et al., 2020). Looking at the Dutch flash delivery market, the current players do not seem to differentiate their delivery service with respect to these factors.

3.4 Data Analyses

The data gathered by the survey is first used to conduct a conjoint analysis. The reason a conjoint analysis is used in this research is because the results of the conjoint analysis allow the researcher to determine what variables are considered as more or less important and calculate the willingness to pay for those variables. Also, comparisons between groups can be made, allowing to determine whether certain variables are predictive in willingness to pay, and comparing patient versus impatient people with respect to their willingness to pay.

Next to the conjoint analysis, the data is also used to compute logistic regressions. Logistic regressions are chosen because they can predict the average effect of certain variables on the odds of a profile being chosen. Next to this, interaction terms can be added to logistic regressions, which allows to check for connections between variables having an effect on the dependent variable. The dependent variable is the binary choice indicator variable (1 if option of chosen, 0 if not) and the independent variables consist of the four variables of interest, demographics and interaction terms. The logit regression therefore takes on this form:

$$ResponseIndicator = \beta_1 * DeliveryTime + \beta_2 * Price + \beta_3 * Freshness + \beta_4 * DeliveryMethod...$$

The logit results are divided into theoretically grounded results and exploratory results. The first and second regression only contain the variables of interest and theoretically grounded interaction terms.

The second regression is clustered by respondents using a mixed-logistic model, whilst the first regression is not. The third regression contains all variables and interaction terms, and should be interpreted as exploratory research rather than theoretically based research.

To prevent researcher bias, no alterations to the data have been performed. The survey was designed to be as objective as possible to prevent pushing respondents to give preferred answers, thereby preventing confirmation bias.

4. Results

4.1 Descriptive Research

The results of this research are divided into two separate parts. First, descriptive results are showed, and the research hypotheses are either accepted or rejected. After this, some exploratory results are showed as well, looking into effects that have been found which were not grounded in the theory of this research.

4.1.1 Research sub-Question 1

Hypothesis 1a – 1d stated that delivery time, price, freshness and delivery method all separately affect willingness to pay. To analyse this, a non-clustered conjoint analysis and logistic regressions have been performed.

Starting with the conjoint analysis, the likelihood ratio test (Table 2) shows that Delivery time, Price, Freshness and Delivery method all have a significant impact on consumers' choice of flash delivery services ($p < 0,05$). It is worth noting that Delivery time has a weaker significance level than the other factors: Price, Freshness and Delivery method are all significant ($p < 0,001$), whilst Delivery time is marginally significant ($p < 0,05$).

	L-R ChiSquare	DF	Prob>ChiSquared	Range (U)	Importance (U)
Delivery time	6,111	2	0,0471*	0,767	0,383
Price	33,760	2	<0,001***	1,292	0,646
Freshness	138,905	2	<0,001***	2,284	1,142
Delivery method	41,117	1	<0,001***	0,795	0,398

Table 2: Likelihood ratio test of the conjoint analysis; *= $p < 0,05$, **= $p < 0,01$, ***= $p < 0,001$, and range and importance for each variable.

The undisputed most important attribute in this analysis is Freshness, having almost double the importance of the second most important attribute. Price is the second most important attribute, almost doubling the importance of Delivery time and Delivery method.

The third most important factor is Delivery method, which has a bit more importance than Delivery time. For the respondents the delivery method is somewhat important, but not as important as price or freshness.

Delivery time ranks lowest on importance, meaning this factor has the smallest marginal effect on the decision between flash delivery services. For the respondents there is not much of a difference between delivery in 10 minutes or delivery in 30 minutes. Perhaps there will be higher importance for this factor when there are also options included with longer delivery times. This option has not been investigated since flash delivery services promise to deliver order within 30 minutes.

Since there is data on the utility of price differences, it can be calculated how much euro is equal to one U. For this, we simply divide the difference in price through the range in utility: $(14-12)/(1,292)=€1,55$ per U. With this information, we can calculate the willingness to pay for each separate effect, see Table 3.

	Marginal Utility (U)	Willingness to pay
Delivery time		
10 minutes	0,389	€0,60
20 minutes	-0,011	€-0,02
30 minutes	-0,378	€-0,59
Per minute	-0,038	€-0,04
Freshness		
1 day	-1,356	€-2,10
1 week	0,427	€0,66
2 weeks	0,928	€1,44
Per day	0,176	€0,27
Delivery method		
E-bike (vs scooter)	0,398	€0,62

Table 3: Marginal utility and willingness to pay for all factors in the conjoint analysis.

Next to the conjoint analysis, logistic regressions have been run to estimate effects of variables on the odds of a profile being chosen. Table 4 shows the results of logistic regression 1, run with only the variables of interest and the interaction terms which are grounded in academic theory. The dependent variable is the binary response indicator. The logistic regression attempts to predict the response indicator based on independent variables.

The factor delivery time is a continuous variable and yields no statistically significant effect on the average odds of a profile being chosen ($p>0,05$). In the time frame of 10 to 30 minutes, no significant effect has been found.

Price is a continuous variable and shows a negative effect on the odds of choosing a profile with a coefficient of -0,854 ($p < 0,001$). If the price is raised with 1 euro, the average odds of that profile to be chosen decline with 0,854. In the data the price ranges from 12 to 14 euros, therefore the data should be interpreted only in the price range of 12 to 14 euros. If this price would have a larger range, the results might be different.

Freshness of fresh products is a continuous variable, and has a positive effect on the odds of a profile being chosen with an estimate of 0,187 ($p < 0,001$), which means that every extra day a product stays fresh, the average odds of that profile being chosen rise with 0,187.

The delivery method shows no significant effect on the odds of a profile to be chosen ($p > 0,05$). For the sample as a whole, no significant preference for delivery by e-bike or scooter has been found.

Hypothesis 1a stated that delivery time affects willingness to pay. Delivery time showed significance in the conjoint analysis, but showed no significance in the logit regression. This means delivery time in the range of 10-30 minutes has no significant effect on the odds of a profile being chosen, and therefore does not affect willingness to pay. Because of this, hypothesis 1a is rejected.

Hypothesis 1b stated that price affects willingness to pay. Price showed significant effects in both the conjoint analysis and the logistic regression. Because of this, hypothesis 1b is accepted.

Hypothesis 1c stated that freshness affects willingness to pay. Freshness showed significant effects in both the conjoint analysis and the logistic regression. Therefore, hypothesis 1c is accepted.

Hypothesis 1d stated that delivery method affects willingness to pay. Delivery method showed significance in the conjoint analysis, but showed no significance in the logit regression. This means delivery method has no significant effect on the odds of a profile being chosen. Therefore it does not affect willingness to pay. Hypothesis 1d is rejected.

Results of Logistic Regressions of Variables on the Odds of a Profile Being Chosen

	Regression 1	Regression 2	Regression 3
	Estimate	Estimate	Estimate
Intercept	9,149*** (0,000)	9,149*** (0,000)	13,149*** (0,000)
Delivery time (minutes)	-0,011 (0,219)	-0,011 (0,270)	-0,008 (0,458)
Price (€)	-0,854*** (0,000)	-0,854*** (0,000)	-1,077*** (0,000)
Freshness (days)	0,187*** (0,000)	-0,187*** (0,000)	0,182*** (0,000)
Delivery method (E-bike)	-0,244 (0,492)	-0,244 (0,238)	-1,828*** (0,000)
Delivery method(E-bike)*Environmental consciousness	0,317** (0,002)	0,317*** (0,000)	0,566*** (0,000)
Delivery time*K value	-0,022 (0,268)	-0,022* (0,040)	-0,093 (0,389)
Price*Employment status(student)			0,527* (0,042)
Delivery method*Education			0,203** (0,013)
McFadden R ²	0,216	0,220	0,235

Table 4: Results of the logistic regression which shows the effects of variables on the choice indicator for choice profiles, *=p<0,05, **=p<0,01, ***=p<0,001

4.1.2 Research sub-Question 2

Hypothesis 2 stated that environmentally more conscious people will have a lower willingness to pay if the delivery method is scooter instead of e-bike. To investigate this, two analysis have been used. Firstly, the conjoint analysis results have been combined with demographics of the respondents, so-called subject effect. The subject-effect Education*Delivery method showed statistical significance ($p < 0,05$).

The data shows that on average, people with the lowest environmental consciousness (1) value delivery by e-bike (-1,899--1,799)= -0,100 U compared to delivery by scooter, people with an average environmental consciousness (3,35) value delivery by e-bike (0,944-- 0,852) = 1,796 U higher compared to delivery by scooter, and people with the highest environmental consciousness (5) value delivery by e-bike (2,936--0,188) = 3,124 U higher compared to delivery by scooter. These results are shown in Table 5, with the willingness to pay added as well. It is clear that how higher the environmental consciousness is, the higher the willingness to pay for e-bike delivery instead of scooter is.

	Delivery by e-bike minus scooter (U)	Willingness to pay for e-bike delivery instead of scooter (€)
Environmental consciousness = 1 (lowest)	-0,100	€-0,16
Environmental consciousness = 3,35 (average)	1,796	€2,78
Environmental consciousness = 5 (highest)	3,124	€4,84

Table 5: Willingness to pay for delivery by e-bike instead of scooter for different levels of environmental consciousness.

Next to this, delivery method is also added to the regressions in Table 4 as an interaction term with environmental consciousness. That interaction term shows a positive significant effect with a coefficient of 0,317 ($p < 0,01$) in regression 1. This means that if the delivery method is e-bike instead of a scooter, environmentally more conscious people are more likely to choose this profile compared to environmentally less conscious people.

For both analysis it can be concluded that environmentally more conscious people have a higher willingness to pay for delivery by e-bike instead of scooter, which automatically means they have a lower willingness to pay for delivery by scooter instead of e-bike. Because of this, hypothesis 2 is accepted.

4.1.3 Research sub-Question 3

The last hypothesis of this research stated that impatient consumers will have a higher willingness to pay for faster delivery compared to patient consumers. To test this, an interaction term of k value and delivery time was added to the regressions in Table 4.

K value is a continuous variable ranging from zero to 0,85, calculated via hyperbolic discounting, equation 2 in this research. If the k value rises, a respondent is considered to have higher discounting on time, is viewed as less patient and will prefer sooner consumption rather than later. Because of this, it was expected to find a significant interaction effect of k value and delivery time. Nevertheless, no significant interaction effect on the odds of a profile being chosen has been found in the first regression.

To check for robustness, k-value has also been calculated via the exponential discounting model, equation 1 of this research. The exponential k-value is also continuous, and ranges from 0,0008 to 0,566. The exponential k value was added to regression 1 as an interaction term with delivery time, replacing the original interaction term of the hyperbolic k value and delivery time. They yield very similar results, with only the coefficient differing a bit. Exponential k value*delivery time showed a coefficient of -0,0322, with exactly the same significance as the original term ($p=0,268$).

For both methods of calculating k values, no significant effect was found in regression 1. Regression 2 contains the same variables as regression 1. The only difference is that regression 2 is clustered by respondent. Clustering by respondent ensures the independence of observations, since observations of the same respondent show high correlation. Mixed logit regression 2 yields a McFadden R-squared of 0,220, which is a bit higher than regression 1. Regression 2 also shows a lower BIC and AIC value, which indicates a better fit for model 2.

Looking at the regression itself, the coefficients have not changed compared to regression 1. However, we do see changes in the statistical significance. Mainly the interaction term of delivery time and k value has become more significant compared to regression 1 ($p<0,05$). Because the k value is unique per respondent, and is the same for that respondent in each data point, it seems logical that the clustering of respondents has had an effect on the significance of this term. When respondents are clustered, the static k values which are equal for all data points of a specific respondent are clustered as well. Therefore, a part of the random error caused by the k value is accounted for in the regression.

Exponential discounting was added to the regression as an interaction term with delivery time in this regression as well, replacing the original interaction term. The interaction term yielded a coefficient of -0,032 with again exactly the same significance as the hyperbolic interaction term ($p=0,040^*$). All other

coefficients and p-values remained the same when the k values were changed, and both McFadden R squared values are the same. Because there seems to be no difference in explanatory value for either one of the equations used to calculate the k value, we can conclude that both methods fit the data equally good. Also, since both methods yield a significant interaction term with delivery method in the clustered regression, we can now that on average people with a higher k value (which indicates impatience) value faster delivery more than people with lower k values.

Because the interaction term of k value (for both discounting models) and delivery time shows a significant effect on the odds of a profile being chosen, we can conclude that it influences the willingness to pay for faster delivery more for impatient people compared to patient people. Therefore, hypothesis 3 is accepted.

4.2 Exploratory Research

This part of the results section should be interpreted as exploratory, since not all variables and interaction terms are theoretically grounded. Starting with the exploratory part of the conjoint analysis, a significant subject effect for education and delivery method was found ($p < 0,05$).

In the data it can be seen that on average, people with a higher education value delivery by e-bike higher than people with a lower education. The utility difference for delivery by e-bike or scooter between the highest education (graduate) and the lowest (secondary school) is $(2,843 - 0,740) - (1,299 - 0,870) = 1,674$ U. This means that people with a graduate degree on average are willing to pay €2,60 more for delivery by e-bike rather than by scooter compared to people with only a secondary school diploma.

	Delivery by e-bike (U)	Delivery by scooter (U)	Difference (U)	Willingness to pay for e-bike instead of scooter (€)
Graduate or professional degree	2,844	0,740	2,104	€3,26
University degree	2,468	1,603	0,865	€1,34
Vocational education	2,451	2,001	0,45	€0,70
Secondary school	1,299	0,871	0,428	€0,66

Table 6: Marginal utility and willingness to pay for different education levels and different delivery methods and the willingness to pay for delivery by e-bike instead of scooter.

Table 6 shows the results of different completed education levels and their average marginal utility for delivery by e-bike or scooter. The willingness to pay for e-bike delivery instead of delivery by scooter for different education levels is shown in Figure 2.

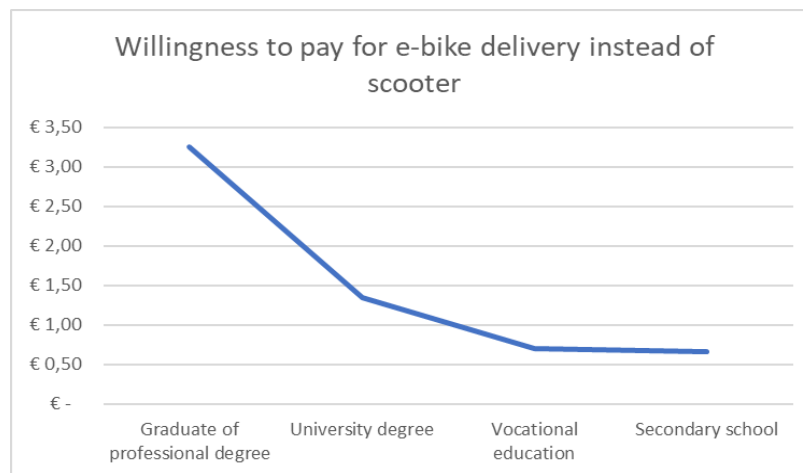


Figure 2: Willingness to pay for e-bike delivery instead of scooter for different completed education levels.

Also, some exploratory results of the logit regressions have been found. To find these, a third regression was performed. Regression 3 is a logit regression clustered by respondent, and contains the same variables as regression 1 and 2, plus added demographics and additional interaction terms. All demographics and the interaction terms Price*Employment status, Delivery method*Education and Freshness*Income have been added to the regression. Of these terms, Price*Employment status(student) and Delivery method*Education are statistically significant ($p < 0,05$). Only these significant terms have been added to Table 2, the complete regression is added to Appendix 3. It can be seen that some of the values have changed compared to regression 2. Model 3 has an McFadden (or adjusted) R squared value of 0,235, which shows a slightly higher explanatory value than model 2. It is also worth noting that model 2 has a lower BIC and AIC value, which indicates a better likelihood and better fit for model 3. The higher McFadden R squared and lower BIC and AIC values could be because the model is being overfitted; many variables are added to the regression, which makes for the model describing the random error rather than the relationships between the variables.

Price*Employment status(student) shows a positive effect with a coefficient of 0,527 ($p < 0,05$). This indicates that students are on average less price sensitive than people who work part- or full-time. To be more precise, if the prices rises with 1 euro, the odds of a profile being chosen increase with an extra 0,527 if the consumer is a student compared to part- and full-time workers. This result seems unlikely, since students usually are considered price sensitive because they have less income than part- and full-time workers. This result might be significant due to overfitting and multiple hypothesis testing.

Delivery method*Education shows a positive effect on the average odds of a profile being chosen ($p < 0,05$). For people with higher education, the average odds of a profile being chosen are higher if the delivery method is e-bike compared to people with lower education.

It is worth noting that Delivery method showed no significant effect in regression 1, but does show a significant effect in regression 2 ($p < 0,001$). The coefficient is -1,828, which seems unlikely, since that would mean that the average odds of a profile with delivery by scooter are 1,828 higher than that same profile but with e-bike delivery. This result is probably found because of overfitting.

4.3 Results Summary

Concluding the results of the descriptive research, two significant effects of specific variables on the willingness to pay for flash delivery services were found using a conjoint analysis as well as logistic regressions. The effects of price and freshness were found to be significant, for delivery time and delivery method no significant effect on willingness to pay was found in this research. Next to this, it is concluded that environmentally more conscious people have an average higher willingness to pay for e-bike delivery than less environmentally engaged people. Lastly, by using a clustered logit regression, a negative significant interaction term of delivery time and k value was found. Therefore it can be concluded that less patient people have a higher willingness to pay for faster delivery compared to patient people. Next to the descriptive research, some exploratory results were presented. These results are not embedded in theory, and should therefore not be interpreted as main findings of this research.

5. Conclusion & Discussion

5.1 Conclusion

Flash delivery services have been active in the Netherlands for about 1,5 years, and have been experiencing growth ever since. Nevertheless, not everything about flash deliverers is considered positive. They also have been the subject of societal discussion due to the disturbance caused by their so-called dark stores, and because they struggled to raise capital, Gorillas has left the Belgium market and is reconsidering doing business in Italy, Denmark and Spain (Reuters, 2022).

To the best of my knowledge there has not been done any academic research yet on flash delivery services, which made it challenging to formulate an extensive literature review for this specific subject. Looking at e-grocery shopping, the main attributes of online grocery shopping this research studied were expected to have an effect on the attitude towards ordering products online. E-grocery could possibly emit less greenhouse gasses than traditional grocery shopping, although there is a concern if this is also the case for flash delivery services (Siragusa & Tumino, 2021). The short delivery times promised by flash deliverers could exploit present bias (Nair & Ananth, 2021). A theory which plays a part in present bias is delay discounting. In general, two equations are widely used to describe delay discounting: exponential discounting (equation 1) and hyperbolic discounting (equation 2).

This paper tried to increase the academic knowledge of this subject, specifically the effects on willingness to pay for specific attributes. To draw a conclusion for this research, let us first look at the stated sub questions and their complementary hypotheses. Sub question one asked to what extent price, delivery time, freshness and delivery method affect the willingness to pay for flash delivery services. The hypotheses stated that these attributes all have a significant effect on willingness to pay. Only price and freshness showed significant effects on willingness to pay, delivery time and delivery method did not. Therefore hypotheses 1b and 1c were accepted, and hypotheses 1a and 1d were rejected.

The second sub question, "Does being environmentally conscious affect willingness to pay", came with the hypothesis that environmentally more conscious people would have a lower willingness to pay if delivery was by scooter instead of e-bike. To test this hypothesis, an interaction term with Delivery method(e-bike) and Environmental consciousness was added to the regressions in Table 4. This interaction term showed a positive significant effect in both theoretically based regressions, and showed that the odds of a profile with e-bike instead of scooter as delivery method rise as environmental consciousness rises. Table 5 also shows a significant positive relation between

environmental consciousness and the willingness to pay for Delivery by e-bike instead of scooter, and therefore hypothesis 2 was accepted.

The third and last sub question asked whether there is a significant difference in willingness to pay for patient consumers compared to impatient consumers. The hypothesis for this question was that impatient consumers will have a higher willingness to pay for faster delivery compared to patient consumers. To test this, an interaction term with delivery time and k-value was added to the regressions and the k-value was added as a subject effect in the conjoint analysis. In the second regression in Table 2, a negative significant interaction term of Delivery time and k-value was found, which indicates that the odds of a profile being chosen declines more per extra minute delivery time for people with a high k-value (which indicated impatience) than for people with a lower k-value. In other words, people who could be considered impatient are willing to pay more for faster delivery than people who could be considered patient. The same was done with k values calculated by exponential discounting instead of hyperbolic discounting, and it yielded similar results. Hypothesis 3 was also accepted.

Considering all of this, let us look at the main research question. The main research question is as follows: "To what extent do time preference and company-specific attributes affect willingness to pay for flash delivery services?". It can be concluded that a significant effect of time preference for delivery time on willingness to pay has been found in this study. It can also be concluded that the company-specific attributes freshness and price have a significant effect on willingness to pay for flash delivery services. A significant effect of delivery method and delivery time on willingness to pay has not been found.

The literature review suggested all main attributes of online grocery delivery studied in this research would have an effect on the attitude towards ordering products online. This research however only found effects of freshness and price, and not of delivery time and delivery method. Therefore the findings of Webber et al. (2010) and Magalhães (2021) are proven to hold in the flash delivery sector. The findings of Yeo et al. (2017) are not proven to hold for flash deliverers. The delivery time for e-grocery however is of a different magnitude than flash deliverers. For instance, Albert Heijn delivers your groceries the next morning if you order before 12:00 AM today (Albert Heijn, 2022). Therefore, "faster delivery" for e-grocery could mean several hours faster delivery, whilst for flash delivery it could (in this research) be at most 20 minutes faster. This could be a reason for the difference in findings between the existing literature and this empirical research. Another finding of existing literature that does not hold in this research is Odum (2011), which showed hyperbolic discounting

having a better fit and higher explanatory value than exponential discounting. This research found no difference in fit nor explanatory value between the two types of discounting.

5.2 Discussion & Recommendations

The flash delivery market is considered homogeneous, since none of the current firms really have specific differentiation points. This research indicates that attributes like freshness and price have an effect on willingness to pay and on the odds of an offering being preferred over another offering. Also, willingness to pay for e-bike delivery instead of scooter was found to be higher for environmentally more conscious people. Managerial implications of this research therefore could be that flash delivery companies like Gorillas or Flink should emphasise on specific attributes and target groups of people for whom this specific attribute is considered important. If they do this, they can create a competitive advantage and attract a specific group of customers. By targeting more specific segments of the market, revenue could grow. Niche companies could very much be a good marketing strategy as well, for instance for people who value freshness a lot, and perhaps price less. Another managerial implication could be for companies in this branch to make sure the freshness of their fresh products is not below the standard. Since this attribute is found to have the highest effect on willingness to pay, this is the attribute that can make or break your offering. Therefore, if you make sure that the freshness of your products is at least average, you avoid this attribute having a large negative impact on your offering.

The results indicate a clear effect of company specific attributes on the willingness to pay for flash delivery services. However, there are some limitations to this research that should be mentioned. Firstly, there are the relatively small ranges chosen for the price and delivery time variables, compared to freshness. Price ranged from 12 to 14 euros, delivery time from 10 to 30 minutes and Freshness from 1 to 14 days. Perhaps that because of these unequal ranges, the effect of Freshness turned out disproportionately large compared to the other effects. Although it can be argued that delivery time should not exceed 30 minutes, since the delivery time of flash deliverers also does not exceed 30 minutes. Another limitation of this research is that in the survey, the second question could already exclude respondents from the survey. Because the demographics were asked after that question, valuable data on what people would not consider using flash delivery services was not collected. Also, this research focusses only on the Dutch market. Most flash delivery services are international companies, but this research might not be applicable to all of their active markets.

For future research, some recommendations can be made. Perhaps diving deeper in the exploratory findings of this research could yield interesting findings. A short qualitative analysis has been done for the comments given at the end of the survey. A recurring theme was that people only tend to use the

service when they need something immediately, so the freshness variable played no part in this. Future research can dive deeper into the understanding on why people use flash delivery services. Also, calculating k-value by area under the curve could provide a more realistic k-value (Myerson et al., 2001). The data in this research was not suitable for that.

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Appendix

Appendix 1 – Data

<https://github.com/Bruno-s-thesis/Data-file>

The data file is accessible via the link above. The conjoint analysis was performed using the consumer research function in JMP. The regressions were performed in Stata. In the link provided above, a Stata do-file is included to repeat the analysis if this is desired.

Appendix 1.1 Data mutations

To extract the usable data from the complete dataset, the following data mutations have to be performed:

- Total N=178
- Respondents that did not give consent were removed (2 respondents)
- Respondents that would never consider using flash delivery services were removed since they are not in the target group (39 respondents)
- Respondents that did not completely fill in the conjoint questions were removed (33 respondents).
- Valid N=104

Appendix 2 – Survey

<https://github.com/Bruno-s-thesis/Data-file/blob/main/Appendix%20%20-%20Survey.pdf>

The survey file is accessible via the link above. The survey was created by Qualtrics.

Appendix 3 Complete regression 3

ResponseIndicator	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
Delivery_time_minutes	-.0078276	.0091162	-0.86	0.391	-.0256951	.0100398
Price	-1.077112	.1390998	-7.74	0.000	-1.349742	-.804481
Freshness_days	.1824915	.0241151	7.57	0.000	.1352267	.2297563
e_bike_delivery	-1.827765	.5342866	-3.42	0.001	-2.874948	-.7805827
age	-.0002175	.0088153	-0.02	0.980	-.0174953	.0170602
male	.0067268	.1294207	0.05	0.959	-.246933	.2603867
education						
3	-.096714	.1945663	-0.50	0.619	-.478057	.2846291
5	-.312644	.2259599	-1.38	0.166	-.7555173	.1302293
6	-.4458577	.2933658	-1.52	0.129	-1.020844	.1291287
7	-.5257126	.6782818	-0.78	0.438	-1.855121	.8036954
employment_status						
2	-6.791511	2.699357	-2.52	0.012	-12.08215	-1.500869
3	-2.423255	2.301348	-1.05	0.292	-6.933815	2.087305
7	-10.3639	7.123261	-1.45	0.146	-24.32524	3.59743
gross_income						
2	-.026345	.235393	-0.11	0.911	-.4877068	.4350168
3	-.0448313	.293003	-0.15	0.878	-.6191067	.529444
4	-.0656701	.3076969	-0.21	0.831	-.6687449	.5374048
5	-.0819867	.3913119	-0.21	0.834	-.8489439	.6849705
6	-.1690951	.4281753	-0.39	0.693	-1.008303	.670113
environmental_awareness	-.3023218	.1164405	-2.60	0.009	-.530541	-.0741026
k_value	1.55773	1.07072	1.45	0.146	-.5408431	3.656303
c.Delivery_time_minutes#						
c.k_value	-.0934839	.0534958	-1.75	0.081	-.1983337	.0113658
c.e_bike_delivery#						
c.environmental_awareness	.5655163	.1563185	3.62	0.000	.2591377	.8718949
employment_status#c.Price						
2	.5271961	.2088426	2.52	0.012	.1178721	.9365201
3	.1892558	.1778386	1.06	0.287	-.1593015	.5378131
7	.803319	.5499644	1.46	0.144	-.2745913	1.881229
c.Freshness_days#c.gross_income	.002953	.0076604	0.39	0.700	-.0120611	.017967
c.e_bike_delivery#c.education	.2026517	.0812649	2.49	0.013	.0433755	.361928
_cons	13.14942	1.855197	7.09	0.000	9.513298	16.78554

Appendix 2.1: Complete results of the logistic regression (regression 3) which shows the effects of variables and interaction effects on the choice indicator for choice profiles, *=p<0,05, **=p<0,01, ***=p<0,001.