REGRET MINIMIZATION OR UTILITY MAXIMIZATION

Do contextual factors have any predictive value on when the Pure-Random Regret Minimization model structurally outperforms the Random Utility Maximization model?

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Abstract The Pure-Random Regret Minimization (PRRM) model forms a regret based counterpart to the Random Utility Maximization paradigm (RUM). Recent research indicates that contextual factors may provide predictive power on when the PRRM model structurally outperforms the RUM model. Therefore, the contextual factors under investigation in this research are taken from the studies of anticipated regret and consumer expertise, namely: Decision Time, Perceived Difficulty, Susceptibility to Interpersonal Influence, and Subjective Knowledge. The propensity of acting more along the lines of the PRRM model or more along the lines of the RUM model is calculated, and the results are captured in a binary variable (*n* PRRM = 37, *n* RUM = 187). This dependent variable is then analysed in respect to the four contextual factors. It is found that consumers with increased Decision Times are more likely to minimize regret ($P<0.05$), while consumers with a lot of Subjective Knowledge are more likely to maximize utility ($P<0.05$). However, the model explains between 4.6% and 7.8% of the variability, which is not enough to be able to have predictive value on structural outperformance.

Preface

As a student, my foremost interest lies in understanding human behaviour and in learning the possible application of this knowledge in order to nudge consumers in their behaviour. It was for this reason that I chose to follow the Marketing Master programme. I vividly remember one of the first lectures, which discussed the concept of the conjoint analysis. This lecture sparked my interest and motivated me to look into the most recent additions in the field of the conjoint analysis. When I read a paper titled RUM vs RRM, I was correctly assuming that the topic was not related to the popular Caribbean drink, but that instead it discussed the most popular decision-rule in the field of choice modelling, named RUM, as well as another new addition named RRM. This, more than anything, brought the pieces together for me, and I began to grasp the link between the study of human behaviour and the mathematical puzzle of the conjoint analysis. Due to the appeal of the latter, the RRM model, the decision to devote my Master's Thesis to the field of this paradigm was quite straightforward, which was a choice that I am happy to have made.

The process of writing this thesis was a lot longer than I had envisioned; at times it was a great challenge to keep myself motivated to work on this project, while at other times I thoroughly enjoyed learning how one thing was connected to the other, which allowed me to explore new skills like running programs in the Linux operating system. First and foremost, however, writing this thesis has taught me how much more there is still to learn, and how eager I am to further explore the field of data analysis.

I would like to thank my supervisor Dr. V.G. Hariharan for his patience and readiness to answer any questions I had, and providing me with guidance where needed. Additionally, I would like to thank C.Chorus and S. van Cranenburgh, both of whom are well known researchers in the field of RRM, who invited me to their office and gave me the opportunity to ask them any questions relating to their work on RRM. Lastly, I thank my parents who always supported my decisions and ensured that there was nothing in the way of finishing this project.

Prelude

Throughout this research paper 'the analyst' (this can be the choice modeller; researcher or whomever may use Discrete Choice Models) will be referred to as "she", while the decision-maker, consumer or respondent will be referred to as "he". This is done to ensure that no confusion within sentences arises and that a gender-neutral stance is taken.

1 Introduction

In the 1960s the introduction of the personal computer allowed researchers to run advanced mathematical models in order to capture highly sought-after insights in consumer behaviour. Marschak and Block (1960) were the first ones to provide a probabilistic representation of individual choice. McFadden extended their research by introducing a model to estimate the choices of a larger population (Batley, 2008; McFadden, 1975; Train, 2002). The model McFadden designed to capture choice behaviour was named the Discrete Choice Model, hereinafter referred to as DCM, which revolutionized the way data was interpreted as it was able to capture the choices and more importantly, the variations of choices within consumer groups.

Since its inception, the use of the DCM has widely grown in popularity. Nowadays it is a common tool in the fields of transportation (Morey et al, 1991; Boeri et al, 2014, Hensher et al, 2013), health economics (Ryan & Gerard, 2003; Lancsar & Louviere, 2008; Ryan et al, 2001), urban planning (Handy, 2002), marketing, labour, energy, and even environmental studies (Train, 2002). The scope of this paper links to the marketing domain, in which the DCM is applied to a variety of different subjects. Examples for its applicability are product line pricing (Allenby & Rossi, 1991), supporting market share calculations (Train, 2002), the impact of product introductions on consumer behaviour (Sammer & Wüstenhagen, 2006), forecasting consumer demand (Louviere & Hensher, 1983), measuring sensitivity to attributes such as brand, price, region, and awards (Lockshin et al, 2006), shopping destination and shopping channel selection (Oppewal et al, 2013; Timmermans et al, 1991), and many more. Its application has been so extensive, that in the year 2000, McFadden was awarded a Nobel Prize for his work (McFadden, 2000).

This thesis focusses on a critical feature of the DCM, namely the so-called decision-rule. The decision-rule determines the processing of the observed variables, which are the variables that the analyst chooses to include. The decision-rule is sometimes referred to as the "mathematical workhorse", as it is the computational foundation of the DCM.

Multiple decision-rules have arisen over the years, however the Random Utility Model (RUM) has remained the status quo option (Chorus, 2012; Kahneman & Tversky, 1979; Train, 2002;). It is built on the notion of utility theory, a concept that postulates that decision-makers are rational agents who aim to maximize their hedonic outcomes (Train, 2002). Another decision-rule that sparked considerable interest amongst choice modellers is the Random Regret Minimization model (RRM). The RRM model is built on the notion of anticipated regret (Chorus, 2008). It stands in direct contrast to the RUM model, as it does not postulate that decision-makers try to maximize their hedonic outcomes, but that decision makers instead try to minimize the regret that may arise from their decisions (Chorus, 2008). Even though this decision-rule is relatively new and not as popular, it does provide a behavioural counterpart to the RUM model, while being very similar in terms of the mathematical structure.

Existing research indicated that differences in the outcomes, when alternating between RUM and RRM, lead to different behavioural conclusions drawn from the analysis, due to e.g. relative changes in elasticities (Chorus et al, 2014; Hensher et al, 2013). Hensher et al (2013) report: "It is exactly those elasticities and associated choice probabilities that determine the responsiveness of individuals to changing circumstances, and they explain why specific segments of the population make alternative decisions. Moreover, this may cause diverging patterns in forecasting methods." Chorus et al (2014) provide a practical example using the data of a hybrid car manufacturer, and point to the discrepancies in the outcomes when alternating between RUM and RRM. They find: "in 26% of the cases the difference between the market share predicted by RRM and RUM was larger than 5 percentage points and in about 4% of the cases it was 10 percentage points or more. In about 7% of choice situations, the RRM and RUM model identified different car-types as the 'winner' in their choice set" (Chorus et al, 2014). This indicates that it is worthwhile to explore under which circumstances which model is most appropriate and has the best predictive power.

Given the discrepancies found in the existing literature it is clear that having a better indication as to when to use one model over the other is highly valuable. In a meta-analysis by Chorus et al (2014) 21 studies are summarized and compared. The aim of their study is "finding out to what extent, when and how RRM can form a viable addition to the consumer choice modeller's toolkit" (Chorus et al, 2014). Their findings are inconclusive, but it appears that surveys that host a more accessible type of topic are better explained using RUM, while more complex subjects have a better model fit with RRM (Chorus et al, 2014). These indications provide a starting point for answering the “when”- for which type of context- one of these choice paradigms structurally outperforms the other. In this thesis the Pure-Random Regret Minimization model (PRRM) will be used instead of the classical RRM model, as research results indicate that it brings out the strongest regret minimizing behaviour, since no rejoice is felt, and thus bigger differences are found when compared to RUM (Cranenburgh et al, 2015). A more in-depth discussion on the differences between these models is provided in co-chapter 2.6.

The aim of this thesis is to investigate whether certain contextual factors provide a guideline on when the choice modeller should favour the PRRM model over the RUM model, and thereby gain new insights into this previously unexplored subject. A guideline is sought by testing four hypotheses that each zoom in on one contextual factor. At the end of this thesis the predictive power of the model including the four contextual factors is taken into consideration, and variance analysis is used to indicate whether enough variability can be explained in order to be able to determine structural outperformance of PRRM over RUM.

The question that is central to this research therefore is: “Do contextual factors have any predictive value on when the Pure-Random Regret Minimization model structurally outperforms the Random Utility Maximization model?”

Instead of using a meta-analysis to find evidence for structural outperformance of one model over the other, in this paper a different approach will be taken. The Latent Class model of Boeri et al (2014) that permits heterogeneity in decision criteria serves as the building block in terms of the type of approach that is taken in this research. Heterogeneity in decision criteria is assumed by allowing the model to distinguish between different behaviourally classes: one including the sequence of choices of decision-makers that indicate they are more likely to minimize regret, while the other includes the sequences of choices from decision-makers that indicate that they are more likely to maximize utility (Boeri et al, 2014). In the literature, similar approaches that are based on separate Latent Classes are referred to as Probabilistic Decision Processes (Boeri et al., 2014; Hensher and Greene, 2010; Hess et al., 2012; Campbell et al., 2012).

The four contextual factors that are investigated in this paper, follow from the strong indications noted by Chorus et al (2014) and the theory on anticipated regret and consumer expertise. More specifically, differences are sought in terms of: (i) Perceived Difficulty, the degree of difficulty that one perceives when making a decision, (ii) Susceptibility to Interpersonal Influence, the extent that one is susceptible to the opinions of others, (iii) Subjective Knowledge - one of the sub dimensions of consumer expertise -, as well as (iv) the Decision Time, which is the time taken to make decisions as presented in the choice task. More elaboration on the reasoning for selecting these variables is provided in Chapter 2.

A multinomial choice set is used to capture the sequence of choices for the respondents. Based on these choice sequences class membership is derived and denoted as the dependent variable. The contextual factors are then used as the independent variables in a logistic regression in order to find potential correlation between these variables.

The remainder of this paper is structured as follows: Chapter 2 outlines the theoretical framework and presents the general workings of DCMs, reviews Utility and Regret theory, and further discusses the behavioural inclinations that follow from RUM and PRRM. The conceptual model, research question and hypotheses are introduced. Chapter 3 provides the research design including the construction of the choice tasks and the selection of the multi-item scales that capture the proposed contextual factors. In Chapter 4 the analysis of the data is performed, support for the hypotheses is evaluated, and conclusions are drawn. Chapter 5 includes a discussion of the research, its assumptions, and restrictions and makes suggestions for future research. Chapter 6 concludes.

2 Theoretical Framework

As outlined in the introduction, DCMs have gained popularity in the past decades and are applicable in numerous fields.

The next co-chapters will serve as a means to introduce how DCMs work. First, the different methods of gathering suitable data for running a DCM will be explained, focussing on stated preference methods. Second, a general illustration is made on how choice-designs are constructed. An introduction is made to explain how data is processed in terms of observed and unobserved preferences. For the latter, an elaboration on the relevant error term structure for this research paper is provided. Lastly, the equations for the decision-rules under investigation, RUM, RRM and PRRM, are presented and differences between them are noted.

2.1 Discrete Choice Models

A Discrete Choice Model is a model that describes choices made by respondents. The model takes into account what is chosen, and what is not chosen and puts numerical values on these choices. When the researcher specifies what sort of features a product is made up of, the so-called attributes and levels, the Discrete Choice Model is able to provide numerical estimates on these features. This information can be used to predict what the most important features are, but also to calculating things such as how much someone would be willing to pay to keep or omit a feature. To provide a basic understanding first the difference between alternatives, attributes and levels is explained.

An alternative is a choice option. When looking for a new mobile phone, the Apple IPhone 6S, the Samsung Galaxy S7 and any other mobile phone can be alternatives to be considered. However, because choice-designs in a research setting are of an experimental nature, non-existing model types are possible alternatives for the analyst that can be included in the choice-design as well.

A mobile phone is made-up of dozens of aspects; differences between mobile phones can be in screen size, GB of memory, colour, brand, material, and even the placement of buttons are variables that a consumer may take into account when choosing between alternatives. More so, it is possible to think of many other variables that can be taken into account. These variables are called the attributes of the product and they are of great importance. It is possible to take an even closer look at the properties of these attributes. If one can choose between a 5”, 5.5” and a 6” screen, then the attribute ‘screen size’ holds three levels. If all phones are in black or silver, then the attribute ‘colour’ holds two levels.

2.1.1 Stated and revealed preference data collection methods

Research methods in the field of consumer behaviour are generally divided into two methods: revealed preference and stated preference.

The idea of revealed preference was founded by Samuelson (1938) when he famously stated “… if an individual selects batch one over two, he does not at the same time select two over one.”

Even though this may seem rather straightforward, its mathematical implications were clearly depicted in his work and provided the academic foundation for further research into best practices. When enough choices of decision-makers are observed, it becomes possible to estimate average probabilities of someone choosing one option over the other. To be more specific, it becomes possible to estimate the amount of influence attributes have on the consumer's choices and even as to how much someone would be willing to spend to keep or omit a feature. In summary, revealed preference methods refers to the method of discovering preferences by observing consumers make choices in an experimental or real life setting. Contrarily, stated preference methods refer to the collection of data from predetermined item-lists, e.g. survey items. One of the advantages of using a stated preference design is that it allows the researcher to test for products or attributes that do not yet exist, or are not yet available, but can rather be envisioned by the respondent (Adamowicz, 1994). Furthermore, it provides a quick way of gathering data. Aside from the aforementioned use of DCMs in market share calculations, consumer demand forecasts, attribute sensitivity measurements, researchers also use stated preference information to improve prediction of scanner- based choice models (Horksy et al, 2004; Shin et al, 2012). Due to the fact that a survey is used to elicit preferences, the stated preference methods are applicable for this research.

2.1.2 Constructing the choice set

When constructing a stated preference design the analyst chooses the attributes and levels that are relevant for the product or service that is investigated. She needs to abide by some assumptions in order for the DCM to work as intended. Train (2002) clarifies the assumptions that each alternative must meet:

1. Exhaustive: all other possible alternatives are included in the choice set.
2. Mutually exclusive: choosing one alternative implies not choosing any of the other alternatives.
3. Finite alternatives: the analyst can count the alternatives and eventually be finished counting.

When the analyst abides by these rules and knows which attributes and levels are relevant for her research, the choice set can be constructed. This is generally done by using a tool that uses the attributes and levels as inputs to generate the maximum amount of possible alternatives. With just a few attributes and levels involved, dozens or even hundreds of alternatives can be constructed[1]. Subsequently the alternatives are to be presented to the respondent for him to

[1] A product with 4 attributes each with three levels accounts for 3^4 = 81 possible choice alternatives.

indicate his preference for each alternative, which would pose an enormous task due to the high number of generated alternatives. Respondent fatigue would very likely affect the preference indication, as an extremely high time and attention span of the respondent would be required. Therefore, generally, an orthogonal or other design is used[2]. This significantly reduces the amount of choice tasks, so that each respondent needs to complete only a limited amount of tasks, while still ensuring that the data on the estimated values of the attributes is reliable. When the choice-design is constructed and tested, respondents are gathered and presented with multiple questions. Each question provides a few alternatives from which they have to choose the alternative that best suits their preference.

Once the respondents have indicated their preferences, the analyst has gathered the so-called observed choices. Having obtained and observed the respondents' choices, it becomes possible to estimate the weights that decision-makers attach to each of these attributes and levels.
In turn, when the observed weights are known, it becomes possible to estimate choice probabilities and other aggregate-level predictions (Train, 2002). It is important to note that these findings are in fact estimates; the unobserved variables that influence the decision-makers' choice are accounted for in the assumed error term structure. The unobserved part thus accounts for all of the attributes and levels, that are not taken into account by the analyst, but are taken into account by the decision-maker. The error term represents the fact that the analyst cannot account for all possible underlying factors and consequently represents the part of the decision-makers' behaviour that remains unobserved (Chorus, 2012).

2.1.3 Purpose of decision-rules

The decision-processes that underlie the decision-making are extremely complex and are assumed to vary per choice setting. DCMs are used to guide the analyst through this complexity and provide a practical tool to estimate choices (Chorus, 2012). This is done by assuming a decision-rule, which aims to represent the way that decision-makers go about making their choices (Chorus, 2012).
As mentioned earlier, most DCMs are built on the notion of the so-called utility maximization decision rule. DCMs that employ this decision rule are generally referred to as Random Utility

[2] The interested reader is pointed towards literature on orthogonal, D-Efficient and full factorial designs.

Maximization models (RUM)[3].

The reason that the RUM model has gained such popularity is because it is derived from and linked to the vast foundation of utility theory. It is the first decision-rule that has been widely used and is coherent with many micro-economical axioms (Chorus, 2012; Mas Colell et al, 1995). Furthermore, its intuitiveness makes it easy to use for practitioners and academics alike (Chorus, 2012).

2.2 Utility Theory

This chapter will depict a brief overview of the relevant utility theory that is postulated to underlie the RUM model. Furthermore, an introduction will be made of the axioms that underlie this behavioural inclination.

The Utility Maximization paradigm stems from utility theory, a concept that postulates that consumers are rational economic agents that make accurate and unbiased forecasts of the hedonic outcomes of potential choices (Kahneman, 2006). Consumers are expected to know their preferences and attach weights to each of them accordingly in order to assess the option that maximizes their preferences. Despite the fact that utility theory assumes consumers are able to attach monetary values to the variety of feelings a choice may invoke, in terms of its mathematical usability, a more generally derived term is required. This is where the term 'utility' stems from.

Utility is a term widely used in economics and in short can be said to capture difficult constructs of thoughts, such as happiness, pleasantness and benefit. Train (2002) defines utility as the measurement of well-being. He notes that it can hold both a positive and negative parameter, but it has no natural level or scale (Train, 2002). Utility serves as a construct that allows the researcher to put numerical values on consumers' preferences (Kahneman, 2006; Train, 2002). Once numerical values are attached to the weights of observed variables, a utility function can be made to represent the cumulative preferences.

Before being able to construct a utility function, general assumptions need to be made about people's preferences. John von Neumann and Oskar Morgenstern proposed several assumptions when they published their book in 1944: 'Theory of Games and Economic Behaviour'. They

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[3] Specifically, to this paper: the linear-additive RUM-based multinomial logit model.

showed that as long as the preference axioms hold, a utility function exists. The axioms that they depicted in their work were the Completeness, Transitivity, Continuity, Monotonicity and Substitution axioms[4]. The first two axioms are the most important for this research paper as they embody the hypothesis of rationality (Mas-Colell et al, 1995).

1. Completeness: For lotteries A and B, we have either $A \geq B$ or $B \geq A$. This means that people are assumed to be able to rank their preferences of the lotteries (alternatives).

2. Transitivity: If lottery A is preferred over lottery B, and lottery B is preferred over lottery C. Then lottery A is also preferred over lottery C. $A > B$, $B > C$, then $A > C$

2.2.1 How violations of one model may be the fundament of others

When predicting choice behaviour, the bounds of rationality are often crossed. These crossings are referred to as deviations, or violations of rational behaviour. The terms often used in literature for examples of deviations from rational behaviour are paradoxes or biases (Allais, 1953; Bell, 1982). Over the years, many of these paradoxes and biases have been widely discussed in the literature (Allais, 1953; Ellsberg, 1961). One of the first paradoxes to be widely documented is the Allais paradox (Allais, 1953).

The Allais paradox shows that a majority of people prefer to take a 10% chance of receiving $5 million over an 11% chance of receiving $1 million. However, when presented with a different situation for which they are asked whether they would prefer to select a prize of receiving $1 million for certain, rather than taking a gamble for a 10% chance of receiving $5 million and a 89% chance of receiving $1 million and 1% chance of receiving nothing, a majority of people choose the safe option that gives $1 million for certain.

[4] The explanations of the latter three axioms are left out, as they are rather complex and irrelevant to this paper. The interested reader is pointed towards the work of Von Neumann and Morgenstern, 1944.

The average pay-outs are denoted below.

$(A)\qquad (P = 0.1\ €5{,}000{,}000\ P = 0.9\ €0\ ) \quad = €500{,}000$

$(P = 0.11\ €1{,}000{,}000\ P = 0.89\ €0\ ) \quad = \ €110{,}000$

$(B)\qquad (P = 1\ €1{,}000{,}000) \qquad = €1{,}000{,}000$

$(P = 0.1\ €1{,}000{,}000\ P = 0.89\ €5{,}000{,}000\ P = \ 0.01\ 0\ ) \quad = €1{,}390{,}000$

One can quickly see that in the first situation (A) people indeed took the option yielding the highest average pay out (500,000 vs 110,000) while in the second situation (B) people chose the option that does not yield the highest average pay outs (1,390,000 vs 1,000,000). This may seem counterintuitive at first, but can be explained by the fear of not having any pay-out ($0), versus a $1,000,000 dollar guaranteed pay-out. The risk of the potential regret is too great and thus people are willing to settle for a smaller average pay-out (Bell, 1982; Loomes & Sugden, 1982)

The Allais paradox is one of many examples that shows that in some cases deviations of classical utility theory exist. Like this example, many more deviations from these principles are presented in the literature; The Ellsberg paradox and the compromise effect are prominent examples (Ellsberg, 1961; Kahneman, 1979). The findings of these deviations gave rise to Prospect Theory, Regret Theory and other behavioural paradigms with the aim of better understanding consumer choice (Bell, 1982; Kahneman & Tversky, 1979).

Bell (1982) hypothesizes that the violations of axioms as such may be caused by decision-makers trying to avoid the consequences of making the wrong decision. He proposes that the systematic deviation of the axioms are not simply paradoxes, or failures of the consumers to comprehend the confines of the choice set, but instead provide rudimentary evidence towards the notion that some consumers take anticipated regret into account when choosing, and that the type of decision-heuristic one uses varies (Bell, 1982). He was one of the first to write on the properties of decisional regret, especially under uncertainty, and his work was received with great attention. The experience of regret is one that people highly prefer to avoid and it comes with no surprise that the wish to undo a certain situation serves as both a learning effect and motivator for avoidance behaviour in the future (Saffrey et al, 2008). Therefore, one may also assume that when choice alternatives are evaluated, some evidence of this regret minimizing behaviour should be detectable in the choices made, leading to significantly different behaviour patterns than expected of those following the rules of utility theory (Boeri et al, 2014).

Over the past decades, many articles emerged on this topic. In marketing literature, these can be divided into two types of categories (Chorus et al, 2014). The first category contains bodies of work that mostly exist of conceptual models, which aim to test the applicability and grounds of anticipated regret in various situations. The models are tested by means of experiments or questionnaires (Simonson, 1992; Spears, 2006; Taylor, 1997). Another body of work forms a more formal approach, as it proposes mathematical models that are usually based on the early work of Bell from 1982. Two examples of proposed mathematical models are 'Regret Theory' and 'Random Regret Minimization'. Regret Theory is first described in 1997 by Inman et al in their paper "A Generalized Utility Model of Disappointment and Regret Effects". The model they propose is the most often cited in the marketing literature (Bleichrodt et al, 2010; Chen & Jia; 2012; Inman et al, 1997).

A more recent approach, the Random Regret Minimization (RRM) model, on the other hand is postulated by Chorus et al (2008). The RRM model provides a robust addition in terms of the available mathematical workhorses of the Discrete Choice Model. This paper takes particular interest in this recent addition, the so-called Random Regret Minimization model (RRM). This regret-based decision-rule model is based on the notion that when people make choices they aim to minimize anticipated regret rather than maximizing utility (Chorus, 2012). This notion is behaviourally very well established and will be further elaborated in co-chapter 2.5.

At this point it should be noted that the "Generalized Utility Model of Disappointment and Regret" by Inman et al (1997) or other regret minimization models for that matter are not under review in this paper. The reasons for this are related to applicability and contrast. When comparing between two objects it is favourable to keep as many variables equal. Due to the fact the properties of the RRM model are highly similar to the RUM model, it is perceived to be the optimal regret minimization model to be compared to RUM. The RRM model is, just like the RUM model, applicable to non-risky choice situations, while other regret minimization models such as the "Generalized Utility Model of Disappointment and Regret"-model are applicable specifically to risky situations under uncertainty (Chorus et al, 2014). Furthermore, when comparing the mathematical makeup and properties of the RUM decision-rule to the RRM decision-rule, it becomes apparent that there are only minor deviations. See co-chapters 2.3 for further explanations on RUM and 2.4 for RRM.

2.3 Random Utility Maximization

For the research conducted as part of this paper the linear-additive Random Utility maximization model is utilized. A linear model is assumed, in which the observed utility has a linear dependence on the summation of the predictor variables (Chorus, 2012). The predictor variables in this case are the attributes and levels. The model thus suggests that before making his choice, the decision-maker first computes the utility he believes each alternative to represent, and subsequently chooses the option that yields the highest utility (Chorus, 2012).

In the term Random Utility Maximization, 'Random' is added to signal the stochastic properties of the assumed error term to capture the unobserved characteristics (Chorus, 2012). See co-chapter 2.6 for elaboration on the specific properties of the error term that is relevant to the model being used.

The RUM model is defined by the following equation (Eq. 1):

$$U_i = V_i + \varepsilon_i = \sum_{\mathrm{m}} \beta_m * X_{im} + \varepsilon_i \tag{1}$$

U_i denotes the total observed and unobserved utility from alternative *i*.

V_i denotes the total observed utility from alternative *i*.

ε_i denotes the error term structure, unobserved utility, assumed for alternative *i*.

β_m denotes the taste parameter to be estimated that is associated with χim.

X_{im} denotes the value of the attribute χm for alternative *i*

2.4 Classical Random Regret Minimization

The classical RRM model is slightly different from the RUM model, and is defined by the following equation (Eq.2).

$$RR_i = R_i + \varepsilon_i = \sum_{j \neq i} \sum_m \ln\left(1 + \exp\left[\beta_m * \left(X_{jm} - X_{im}\right)\right]\right) + \varepsilon_i \qquad (2)$$

RR_i denotes the total observed and unobserved regret from alternative *i*.

R_i denotes the total observed utility from alternative *i*.

ε_i denotes the error term structure, unobserved utility, assumed for alternative *i*.

β_m denotes the taste parameter to be estimated that is associated with χjm.

X_{jm} denotes the value of the attribute χm for alternative *i*.

There are several important properties to note about the classical RRM equation (Eq.2): the parameter β_m depends on the differences between the values of the attributes *i* and *j* (Eq. 2.1).

$$\beta_m * (X_{jm} - X_{im}) \qquad (2.1)$$

This implies that the model postulates that decision-makers compare attributes between alternatives during the decision-making process (Chorus, 2012). When the value of an attribute *m* of alternative *i* performs worse than the value of that attribute for alternative *j* it is assumed (partial) regret is anticipated. In most choice situations, consumers find that differences between product alternatives lie relatively close to each other. Because of this, it often occurs that sacrifices have to be made on the attribute level, which means that regret is often felt. Contrary to feelings of regret, the RRM model also allows for feelings of rejoice (Chorus, 2008). Mathematically this is done by taking the opposite of regret. When an attribute *m* in alternative *i* is superior to that of another alternative *j*, a feeling of rejoice is felt by the decision-maker.

The natural logarithm of this function is taken, is taken as this smoothens the regret curve, thus making it statistically sound and easier to compute[5] (Chorus, 2014). This is seen in Eq.2.2.

$$ln(1 + exp[\beta_m * (X_{jm} - X_{im})]) \tag{2.2}$$

2.5 Pure-Random Regret Minimization

The PRRM model works slightly different than the classical RRM model and is defined by the following equation (Eq.3):

$$R_i^{P-RRM} = \sum_m \beta_m \chi_{im}^{P-RRM} \tag{3}$$

$$where\ \chi_{im}^{P-RRM} = \begin{bmatrix} \sum_{j \neq i} Max(0, \chi_{jm-}\ \chi_{im}) & If\ \beta_m > 0 \\ \sum_{j \neq i} Min(0, \chi_{jm-}\ \chi_{im}) & If\ \beta_m < 0 \end{bmatrix} \tag{3.1}$$

R_i^{P-RRM}	denotes the total observed and unobserved regret from alternative *i*.
β_m	denotes the taste parameter to be estimated that is associated with χjm.
X_{jm}	denotes the value of the attribute χm for alternative *i*.

The PRRM model postulates that when decision-makers choose, they compare the alternatives on all relevant attributes and choose the one minimizing regret. The PRRM model functions quite similarly as the Classical RRM model, however an important aspect that is added are the maximum and minimum-operators. The maximum and minimum-operators that are part of the so-called attribute-level-regret function (Eq.3.1) guarantee that only positive signs enter the equation, and thus no rejoice is considered. For example, when price is an attribute the sign of the $\beta_m$parameter is expected to be a minus[6]. However, when the level of an attribute denoted as χ_{jm} outperforms the chosen attribute's level χ_{im} the minimum-operator ensures that the value zero is used in the equation. This indicates that no rejoice is felt for choosing an alternative that is cheaper than another alternative. The opposite holds true for an attribute β_m with a

[5] The interested reader is pointed towards the work of Chorus (2014) where the rationale behind adding a natural logarithm to the regret function is explained.

[6] Under normal circumstances, a lower price for an otherwise equal product is always preferred.

positive sign. For this reason, it is said that the PRRM model brings out the strongest regret minimizing behaviour possible within the RRM framework, and within the context of this model no rejoice is experienced (Cranenburgh et al, 2015).

In this paper, the PRRM model is used for comparison with the RUM model. Van Cranenburgh et al (2015) report that differences in terms of model fit between PRRM and RUM models are generally larger compared to differences between RUM and classical RRM. So, the PRRM model can be expected to yield a clearer distinction in the differences between the utility maximization and regret minimization paradigms (Cranenburgh et al, 2015). The assumed error term that is relevant for the PRRM model is presented in the following co-chapter.

2.6 Error term structure

The purpose of the error term is to account for all of the unobserved variables that influence the decision-makers' decision. The unobserved part thus accounts for all of the attributes, and levels of attributes, that are not taken into account by the analyst, but are taken into account by the decision-maker. The error term represents the fact that the analyst cannot account for all possible underlying factors and consequently represents the part of the decision-makers' behaviour that remains unobserved (Chorus, 2012).

In this paper, when referring to the use of a DCM, the multinomial logit model is assumed. The error term structure that is most often used in this context is the independent and identically distributed (i.i.d) random error with an Extreme Value Type-I distribution, which constitutes a variance of $\frac{\pi^2}{6}$ (McFadden, 1974). The aim of a random error is to represent unobserved heterogeneity in regret or utility that is derived from one of the following factors: measurement error, omission of relevant attributes, and random behaviour by respondents (Chorus, 2010). In layman terms, the error term accounts for the fact that some decision-makers act randomly and/or have varying tastes, and the fact that researchers sometimes do not include the relevant attributes in the choice set (Chorus, 2012).

The i.i.d random error term structure is often chosen as it is parsimonious and requires less computational time than other error term structures (McFadden, 2000). In line with what is often chosen in the literature, the i.i.d Extreme-value Type-I error term structure is chosen for both the RUM as the PRRM model. This error term allows for a closed-form formulation of choice probabilities. Since both equations are similar, this allows for an easy comparison between the models.

See equation 4 and 5 for the closed-form formulation of choice probabilities.

$$\begin{aligned} P(i) \quad &= P\left(U_i > \ U_{j,} \ \forall j \neq i\right) && (4) \\ &= P(V_i + \varepsilon_i > V_j + \varepsilon_{j,} \forall j \neq i) \\ &= \frac{\exp(V_i)}{\sum_{j=1..J} \exp(V_j)} \end{aligned}$$

A similar closed-form formulation is found for the PRRM model (Chorus, 2012; Cranenburgh, 2015).

$$\begin{aligned} P(i) \quad &= P\left(RR_i < RR_j, \forall j \neq i\right) && (5) \\ &= P\left(-RR_i > -RR_j, \forall j \neq i\right) \\ &= P\left(-(R_i + \varepsilon_i) > -\left(R_j + \varepsilon_i\right), \forall j \neq i\right) \\ &= P\left(-R_i - \varepsilon_i > -R_j - \varepsilon_j, \forall j \neq i\right) \\ &= \frac{\exp(-R_i)}{\sum_{j=1\ldots J} \exp(-R_j)} \end{aligned}$$

2.7 Regret theory

The natural tendency to anticipate and consider regret, consciously and unconsciously, when making a decision is presumably accounted for in the RRM and PRRM model (Chorus, 2014). This is in contrast with the behavioural beliefs upon which the RUM model is built. Therefore, this thesis leans towards the work of anticipated regret to find contextual factors that underlie the arousal of anticipated regret, and thus serve as clues to when one model should structurally outperform the other. Since DCMs aim to capture consumer choice behaviour, this paper also looks for relevant contextual factors in the theory of consumer expertise.

In the following co-chapter, the term 'regret' will be defined and a division between anticipatory and counterfactual regret is made. At the end of the chapter the proposed hypothesis as well as the conceptual framework will be introduced.

2.7.1 Introduction to regret

A person makes hundreds of decisions a day; some decisions are small, sometimes so small we hardly notice them. Think of setting your alarm or choosing between ordering a cup of coffee or tea. Other decisions may be influential decisions that require more time and attention before coming to a conclusion. This could be the case when the decision involves larger sums of money, time, or when choices have long-term implications; examples are purchasing a car, buying goods with a down payment, and purchasing insurance policies. The difference in the way we handle these decisions is (co-)determined by the risk they carry, the risk of regret (Chorus et al, 2014).

An important distinction in the study of regret has to be made. When speaking of regret, one usually thinks of counterfactual regret. The term counterfactual means "contrary to the fact". In psychology, this term is often used to describe the pattern of thinking where one takes a factual situation (e.g. a car crash), imagines an antecedent (e.g. if I had insurance) and alters this antecedent to assess the outcome (Roese & Olsen, 1995).

The learning effects that occur from the wish to avoid counterfactual regret in the future contribute to feelings of anticipated regret. Therefore, as a starting point, an elaboration on counterfactual regret will be given in the next paragraph.

When people reflect on their choices and benchmark their current situation with the situation they could have been in, an unpleasant feeling may arise that is called counterfactual regret (Coricelli et al, 2005). The feeling of self-blame and the wishes to undo the causes of the current situation best describe regret (Zeelenberg & Pieters, 2007). It is a counterfactual emotion resulting from thinking about what could have been (Kahneman & Miller, 1986). A counterfactual emotion is different from primal emotions, such as anger or happiness, as it is an emotion that does not come with birth, or is seen in animals, but instead is developed during childhood (roughly at the age of seven). This is because it requires higher order cognitive processes (Guttentag & Ferrell, 2004). Furthermore, there is no clear facial expression for regret; "regrets are universal; nearly everyone has them. Regret transcends age, gender, race, culture, nationality, religion, language, social status and geographic location" (Cadish 2001, as in Zeelenberg 2007).

What makes regret stand out from other emotions is the fact that it is unavoidable and occurs frequently. Its inevitability is captured in the words of Kierkegaard (1843): *"I see it all perfectly; there are two possible situations - one can either do this or that. My honest opinion and my friendly advice is this: do it or do not do it - you will regret both*". One can experience regret from making decisions, or from failing to make decisions. It is said to be the only emotion that is always caused by choice. A study by Saffrey et al (2008) tested the perception of a range of 12 negative emotions, namely: regret, guilt, sadness, disappointment, shame, fear, frustration, anxiety, disgust, anger, boredom and jealousy. Respondents indicated regret as the most often felt and the most intense of all negative emotions. Simultaneously, "regret was seen to be the most beneficial of 12 negative emotions on five functions, namely: making sense of past experiences, facilitating approach behaviours, facilitating avoidance behaviours, gaining insights into the self, and in preserving social harmony" (Saffrey et al., 2008). Regret is thus indicated by respondents as the most useful emotion to help improve decision making in the long-term and has often been under review in a consumer behaviour setting since the 1990s. This has led to a more widespread acceptance of the influence of regret on the decision making process (Zeelenberg, 2007).

Approach and avoidance behaviours are one of the learning effects that may steer decisions in the future. One learn from their mistakes and in some situations this may even alter the thought process that leads up to the decision-making itself. The learning effects that may ensue from the impact of counterfactual regret may lead to more cautious behaviour in the future. Caution in turn increases the time taken to make a decision, as one will more thoroughly evaluate the available options. Taking more time allows for more feelings of anticipated regret to arise (Tochkov, 2007).

It is noted that counterfactual and anticipated regret are linked in this way. One may lead to the other. The roles and functions of anticipated regret will be outlined in the next co-chapters as they are postulated to underlie the regret minimization paradigm.

2.7.2 Introduction to anticipated regret

Contrary to the backwards approach of counterfactual thinking, the forward approach entails prefactual thinking. Prefactual thinking describes a cognitive strategy, in which people imagine possible outcomes of a future scenario. For example: *what if I buy this car for the full price now, but find it for sale later?* Anticipated regret is the type of regret that takes place prior to concluding a decision, and is therefore of a so-called prefactual nature.

In this study the term ‘anticipated regret’ will be characterized as a prefactual thought that gives rise to perceptions of risk associated with, and actively influencing, decision making.

In a preliminary study by McConnell et al (2000) it was demonstrated that consumers often produce prefactuals when considering a major purchase. Even though this effect were to be expected, their study provides elementary support for the notion that anticipated regret comes to mind spontaneously and does not have to be prompted.

It is important to shed light on the conditions that increase the likeliness of anticipated regret to occur. In the words of Janis and Mann (1977) “arousal of anticipatory regret, a major precondition for the coping pattern of vigilance, has the constructive effect of deterring a person from indiscriminately seizing upon a seemingly attractive opportunity without forethought about the consequences”. They describe anticipated regret as an instinctive mental tool, of which its purpose is to support well-weighed decision-making. The influence of anticipated regret is well illustrated in the following example (Simonson, 1992): *“When searching for a name on a list, it is reasonable to assume that starting at the beginning rather than at the end of the list is seen as the default option. Consequently, an individual who decided to start at the end and finally found the name at the beginning of the list would be expected to feel greater regret and be more upset with the search strategy than one who started at the beginning and found the name at the end of the list.”* The example illustrates that when the default option is known to the decision maker it is likely to be taken into account when deciding. Even though the starting point for searching a name on a list should not matter in a probabilistic and rational manner, it can easily be imagined that it is odd to deviate from the default option. Divergence from the default option would expose the decision-maker to additional risk of regret, which is a negative emotion and is preferably avoided, thus the default option directs the decision maker in his choices. This effect was found by prompting participants to think about the regret that their choice could produce when found out later that the wrong decision had been made. A control group was used to compare outcomes of decisions, and a significant impact of anticipated regret was found, which was believed to account for the deviations in choice outcomes. (Simonson, 1992; White et al., 2007; Hetts et al., 2000). It was found that consumers who have feelings of anticipated regret more often make their decisions in congruence with a regret minimizing, or avoidance strategy. To be specific, Simonson (1992) found that consumers who note the presence of anticipated regret prefer to choose the status quo. An example would be a more highly priced familiar brand versus a cheaper generic product. They also prefer to not make a decision at all in order to avoid the risk of regret from making the wrong choice (White et al., 2007) and pay an insurance fee to negate the risks of regret (Hetts et al., 2000).

2.7.3 Conditions to arouse anticipated regret

On the account of their interviewees, Janis and Mann (1977) formulated five conditions that correspond to the induction of anticipated regret.

The first condition that relates to the arousal of anticipated regret is that "*the most preferred choice is not necessarily superior to another alternative"*. One can imagine that when a product performs better on all attributes than another product, it is a lot easier to be rational about the choice. The risk of regret becomes less probable. This also means that when no clear monotonic preferences between choice alternatives or attributes are present, the chances of choosing a suboptimal option increases. The idea behind this first message is that when it is difficult to be rational about the choice at hand, people will compare alternatives more thoroughly which makes them more watchful, thus allowing for feelings of anticipated regret to arise (Sugden, 1985; Zeelenberg, 1999). The process of reaching a decision thus takes longer to complete (Janis & Mann, 1977; Tochkov, 2007). This serves as the basis for the first two hypotheses.

Hypothesis (1): Consumers who take more time to decide are more likely to choose in line with the Pure-Random Regret Minimization model than with the Random Utility Maximization model.

When one option is a lot better than another option, the choice becomes easy to make. When in the future one finds out that the wrong choice was made, there is less self-recrimination than when the choice was difficult to make (Sugden, 1985; Zeelenberg & Pieters, 2007). Inversely, it can be extrapolated that when making a choice is difficult it becomes more probable that it will give rise to feelings of anticipated regret (Sugden, 1985). A similar observation was made by Chorus et al (2014) who note that it appears that surveys that host a more accessible type of subject are better explained using RUM, while more complex subjects have a better model fit with RRM (Chorus et al., 2014). It is therefore hypothesized that:

Hypothesis (2): Consumers who perceive decision-making as difficult are more likely to choose in line with the Pure-Random Regret Minimization model than with the Random Utility Maximization model.

The second condition that relates to the arousal of anticipated regret is that "*the negative consequences that might ensue from the decision could start to materialize almost immediately* *after the decision is made".* The effects more or less relate to the innate function of the choice at hand. Loewenstein & Prelec (1992) found that people have the tendency to discount the outcomes of their choices when they are further away in the future. Their findings appear to also link to how people deal with regret. Richard et al (1996) provide a practical example of this link. In a campaign that aims to reduce the spread of HIV, they find that promoting unpleasant affective states, such as worry and regret, rather than promoting the consequences of attracting HIV, are more likely to make people do what is necessary to avoid sexually risky behaviour. The rationale behind this is that the chance of attracting HIV is seen as unlikely, in any case too small to be taken into serious consideration, and therefore likely to be discounted. To the contrary, feelings of worry and regret are easier to imagine and more likely to occur straight after intercourse. The awareness that an action can have immediate negative consequences is determinative of the presence of anticipated regret (Zeelenberg, 1999).

The third and fourth condition of Janis and Mann (1977) dictate that, *"significant persons in the decision maker's social network view the decision as important and will expect him to adhere to it"* and *"significant persons in the decision maker's social network who are interested in this particular decision are not impatient about his current state of indecision and expect him to delay action until he has evaluated the alternatives carefully".* Anticipated regret arises when the decision maker is not put under time pressure by his social peers. Instead, a different type of social pressure should be present that communicates that the decision makers is expected to think carefully about the decision, and which allows for sufficient time to be taken to assess the necessary information and make a well-considered choice.

In line with Janis and Mann (1977), Zeelenberg and Pieters (2007) propose that when the outcome of the decision is perceived as important by significant others in the network of the decision-maker, a failure to select the correct alternative will lead to more intense regret. This anticipation in turn leads to more anticipated regret when deciding. It logically follows that interpersonal communication is a strong determinant of choice behaviour. However, some individuals may find themselves more likely than others to be influenced by interpersonal influences (Bearden et al., 1989; McGuire, 1968). It is thus expected that decision makers who are more susceptible to the opinion of others choose more in line with the RRM paradigm than the RUM paradigm. Hence, the third hypothesis is that:

Hypothesis (3): Consumers who are susceptible to interpersonal influence are more likely to choose in line with the Pure-Random Regret Minimization model than with the Random

Utility Maximization model.

Janis and Mann's fifth condition is regarding the receipt of new information: *"new information concerning potential gains and losses can be obtained".* This condition consists of two parts. Firstly, by searching for more (new) information, hope is fostered to find a better alternative. The consumer may feel that if he makes his choice prematurely, he misses future opportunities that may yield better results. Secondly, the availability of (new) information can induce risk-seeking and risk-aversive behaviour. This is supported by a study of Zeelenberg et al (1999), in which respondents had to choose between two options of financial stock. Respondents were divided into two groups: group A was offered to learn the outcome of the safe option if chosen, and group B was offered to learn the outcome of the risky option if chosen. A pattern was found that indicated that participants preferred the option that disclosed the outcome. Not only supporting the notion of Janis and Mann's fifth condition, but also demonstrating that regret-aversion can induce risk-seeking and risk-aversive behaviour.

Contrary to the average decision-maker, experts are well versed with the presented problem and are assumed to be able to make their choices in a more rational manner. One can imagine that expertise with the subject at hand allows the decision-maker to use better judgement, consider more (relevant) variables and have fewer feelings of doubt (Brucks, 1985). It is therefore expected that decision-makers that have some form of expertise are less likely to anticipate feelings of regret. Consumer expertise is therefore selected as the fourth contextual factor that will be investigated.

Consumer knowledge is divided into three main categories as defined by Brucks (1985). Brucks states that a distinction needs to be made between 'objective knowledge', meaning what there is to know and how much a consumer knows and 'Subjective Knowledge', meaning how much the consumer thinks he knows and 'prior experience with the product category' (Brucks, 1985). Her findings are later used to build on by Alba & Hutchinson (1987) who further elaborate on these constructs, and are the first to form a basis for this field of research. They propose that consumer knowledge is based on the notion of consumer familiarity and consumer expertise, each with its own sub-dimensions (Alba & Hutchinson, 1987). Brucks (1985) has shown that objective knowledge positively affects the number of attributes considered by an information-searching consumer, while Subjective Knowledge has been shown to be a stronger motivation of purchase-related behaviour than objective knowledge (Selnes and Gronhaug, 1986). Consumer knowledge as a whole is interesting for the research in this thesis, but Subjective

Knowledge seems to be the best-suited sub-dimension in terms of empirical support and feasibility in the research design. The latter is supported by Park et al (1994) who propose how to measure objective knowledge. In their paper, they state that it is not an easy feat; one must make a uniquely tailored item scale for the subject under consideration, and then assess how well experts score on a test using this scale. This is then used as a benchmark when testing novices. This is a process that is seen as difficult to implement. On the other hand, Subjective Knowledge is a very interesting sub-dimension, which is rather easy to investigate, since it is self-assessed. In their research, Park et al (1994) note that respondents generally score higher on subjective item scales when they are confident by nature. Brucks (1985) found that Subjective Knowledge influences the selection of search strategies. For example, people who have a lot of Subjective Knowledge give recommendations of sales personnel less importance. This cannot be expected of a regret minimizing decision-maker; it is expected that such a person puts a lot of weight into advice given by sales personnel or expert. Brucks (1985) findings seem to suggest that decision-makers that have a lot of Subjective Knowledge feel that they know what they are looking for and are more likely to be utility-maximizing. Boeri et al (2014) make a similar preliminary finding; they indicate that decision-makers that are unfamiliar with the choice context are more likely to be regret minimizers than utility maximizers (Boeri et al, 2014). Therefore, it is hypothesized that:

Hypothesis (4): Consumers who have a lot of Subjective Knowledge are less likely to choose in line with the Pure-Random Regret Minimization model than with the Random Utility Maximization model.

Lastly, Bettman & Park's (1980) findings suggest that decision-makers with moderate knowledge and experience tend to spend more time on processing available information (Bettman & Park, 1980). Park & Lessig (1981) find that the group of decision-makers marked as the "low-familiarity" group required the longest time to make a decision. These findings are in congruence with hypothesis (1) that states that decision-makers who spend more time concluding their decision act more along the lines of Random Regret Minimization model than with the Random Utility Maximization model. Research suggests that the way that information processing works is markedly different for subjective and objective knowledge (Bettman & Park, 1980; Brucks, 1985; Mazundar & Monroe, 1992; Park and Lessig, 1981). It has been shown that what people think they know often does not correspond to what they actually know. For this reason, it cannot be empirically assumed that the Subjective Knowledge variable moderates the relation between Decision Time and decision-heuristic (PRRM or RUM).

In summary, the hypothesis and research question are presented below.

Research question: Do contextual factors have any predictive value on when the Pure-Random Regret Minimization model structurally outperforms the Random Utility Maximization model?

Hypothesis (1): Consumers who take more time to decide are more likely to choose in line with the Pure-Random Regret Minimization model than with the Random Utility Maximization model.

Hypothesis (2): Consumers who perceive decision-making as difficult are more likely to choose in line with the Pure-Random Regret Minimization model than with the Random Utility Maximization model.

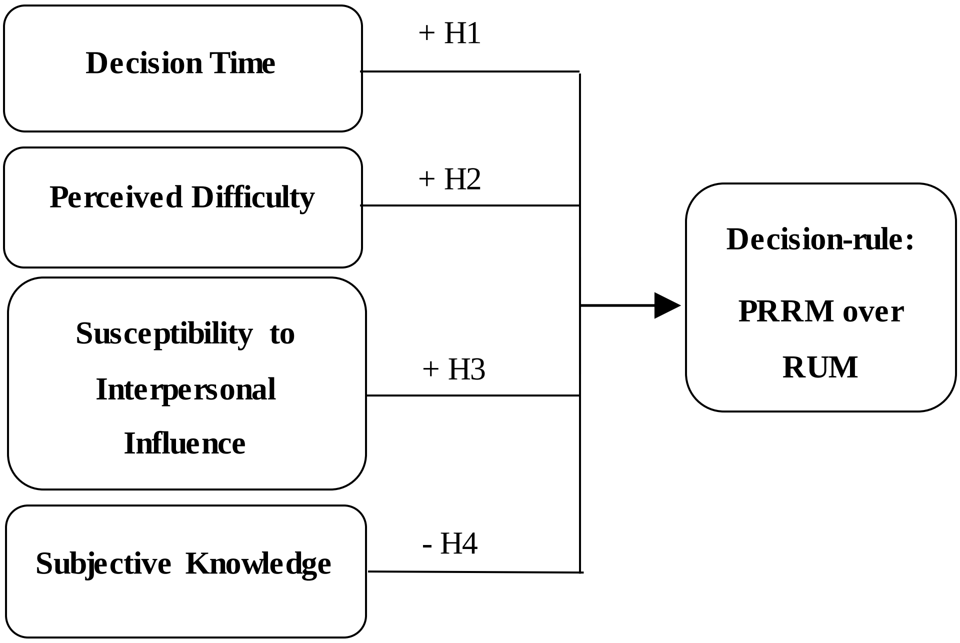
Hypothesis (3): Consumers who are susceptible to interpersonal influence are more likely to choose in line with the Pure-Random Regret Minimization model than with the Random Utility Maximization model.

Hypothesis (4): Consumers who have a lot of Subjective Knowledge are less likely to choose in line with the Pure-Random Regret Minimization model than with the Random Utility Maximization model.

The following figure represents the conceptual model that is derived from the theoretical Framework provided in this chapter.

Figure 1.

Conceptual Framework



Note. The positive relationship between Perceived Difficulty, Decision Time, Susceptibility to Interpersonal Influence and the 'decision-rule PRRM over RUM' is denoted by a (+)-sign. The negative relation between Subjective Knowledge and the 'decision-rule PRRM over RUM' is denoted by a (-)-sign.

3 Research Design

This chapter encompasses the setup of the survey and the precautions that are taken in this process in order to achieve reliable measurements. The scope of the design is outlined and the multi-item scales that are used to capture the independent variables are introduced. Where applicable, a statement is made as to why this particular item scale is chosen over others that are more commonly found in the literature.

3.1 Survey Design

The survey that was designed for this research contains nine choice tasks and 17 additional questions on decisional values. Therefore, care had to be taken to avoid respondent fatigue and thus the setup of the survey was constructed to emphasize the importance of the survey itself. Psychological anchors were provided to decrease the dishonesty of respondents and increase awareness for the importance of the research and the responsibility the respondent has towards its answers. This was accomplished by having the respondents fill out an open form field, in which they confirmed that the answers they would provide were honest, and were given their full attention. This idea was taken from recent research by Shu (2012), who provides evidence for the fact that “signing at the beginning makes ethics salient and decreases dishonest self-reports…”. In line with this finding the respondents of this survey were asked to type out and sign the following, ‘I will not be distracted and answer honestly’, before proceeding with their answers.

The survey was conducted in English, despite the fact that most respondents were expected to be of Dutch origin. This approach was chosen so that item scales did not need to be translated, which could have resulted in a change and/or loss of meaningfulness and validity. Furthermore, by asking respondents to sign at the beginning of the survey, rather than at the end, a threshold and way of controlling whether people are fully capable of understanding the English text is created.

3.2 Choice task design

To capture choice behaviour a stated preference design is used. More specifically, a multinomial design with three choice options is chosen. Each choice option has four attributes with three levels. When making the design, this framework was chosen for ease of use and to ensure that the choice task would not become overly time consuming. Using the software tool Ngene, an orthogonal design is created with a minimal viable amount of choice tasks for such a configuration, which resulted in nine choice tasks to be included (Ngene, 2014). As stated earlier, this was done to avoid respondent fatigue; as the total size of the questionnaire would have been rather large if the item scales to measure Perceived Difficulty, Subjective Knowledge, Susceptibility to Interpersonal Influence and demographic questions were added, these measurements were rather to be recorded from additional questions.

It is expected that learning effects would be present on a respondent-basis, however, to control for the learning effects on a group-basis, the choice tasks were randomly distributed in order for the learning effects to be spread out evenly amongst the choice tasks. This ensures that learning effects would not invalidate the output of the conjoint analysis.

Choice tasks were presented one by one, which allowed for a very precise measurement of time taken by the respondent to answer each question. This prevents people from going back and altering their previous responses, while tracking time also provides a good source of insights in the case that outliers are found in the data.

The attributes used in the choice task are derived from a preliminary survey questioning 18 respondents, who were asked what they thought were the most important variables when considering a holiday destination.

The results from the preliminary survey can be found in Table 1.

Table 1

Mean analysis of attribute ranking in preliminary survey

Variable	*n*	*M*	*SD*
Destination country (for example Italy, Norway)	18	2.11	2.02
Scenery (whether it is in a city, countryside, or near a beach for example)	18	3.22	1.47
Duration of stay (for example 3, 5 or 7 days)	18	3.83	1.8
Type of accommodation (whether you stay in a villa, cottage or hotel for example)	18	4.47	1.79
Climate (for example cold - 15°C, warm - 22°C, hot - 30°C)	18	4.67	2.38
Amount of pocket money per person per day (for example: 40, 60 or 80 euro)	18	5.94	1.99
Touristic attractions (Heritage such as museums; Outdoor sports such as rafting or Nightlife)	18	6.00	1.97
Culture (language, ideas, belief of a people)	18	6.39	2.09
Name of the airline carrier (for example KLM, Transavia, EasyJet)	18	8.11	1.41

Note. Respondents were asked to rank the variables for which 1 indicates the most important variable and 9 indicates the least important variable.

The results from this preliminary survey indicate that the country, type of scenery, type of accommodation and the duration are the most important attributes when considering a vacation. Each of these attributes is subsequently assigned three levels. The levels of the attributes are chosen in such a way, that they align with the first condition of Janis and Mann (1977): "*the most preferred choice is not necessarily superior to another alternative"*. It was important to select attribute levels that are not of a monotonic nature, but do bear the expected sign[7]. See Table 2 for an overview of the attributes and levels used in the choice task.

Table 2

Attributes and levels part of the multinomial design

Attribute	*Levels*		
Country	Ireland	Norway	Greece
Scenery	Countryside	Urban	Beach
Accommodation	Cottage	3-star Hotel	Villa
Duration	3	5	7

The respondents were asked to imagine winning a lottery with the prize being a free holiday for six people, outlining they could bring five friends or family members. They were asked to make a choice out of a selection of three options. This experiment was repeated nine times with each respondent, with the levels of the attributes alternating between choice tasks. For example, the level for the attribute accommodation is cottage, 3-star hotel and villa. The respondents were asked the following: "Consider winning a vacation in the lottery for 6 people. You are asked to make your choice straight away and these are the only alternatives, which one would you prefer the most?" In the following, an example is given of the choice options for two questions a respondent may be presented with.

Staying at a cottage, in a city of Greece for the duration of 3 days	Staying at a 3-star hotel, in the countryside of Norway for the duration of 5 days	Staying at a villa, near the beach of Ireland for the duration of 7 days

Staying at a villa, in a city of Norway for the duration of 5 days	Staying at a cottage, in the countryside of Ireland for the duration of 7 days	Staying at a 3-star hotel, near the beach in Greece for the duration of 3 days

The choice options for all questions are constructed in the same manner, with the levels of the attributes changing from question to question.

[7] Greece > Norway > Ireland, Beach > Urban > Countryside, Villa > 3-star Hotel > Cottage, longer duration preferable over shorter duration. Chapter 4.3.1, table 8, shows that is indeed the case.

The choice task information and instructions are written in a way that it prompts several of the previously described conditions of Janis and Mann (1977). By writing that the decision-maker is allowed to bring friends, the emphasis is put on the decision-makers' social network, which prompts the third condition of Janis & Mann (1977, namely that *"significant persons in the decision maker's social network view the decision as important and will expect him to adhere to it"*.

See Table 3 for an overview and the specification of the nine choice tasks.

Table 3

Multinominal choice set with three choices and four attributes, with each having three levels

Question	*1*	*2*	*3*
1	Staying at a cottage, in a city of Greece for the duration of 3 days	Staying at a 3-star hotel, in the countryside of Norway for the duration of 5 days	Staying at a villa, near the beach of Ireland for the duration of 7 days
2	Staying at a villa, in a city of Norway for the duration of 5 days	Staying at a cottage, in the countryside of Ireland for the duration of 7 days	Staying at a 3-star hotel, near the beach in Greece for the duration of 3 days
3	Staying at a 3-star hotel, in a city of Ireland for the duration of 7 days	Staying at a villa, in the countryside of Greece for the duration of 3 days	Staying at a cottage, near the beach of Norway for the duration of 5 days
4	Staying at a 3-star hotel, in the countryside of Norway for the duration of 3 days	Staying at a villa, near the beach of Ireland for the duration of 5 days	Staying at a cottage, in a city of Greece for the duration of 7 days
5	Staying at a cottage, in the countryside of Ireland for the duration of 5 days	Staying at a 3-star hotel, near the beach of Greece for the duration of 7 days	Staying at a villa, in a city of Norway for the duration of 3 days
6	Staying at a villa, in the countryside of Greece for the duration of 7 days	Staying at a cottage, near the beach of Norway for the duration of 3 days	Staying at a 3-star hotel, in a city of Ireland for the duration of 5 days
7	Staying at a villa, near the beach of Ireland for the duration of 3 days	Staying at a cottage, in a city of Greece for the duration of 5 days	Staying at a 3-star hotel, in the countryside of Norway for the duration of 7 days
8	Staying at a 3-star hotel, near the beach of Greece for the duration of 5 days	Staying at a villa, in a city of Norway for the duration of 7 days	Staying at a cottage, in the countryside Ireland for the duration of 3 days
9	Staying at a cottage, near the beach of Norway for the duration of 7 days	Staying at a 3-star hotel, in a city of Ireland for the duration of 3 days	Staying at a villa, in the countryside of Greece for the duration of 5 days

Note. Additional information was present relating to details considering the accommodation, scenery, weather and traveling times to destinations.

3.3 Time measurement

A timer was running in the background during the nine choice tasks to keep track of the time it took respondents to go through each choice task. The respondents were not aware of the fact that they were being timed. Before beginning the timed choice tasks respondents were provided with the full instructions of what they were expected to do. Once they accessed the first choice task the timer started running. Upon proceeding to the next choice task the timer recorded and saved the time taken and started measuring the time taken for answering the next question. These measurements were used for the variable Decision Time.

Now that the construction of the choice task is outlined and it is explained how the Decision Time variable will be tracked, it is important to explain how the measurement of the remaining three variables, namely Perceived Difficulty, Susceptibility to Interpersonal Influence and Subject Knowledge, are measured.

3.4 Multi-item scale for Perceived Difficulty

One of the most popular articles relating to multi-item scales that measure Perceived Difficulty is by Schwartz et al (2002). Schwartz et al (2002) report a multi-item scale for measuring whether respondents take a maximizing or satisficing approach; the scale is divided into three sub-dimensions: decision difficulty, regret, and alternative search.

The original item scale by Schwartz et al (2002) incorporates 13 items, but does not report reliability and validity parameters. In a meta-analysis conducted by Nenkov et al (2008) various reliability and validity studies are conducted on this 13-item scale, as well as on a smaller nine, six and three-item scale. The Nenkov et al (2008) results indicate a superior fit for the six-item scale based on chi-square values, RMSEA values, and goodness of fit test, while the 13-item scale performs best on the validity index. This does not come as a surprise, as an increase in items usually is accompanied by a better score on the validity index. Looking at the results by Nenkov et al (2008), they report a Cronbach's alpha, which is a measure of reliability and internal consistency, that has a value of 0.70 for the 13-item scale, which is conform to literature standards of alpha ≥ 0.70. Regarding the choice between a 13, nine, six, and three-item scale, Nenkov et al (2008) report that the six-item scale performs better than the 13, nine and three-item scale, and suggest this scale should be used in future research.

Nenkov et al (2008) further measure the Cronbach's alpha for the 13-item decision difficulty dimension, and report a value of 0.62. They also measure the Cronbach's alpha for the six-item difficulty dimension, and report a value of 0.47, which is even lower. Lastly, they note the need of re-examining the three sub-dimensions separately. The sub-dimensions are found to correlate unreliably with the underlying constructs of the sub-dimensions. The implications of results like the ones found by Nenkov et al (2008) warrant suspicion and raise the question whether there are spurious relations that underlie the theory of the maximization scale. The authors note that clarification of the conceptual underpinnings of the maximization construct is to be sought by researchers and that a more refined scale is needed (Nenkov et al., 2009). Lia (2010) replicates and extends prior research on the maximization scale of Schwartz et al (2002). Her findings suggest that the decision difficulty sub-dimension should be conceptualized as a separate dimension and should not be part of the maximizing construct. Taking into account that the contradictions concerning the decision difficulty scale found in recent literature and the insufficient Cronbach's alpha of 0,62 for the separate sub-dimension of decision difficulty, it is rather apparent that these can be considered valid reasons as to why the maximization scale and the originally presented decision difficulty item scale should not be incorporated. Therefore, the advice of Lia (2010) is adhered to and a different perceived decision difficulty item scale is sought.

In the search for a better Perceived Difficulty item-scale, a scale by Hanselmann & Tanner (2008) is considered, which seems to be a good fit. Their scale is a five-item scale and their test is designed to measure various aspects of decision difficulty, such as ambivalence, certainty of decision, readiness to decide, and the need for additional time.

For their test they report a Cronbach's alpha of 0.89, which is considerably larger than the threshold of 0.70 and indicates good internal consistency. Respondents indicate their answers using a seven-item Likert scale and follow the format of indicating the extent to which they agree with a statement by choosing from 1 = very easy to 7 = very difficult, and 1 = strongly disagree to 7 = strongly agree.

Based on the sufficient value of the Cronbach's alpha, Hanselmann and Tanner's (2008) scale is adopted for this research, with some minor modifications that needed to be made. Items one, four and five are rephrased from a singular manner to a plural manner to match the context of the nine choice tasks to which they relate. "For me, this decision is..." becomes "for me, these decisions were"; "For this decision, I feel certain which option to choose" becomes "for most decisions, I felt certain which option to choose"; "I feel very ambivalent about this decision" becomes "I feel unsure about most of the decisions". Not only is this re-written from singular to plural, but the term 'term ambivalent' is replaced with 'unsure', as this is assumed to be easier to interpret by Dutch people, while holding a similar meaning. See Table 4 for the Perceived Difficulty multi-item scale used in this research.

Table 4

Perceived Difficulty multi-item scale

Item	
1	For me these decisions were
2	I would need more time to decide
3	I would not ponder for a long time on such a decision*
4	I feel unsure about most of the decisions
5	For most decisions, I felt certain which option to choose*

Note. Participants responded to all survey items using a 7-point Likert scale (from 1 = "Strongly disagree" to 7 = "Strongly agree", however the first item ranged from 1 = "Very easy" to "Very difficult"). * indicates items were reverse coded.

3.5 Multi-item scale for Susceptibility to Interpersonal Influence

In 1989 Bearden et al created a multi-item scale to measure consumer Susceptibility to Interpersonal Influence. Bearden et al (1989) propose a 12-item scale for Interpersonal Susceptibility. Their list of items contains four informative and eight normative questions. The informative questions relate to the tendency to accept information from others as evidence, either by searching for information or by making inferences about the observations of others' behaviour. The normative questions relate to the tendency to conform to the expectations of others.

Due to the fact that only the eight normative questions from Bearden et al (1989) are applicable to this research they are adopted in this research, and the informative items are omitted. Furthermore, Hoffmann & Broekhuizen (2009) conduct research in which they also only make use of the normative questions from Bearden et al (1989), however they omit the first question from the original eight, as it is a question that is highly specific to the topic of fashion and is therefore not generalizable with a new product category. For their adapted scale Hoffmann and Broekhuizen (2009) report a Cronbach's alpha of 0.86.

As in Hoffmann & Broekhuizen (2009), the scale used in this research consists of the normative questions of Bearden et al (1989), with the first of the eight questions being omitted, resulting in a seven-item scale that is used to measure susceptibility to normative influences. See Table 5 for the Susceptibility to Interpersonal Influence item scale that is used in this research.

Table 5

Susceptibility to Interpersonal Influence multi-item scale

Item	
1	It is important that others like the products and brands I buy
2	When buying products, I generally purchase those brands that I think others will approve of
3	If other people can see me using a product, I often purchase the brand they expect me to buy
4	I like to know what brands and products make good impressions on others
5	I achieve a sense of belonging by purchasing the same products and brands that others purchase
6	If I want to be like someone, I often try to buy the same brands that they buy
7	I often identify with other people by purchasing the same products and brands they purchase

Note. Participants responded to all survey items using a 7-point Likert scale (from 1 = "Strongly disagree" to 7 = "Strongly agree").

3.6 Multi-item scale for Subjective Knowledge

In their paper "A short, reliable measure of Subjective Knowledge" Flynn and Goldsmith (1999) create a reliable and valid Subjective Knowledge multi-item scale. After reviewing their initial set of 12 statements concerning Subjective Knowledge for face validity, they omit three statements, so that nine statements remain. For later tests four more statements were removed from the list. When testing the remaining five items for internal validity a Cronbach's alpha of 0.93 was reported, which indicated good internal consistency of these statements. Further tests of these five statements evaluated the psychometric properties and the generalizability within a new product category[8]. It was shown that the subjects did not respond in a socially desirable way and that changing the subject of the multi-item scale did not change the reliability of the test. This implies that altering the subject from a fashion-themed to a holiday-themed subject

[8] Construct reliability, average variance extracted, convergent, criterion and nomological validity and many more tests were executed and were also of a satisfactory level. The interested reader is pointed towards the work of Flynn & Goldsmith (1999) for the outline.

should not affect validity. Based on the Cronbach's alpha measure and the generalizability of the scale it is seen as appropriate to use this multi-item scale in this research. See Table 6 for the Subjective Knowledge multi-item scale that is used in this research.

Table 6

Subjective Knowledge multi-item scale

Item	
1	I know pretty much about arranging a vacation.
2	I do not feel very knowledgeable about arranging a vacation*
3	Among my circle of friends, I'm one of the "experts" on arranging a vacation.
4	Compared to most other people, I know less about arranging a vacation*
5	When it comes to arranging a vacation, I really don't know a lot*

Note. Participants responded to all survey items using a 7-point Likert scale (from 1 = "Strongly disagree" to 7 = "Strongly agree"). * indicates items were reverse coded.

3.7 Demographic questions

Demographic questions relating to age, income, education and gender were added to the survey to be able to identify potential effects in sub-samples. For the variable 'age' an open form field was used, in which respondents could enter their age. For income 5 options were provided in the form of intervals ranging from annual income of '0 - 20,000'; '20,000-35,000'; '35,000 - 50,000'; '50,000+' and 'prefer not to answer'. The option not to answer was added, as questions relating to income is a sensitive topic for some people. For gender a binary option was provided, with male and female. For the education variable the options 'no schooling'; 'vmbo'; 'havo'; 'vwo'; 'MBO'; 'HBO'; 'Bachelor's degree'; 'Master's degree' and 'other not specified: *specify*' were added.

3.8 Distribution of the survey

The survey for this research paper was created using www.qualtrics.com, a freeware that provides an online platform to host surveys. An invitation with the link to the online survey was sent to friends and peers from the Erasmus University Rotterdam, as well as acquaintances and family members via email, Facebook and the mobile messaging service WhatsApp. The recipients of the invitation were also asked to share the survey link with their friends and acquaintances in order to generate a larger group of respondents. The link directs the invitation recipient to the online survey, which was available 24/7 for a two-week period. The respondents could give their answers to the survey anonymously.

4. Analysis

The previous chapter described the construction of the survey and the setup for collecting the data. This chapter will discuss how the collected data is filtered, ordered, prepared and analysed.

4.1 Outliers

450 people were contacted and asked to fill in the survey, of which 272 people started the survey. A first glance at the data indicates that 49 people did not provide data on all questions, marking their entry as incomplete, and should thus be deleted. This was mostly caused by respondents exiting the survey early in the progress, but also in three cases by what seems to be an error in the data collection in Qualtrics. The latter case was detected due to fact that data was missing at points where it could not have been missing, since there were checks in place to prevent respondents from continuing beyond this point without filling in an option. Furthermore, one respondent was deleted from the sample as a seven-item scale was completed in the unrealistic time frame of just five seconds, while also providing a homogenous answer.

4.2 Sample population

Table 7 shows that 79% of the sample population is made up of respondents who are between 18 and 27 years of age. The total sample population consists of 129 males and 91 females, of whom most fall into the category of higher education. It can easily be seen that the sample used in this research is not close to being representative of the average Dutch person. However, it is believed that this should not invalidate the results obtained from the analysis, since the independent variables are of a psychometrical nature. There is no reason a priori to assume that the demographic variables moderate the relation between the dependent and independent variables.

Table 7

Demographic profile with gender, age, education and annual income as variables

Variable	*n*	%
Gender		
Male	129	59
Female	91	41
Age		
18-27	163	74
28-44	26	12
45-60	14	6
Older than 60	17	8
Education		
Havo	2	1
Vwo	8	4
MBO	10	4
HBO	31	14
Bachelor's degree	67	30
Master's degree	97	44
Other	5	2
Annual income		
€0 - 20.000	119	54
€20.000 - 35.000	26	12
€35.000 - 50.000	26	12
€50.000+	34	15
Prefer not to answer	15	7

4.3 Dependent variable.

The data on the nine choice tasks from all respondents was gathered and re-ordered to follow the required data-format for Biogeme. Biogeme is an open source freeware designed to estimate parameters of all sorts of predetermined discrete choice models (Bierlaire, 2003). Biogeme is intuitive to use and has an active community that shares information regarding the modulation of Discrete Choice Models. The website www.biogeme.epfl.ch provided a starting point on how to estimate RUM utility values for the multinomial design used in this thesis (Bierlaire, 2003). For calculating the PRRM regret values a template was found on www.advancedrrmmodels.com (Cranenburgh, 2015). This template needed to be adjusted to the dimensions of the choice set and altered to allow for the estimation of dummy variables. The summary of the results for both model estimations are presented below in Table 8.

Table 8

Summary of model results with t-values in brackets

	RUM	*PRRM*
dCountry_Ireland	-0.267 (-4.52) ***	-0.268 (-4.53) ***
dCountry_Norway	-0.133 (-2.33) ***	-0.134 (-2.34) ***
dCountry_Greece	---	---
dScenery_Countryside	-0.102 (-1.72) *	-0.102 (-1.71) *
dScenery_Urban	0.034 (0.58)	0.033 (0.57)
dScenery_Beach	---	---
dHousing_Cottage	-0.396 (0.0597) ***	-0.397 (-6.64) ***
dHousing_Hotel	-0.086 (-1.55)	-0.087 (-1.55)
dHousing_Villa	---	---
Duration	0.285 (19.04) ***	0.214 (19.36) ***
Model Fit		
Log-likelihood	-1966.415	-1941.269
N	1998	1998

Note. *p < .1. ** p < .05. *** p < .01.

Looking at the result in Table 8, it can be seen that not all utility and regret-parameters are significant. At a 90% confidence interval the dummy parameters Housing_Hotel and Scenery_Urban do not significantly deviate from zero. It is therefore assumed that the utility and regret values are zero. The dummy parameters Greece, Beach, Villa that were not calculated are the benchmark and are by default zero.

By looking at the values of the utilities and regrets it can be seen that the variables did have the expected sign. Table 8 shows that people preferred the country Greece over Norway and Norway over Ireland, while for the scenery beach does not significantly deviate from urban and urban is preferred over countryside. When looking at the values for the accommodation it is noted that people assign as much utility (or regret) values to villa as they do to hotel, but prefer hotel over cottage. The duration parameter shows to have the most impact, and as expected, people preferred a longer holiday over a shorter holiday. It can also be seen that when comparing between RUM and PRRM the dummy variables do not significantly deviate from one another; due to the similarities of the RUM and PRRM formula these results could have been expected when dealing with dummy variables (van Cranenburgh, Personal communication, 2 September 2015). This has important implications when calculating whether someone acts more along the lines of the RUM or PRRM model. Most of the variance thus comes from the Duration parameter. These limitations are further discussed in Chapter 6.

Alternative specific constants were not added because this study has no interest in describing the relationship between psychometrical variables, such as expertise, or demographic variables such as age and the attributes used in this choice design. Instead the interest lies in finding the model that best fits the sequence of choices made by each respondent.

4.3.1 Do consumers act more along the lines of the PRRM or the RUM model?

To determine if respondents act more along the lines of the PRRM or RUM model a closer look is taken at the closed form choice probabilities as proposed in chapter 2.8. These choice probabilities are devised by taking into account the distribution of the error terms, which are assumed to be independent and identically distributed random errors with an Extreme Value Type-I distribution.

The close form formulation found in Eq. 4 and Eq. 5 can be used to calculate the choice probability of the chosen alternative by the respondent for both the RUM and PRRM model. We can then multiply the probabilities with each other and find the choice probability of the sequence of choices made by the respondent according to RUM and PRRM. Due to the computational straightforwardness of this calculation this is done in Microsoft Excel 2016[9]. The choice probabilities for the sequence of choices for RUM and PRRM are compared and it is assumed that a higher choice probability denotes that the respondent has acted more along the lines of the corresponding model. A new variable is created to signal this property. Thus, the dependent variable 'PRRMoverRUM' is created. A binary value is assigned to this variable based on the choice probability of the sequence of choices, with 0 for RUM and 1 for PRRM. See Table 9 for the frequency of each sub-group in the sample.

[9] The calculation of the sequence of choices is relatively straightforward in comparison to examples from the literature where the model accounts for a degree of heterogeneity of taste within behavioural classes. See Boeri et al (2014) for an example.

Table 9

Frequency of dependent variable PRRMoverRUM

		Frequency	*Percent*
RUM	0	183	83.2
PRRM	1	37	16.8
	Total	220	100.0

It must be noted that mathematical models such as the RUM and the PRRM model aim to best represent consumer behaviour and are based on behavioural inclinations such as utility maximization and regret minimization. This however does not mean that a regret minimizers behaviour may not be better captured by RUM than PRRM, and vice versa. For some respondents some choices may be better estimated by RUM, while other choices are better estimated by PRRM. It is worth stating again, that the dependent variable is generated by looking at the choice probability of the sequence of choices.

4.4 Independent variables.

There are four independent variables: Decision Time, Perceived Difficulty, Susceptibility to Interpersonal Influence, and Subjective Knowledge. The measurement of Decision Time is discussed first. The remaining three of these four independent variables are processed similarly. It is checked if one construct underlies the item scale and reliability analysis is conducted to verify if the Cronbach's alphas are in line with those reported in the literature. The results are presented in each subsequent co-chapter.

4.4.1 Decision Time

This co-chapter deals with the processing of the Decision-Time data. The question arises how the time variable should be constructed. It is expected that the first questions that are presented to the respondent will take the longest and yield the most fruitful information, since learning effects will manifest thereafter. It is assumed that anticipated regret is especially measurable in the first choice tasks because people who are less knowledgeable and not familiar or experienced with the task at hand are expected to need additional time to make a decision (Bettman & Park, 1980; Brucks, 1985).

The data is explored and it is found that a notable amount of respondents take more than 200 seconds to complete a single task[10]. In most of these cases the respondent only produced one of these lengthy time intervals, while the sample-mean for completing a task was 25 seconds. The question that arises is whether the increased duration holds valuable information, or it is simply an experimental error, which arises due to the fact that respondents may have been distracted during the task. Since it is presumed that respondents take additional time on the first few choice tasks, it would be intuitive to check if the increased duration for completing a task occurs at this stage of the choice set. Unfortunately, the survey software Qualtrics does not provide this kind of information on randomly distributed questions. It seems that trying to prevent learning effects from significantly adjusting the results from the conjoint analysis has had a negative effect on the exploratory analysis of the time variable.

Since it cannot be checked if the questions with an increased duration are in fact the first questions, it could be insightful to take a closer look at time-values of individual respondents. A quick glance indicates that a notable amount of respondents has outlier values in their time responses. The question then arises how to deal with these outliers; a closer look must be taken. To illustrate the difficulty of this task some of the most extreme outliers are presented in Table 10.

Table 10

Example of completion time per page values of respondents that are potential outliers

Respondent	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*
86	36.99	27.66	**156.2**	35.71	26.42	16.81	46.48	58.4	25.82
92	32.46	26.2	28.56	**105.68**	59.16	36.29	55.32	20.9	38.49
122	**106.61**	46.74	29.19	14.49	13.78	8.02	30.66	14.2	27.99
133	68.34	20.1	17.21	129.56	18.18	**497.8**	60.8	13.3	29
184	29.73	10.24	**230.67**	127.92	42.27	62.67	13.67	167.4	85.48
197	9.92	11.71	**183.18**	18.49	16.43	32.23	37.7	64	35.11
205	**802.33**	12.33	10.9	5.15	26.22	6.82	17.81	8.7	34.87

[10] Eight respondents were found that took more than 200 seconds to finish a single conjoint task. In the most extreme case 802 seconds were needed.

The difficulty lies with judging whether the outliers hold meaningful information, as may be expected from respondent 92 and 184 for example. They do not only have one value that exceptionally deviates from the sample mean of 25, but have multiple values that are far greater than the mean value. This indicates that it is likely they genuinely took longer to complete the questions and we are not dealing with an experimental error. On the other hand, looking at the data depicted by respondent 205 it would be very likely to assume we are dealing with an experimental error, because the most extreme time value is approximately 40 times larger than the mean value for this respondent.

Many of these outliers however, are not as easily identifiable as those mentioned above. The question then focuses on whether the full data set should be used as is, or if a tool for outlier detection like the one proposed by Hoaglin et al (1986) should be used, or whether the data set should be reduced by taking out the maximum time values for every respondent, or if the Decision Time should simply not be used as a variable at all. To get a better feel for the impact that each of these alternatives has on the reliability of the data, the choice was made to take a closer look at each of these propositions. The next co-chapters describe the preparation of the variables under these propositions, pointing out the disadvantages of each, and a conclusion to which one should be chosen is drawn.

4.4.1.1 Keeping all time variables

Using the full dataset with nine-time data points means using the data that has outliers. A scatterplot could be created for each of the nine variables and outliers could be deleted based on the values that deviate too far from the rest of the data points. The downside of this method is that it does not take into account the relative distance from the other respondent-specific eight-time data points. This is the same problem that is described in the previous co-chapter with the help of Table 10. Alternatively, using a cut-off value for excluding outliers, yields the same problem.

4.4.1.2 Outlier detection based on Hoaglin et al (1986)

Hoaglin et al (1986) propose an outlier detection protocol. For every variable the first (Q1) and third (Q3) quartile must be taken; the interquartile range Q3-Q1 (IQR) is then calculated and multiplied by 1,5. This IQR is used in the formula for the lower limit Q1 – (1,5*IQR) and the upper limit Q3 + (1,5*IQR). The lower and upper limit are presented in Table 11.

Table 11

	First quantile	*Third quantile*	*IQR*	*Lower limit*	*Upper limit*
Decision Time value 1	10.78	28.09	17.31	0.00	54.06
Decision Time value 2	11.83	29.15	17.32	0.00	55.14
Decision Time value 3	12.00	30.27	18.27	0.00	57.68
Decision Time value 4	10.57	30.49	19.92	0.00	60.38
Decision Time value 5	10.04	26.21	16.16	0.00	50.46
Decision Time value 6	10.29	27.51	17.22	0.00	53.34
Decision Time value 7	12.16	30.60	18.43	0.00	58.26
Decision Time value 8	10.37	28.12	17.75	0.00	54.75
Decision Time value 9	11.09	28.59	17.50	0.00	54.84

This method would result in marking 78 respondents as outliers, leaving the PRRM group with a mere 19 respondents. Van der Ploeg et al (2014) report that, as a guideline, a valid sample for logistic regression should have a minimum of 10 values per predictor variable in either of the dichotomous endpoints. Taking the four hypotheses into consideration, this falls short of this guideline by 52.5%. Secondly, it also means that roughly 35% of the initial dataset should be omitted. The most important argument to not use this method is however, that such an outlier detection method is best applied to univariate data, and does not take into account the relative distance to other variables. Due to the many downsides of this technique this option is not taken into further consideration.

4.4.1.3 Deleting the maximum time-values

Another option of dealing with outliers is to delete the maximum time-values for every respondent. This entails that for every respondent the highest time value is deleted and thus no longer nine time-data points are usable but instead only eight remain. In theory this means that for respondents that have one experimental error in their time values, the data is valid thereafter. However, for respondents that completed the choice task without experimental error this means, most likely deleting the timing of the first choice task, and thus deleting the time variable that holds the most insightful information.

4.4.1.4 Conclusion on Decision Time variable

To conclude, it can be said that using an outlier detection technique gravely impairs the data and moreover, does not consider the multivariate makeup of the data. The same applies when using a cut-off value or scatter plot. Therefore, the choice is made to remove the maximum value for every respondent. This Decision Time value will be used throughout the analysis, but an additional model that includes the full nine decision-times will be run, in order to estimate the effect that deleting this particular time value for each respondent has.

It should be noted that this method is rigorous and far from ideal, but it is believed that taking the average of the eight variables is the best way to keep the structure of the data intact. The new variable is named 'Decision Time (8)'.

4.4.2 Perceived Difficulty

The answers to the multi-item scale that measures Perceived Difficulty is gathered and a common term is sought. The data is then prepared by recoding the reverse coded items three and five. Using SPSS, a Principle Component Analysis with Varimax Rotation is run, that shows there is only one factor with an Eigenvalue larger than one (IBM Corp, 2013). The Varimax Rotation is chosen instead of other rotation methods, such as Oblique and Promax, because according to the literature we can expect one construct to underlie the multi-item scale (Hanselmann & Tanner, 2008). As a result, it makes no sense to assume correlation amongst factors. The same assumptions hold for Subjective Knowledge and Susceptibility to Interpersonal Influence in the next two co-chapters.

The test results of the factor analysis are presented in Table 12.

Table 12

Factor analysis of Perceived Difficulty multi-item scale

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.590	51.796	51.796	2.590	51.796	51.796
2	.804	16.088	67.884			
3	.614	12.272	80.157			
4	.555	11.095	91.251			
5	.437	8.749	100.000			

Note. Extraction Method: Principal Component Analysis.

The results indicate that one construct underlies the multi-item scale for Perceived Difficulty. This is in line with what is presented in the literature by Hanselmann & Tanner (2008). Furthermore, reliability analysis reports a Cronbach's Alpha of 0.762, which is greater than the 0.70 benchmark found in literature (Cronbach, 1951). See Table 13 for the reliability analysis results.

Table 13

Reliability analysis of Perceived Difficulty multi-item scale

Cronbach's Alpha	N of Items
.762	5

In summary, one construct underlies the multi-item scale with good internal consistency. The average value for Perceived Difficulty is taken of the total multi-item scale. This variable is named 'Perceived Difficulty'.

4.4.3 Susceptibility to Interpersonal Influence

Using SPSS, a Principle Component Analysis with Varimax Rotation is run that shows there is only one factor with an Eigenvalue larger than one (IBM Corp, 2013). The test results of the factor analysis are presented in Table 14.

Table 14

Factor analysis of Susceptibility to interpersonal influence multi-item scale

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	4.536	64.807	64.807	4.536	64.807	64.807
2	.647	9.241	74.048			
3	.531	7.580	81.628			
4	.383	5.466	87.094			
5	.370	5.286	92.380			
6	.289	4.124	96.504			
7	.245	3.496	100.000			

Note. Extraction Method: Principal Component Analysis.

The test results in Table 13 indicate that one construct underlies the multi-item scale for Susceptibility to interpersonal influence. This is in line with what is presented in the literature by Bearden et al (1989). Furthermore, reliability analysis reports a Cronbach's Alpha of 0.908, which is greater than the 0.70 benchmark found in the literature (Cronbach, 1951). See Table 15 for the results from the reliability analysis.

Table 15

Reliability analysis of Susceptibility to interpersonal influence multi-item scale

Cronbach's Alpha	N of Items
.908	7

In summary, one construct underlies the multi-item scale with good internal consistency. The average value for Susceptibility to Interpersonal Influence is taken of the total multi-item scale. This variable is named 'Susceptibility'.

4.4.4 Subjective Knowledge

The data is prepared by recoding the reverse coded items two, four and five. Using SPSS a Principle Component Analysis with Varimax Rotation is run that shows there is only one factor with an Eigenvalue larger than one (IBM Corp, 2013).

The test results of the factor analysis are presented in Table 16.

Table 16

Factor analysis of Subjective Knowledge multi-item scale

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3,798	75.967	75.967	3.798	75.967	75.967
2	.390	7.804	83.771			
3	.357	7.138	90.909			
4	.265	5.291	96.200			
5	.190	3.800	100.000			

Note. Extraction Method: Principal Component Analysis.

The test results in Table 15 indicate that one construct underlies the multi-item scale for Subjective Knowledge. This is in line with what is presented in the literature by Flynn & Goldsmith (1999). Furthermore, reliability analysis reports a Cronbach's Alpha of 0.92, which is greater than the 0.70 benchmark found in the literature (Cronbach, 1951). See Table 17 for the reliability analysis results.

Table 17

Reliability analysis of Subjective Knowledge multi-item scale

Cronbach's Alpha	N of Items
.920	5

In summary, one construct underlies the multi-item scale with good internal consistency. The average value for Subjective Knowledge is taken of the total multi-item scale. This variable is named 'Subjective Knowledge'.

4.5 Analysis

At this point it is possible to run descriptive tests in preparation for the main analysis, as the dependent variable and independent variables have been constructed.

Firstly, a test is run to test for possible multicollinearity within the predictor variables. Using SPSS, a linear regression is run with collinearity statistics to obtain VIF statistics. Secondly, a bivariate correlation analysis is run. Table 18 shows the VIF statistics and binary correlation matrix.

Table 18

Pearson correlation matrix and VIF statistic

	Decision Time	*Perceived Difficulty*	*Susceptibility*	*Subjective Knowledge*
Decision Time (8)	1	.231**	-.101	.008
Perceived Difficulty	.231**	1	.104	-.290**
Susceptibility	-.101	.104	1	-.162*
Subjective Knowledge	.008	-.290**	-.162*	1
Descriptive				
VIF	1.079	1.17	1.046	1.118

Note. *. Correlation is significant at the 0.05 level (2-tailed), **. Correlation is significant at the 0.01 level (2-tailed).

As can be seen in the table, the VIF statistic centres around one, which is below the rule of thumb of four, indicating that it is unlikely for multicollinearity to exist among the predictor variables. This is supported by the results of the correlation matrix; from which it can be seen that the highest absolute correlation is 0.290. This is below cut off values used in the literature that are between 0.7 and 0.9. Therefore, it can be said that there is no multicollinearity within the predictor variables and the main analysis can be run.

The logistic regression model is a tool used to estimate the relationship between a dichotomous dependent variable and one or more - ordinal, interval or ratio - independent variables (Cox, 1958). Since the dependent variable is binary, and the independent variables are Likert-type scales, the logistic regression model is suited best for this type of analysis.

The assumption that underlies logistic regression is that the relationship between the logit, also referred to as the link-function, and the continuous independent variables is linear.

So, before plotting the logistic regression, it has to be checked that this assumption is indeed met. It is assumed that the seven-item Likert scales are classed as continuous variables, even though there is much dispute surrounding this in the literature. A Box-Tidwell test is conducted to test the null-hypothesis that a linear relation between the log odds and the predictor variables exists (Box & Tidwell, 1962). Therefore, the natural log of ‘Decision Time’, ‘Perceived Difficulty, ‘Susceptibility’ and ‘Subjective Knowledge’ are computed and included in the model as first order interactions. If the output of the analysis indicates a p-value ≤ 0.05 it is assumed that the relationship between the logit and the predictor variable is non-linear. Table 19 presents the output of the Box-Tidwell test.

Table 19

Box-Tidwell test to check for non-linearity in the relationship between the log-odds and the predictor variables

	B	*S.E.*	*Wald*	*Sig.*	*Exp(B)*
Decision Time (8)	-.100	.268	.140	.709	.905
Perceived Difficulty	.729	1.893	.148	.700	2.073
Susceptibility	-2.289	1.259	3.307	.069	.101
Subjective Knowledge	-.224	2.216	.010	.919	.799
LN(Decision Time) by Decision Time	.033	.063	.276	.599	1.034
LN(Perceived Difficulty) by Perceived Difficulty	-.318	.864	.135	.713	.728
LN(Susceptibility) by Susceptibility	1.109	.609	3.324	.068	3.033
LN(Subjective Knowledge) by Subjective Knowledge	-.055	.901	.004	.951	.946
Constant	1.570	4.819	.106	.745	4.809

In the above table it can be seen that none of the interaction variables is significant at a significance level of $\alpha = 0.05$. Thus, it can be assumed there is a linear relation between the predictor variables and the dependent variable. The independent variables are standardized and captured in a single factor. Standardization is achieved by following equation (Eq. 6), which makes the interpretation of the output more meaningful.

$$X_{standardized} = \frac{x-\mu}{\sigma} \tag{6}$$

Since the required assumptions are met, a standard logistic regression model is run according to the Enter method. Based on the theoretical framework it can be assumed that the four variables are related to the dependent variable, which is why this particular method is chosen. A stepwise method is not used, as this approach would seek to exclude non-significant variables, which would interfere with the statistical reliability of the model.

The results of the logistic regression model are outlined in Table 20.

Table 20

Summary of the logistic regression

	B	*S.E.*	*Wald*	*Sig.*	*Exp(B)*
Decision Time (8)	.372	.175	4.554	.033**	1.451
Perceived Difficulty	.015	.190	.006	.937	1.015
Susceptibility	-.016	.188	.008	.930	.984
Subjective Knowledge	-.425	.192	4.894	.027**	.654
Constant	-1.702	.195	75.885	.000	.182
Descriptive					
Chi-Square		0.034**			
Cox & Snell R-Square		0.046			
Nagelkerke R-Square		0.078			
Log-likelihood		188.882			

Note. *B* = standardized regression coefficients. Results are from the first step (method Enter). **, p < .05.

The logistic regression model uses a chi-square test to indicate how well the model fits the data. The null-hypothesis is that the independent variables have no effect on the dependent variable. Given the chi-square value of 0.034 at a significance level of $\alpha = 0.05$, it can be concluded that the null hypothesis is rejected. Thus, the model explains the data better than the baseline model without variables.

The Cox & Snell R-Square and Nagelkerke R-square test are so-called pseudo R-Square tests and are two of many tests that aim to mathematically represent how well the predictor variables interpret the model's variance. They provide rough estimates, but as an approximation, it can be said between 4.6% and 7.8% of the variance is explained by the model.

For a significance level of $\alpha = 0.05$ a significant relation is found between the independent variable 'Decision Time' (P-value = 0.033) and the dichotomous dependent variable 'PRRMoverRUM'. Furthermore, the coefficient is of the expected positive sign. For the independent variables 'Perceived Difficulty' and 'Susceptibility to interpersonal influence' it can be said that no significant relation is found at a significance level of $\alpha = 0.05$. Lastly, a significant relation between the independent variable 'Subjective Knowledge' (P-value = 0.027) and the dependent variable 'PRRMoverRUM' is found at a significance level of $\alpha = 0.05$. Furthermore, the coefficient is of the expected negative sign.

4.5.1 Adding demographic variables

Since two of the four variables are significant, it is worthwhile to check how the relationship between PRRMoverRUM and the significant predictors 'Decision Time' and 'Subjective Knowledge' changes when demographic variables are added.

The 'Education' variable is added to the model because it is expected that those with higher forms of education have more Subjective Knowledge and can thus be expected to have decreased Decision Times. An ordinal variable is created, for which elementary school and vmbo signal the group 'lower education', havo, vwo and MBO signal the group 'Secondary Education' and HBO and WO (bachelor's' and master's degree) are 'Higher Education'. These groupings are in line with the commonly used groupings by the Dutch Central Bureau of Statistics (CBS, 2014). The few respondents who indicated 'other' were put into the subgroup that best fits their level of education, for example: PhD is grouped into the category 'higher education'.

Furthermore, the 'Gender' variable is entered into the model. According to the literature it can be expected that women are more indecisive than men (Rassin & Muris, 2005). Rassin & Muris (2005) link indecisiveness to needing more time to reach a decision and the inability to complete a decision, thus indicating that it is worthwhile to check for the effect of gender and its interactions on Decision Time and Perceived Difficulty. A binary variable is generated with the values for male = 0 and female = 1.

Before starting this analysis, a test for multicollinearity is run to check if these variables are not interrelated with the psychometric predictor variables. Table 21 shows the VIF statistics and correlation matrix for this test.

Table 21

Pearson correlation matrix and VIF statistic

	Decision Time	*Perceived Difficulty*	*Susceptibility*	*Subjective Knowledge*	*Education*	*Gender*
Decision Time (8)	1	.231**	-.101	.008	-.268**	.137*
Perceived Difficulty	.231**	1	.104	-.290**	.135*	-.005
Susceptibility	-.101	.104	1	-.162*	.097	-.193**
Subjective Knowledge	.008	-.290**	-.162*	1	.032	.199**
Education	-.268**	.135*	.097	.032	1	.051
Gender	.137*	-.005	-.193**	.199**	.051	1
Descriptive						
VIF	1.131	1.181	1.074	1.169	1.054	1.094

Note. *. Correlation is significant at the 0.05 level (2-tailed), **. Correlation is significant at the 0.01 level (2-tailed)

From the table above it can be seen that there is no multicollinearity, since the largest absolute correlation between the demographic variables and the contextual factors is 0.268 and thus none of the variables pass the correlation threshold of 0.7 - 0.9, that is used as a rule of thumb in the literature. Furthermore, the fact that the VIF statistics centres around one, lends support to this statement and shows that correlation amongst variables should not be expected.

4.5.2 Adding demographic variables

A logistic regression test is run that includes the first order interaction variables of the education and gender variables with the predictor variables. To avoid data dredging, only those interaction variables enter the model, for which it can hypothesized that a relation exists, namely Education by Subjective Knowledge, Education by Decision Time and Gender by Decision Time and Gender by Perceived Difficulty. At a significance level of $\alpha = 0.05$, no significant effect could be found amongst the first order interaction variables.

Therefore, a second test is run. This test does not contain the first order effects, but simply enters the demographic variables alongside the contextual predictor variables. In comparison to the previous model this leads to a small increase in the degrees of freedom, and allows the reassessment of how adding demographic variables may change the relation between the significant predictor variables Decision Time and Subjective Knowledge and the dependent variable PRRMoverRUM. The results of this analysis are shown below in Table 22.

Table 22

	B	*S.E.*	*Wald*	*Sig.*	*Exp(B)*
Decision Time (8)	.356	.182	3.833	.050**	1.427
Perceived Difficulty	.060	.194	.094	.759	1.061
Susceptibility	-.064	.190	.113	.736	.938
Subjective Knowledge	-.358	.197	3.281	.070	.699
Education	-.820	.538	2.323	.128	.440
Gender	-.433	.412	1.104	.293	.648
Constant	.010	1.024	.000	.992	1.010
Descriptive					
Chi-Square		.030**			
Cox & Snell R-Square		.062			
Nagelkerke R-Square		.103			
Log-likelihood		185.326			

Note. Decision Time, Perceived Difficulty, Susceptibility and Subjective Knowledge are standardized regression coefficients. Results are from the first step (method Enter). **, $p < .05$.

At a significance level of $\alpha = 0.05$, it is indicated that the model performs significantly better than the baseline model where no variables are entered (chi-square-value of 0.030). Thus, the variables can be interpreted. It is noted that the previously significant Subjective Knowledge variable (P-value = 0.070) is no longer significant at $\alpha = 0.05$, while the Decision Time (8) variable (P-value = 0.050) remains statistically significant at this significance level. Furthermore, in terms of explained variability it seems that the model is improved, from between 4.8% and 7.6% variability explained to 6.2% and 10.3% variability explained. However, a more formal test is required to answer the question whether the fuller, alternative, model performs significantly better than the null model with four contextual factors. This can be tested by using a likelihood ratio test.

A likelihood ratio test is run that tests the null hypothesis of no differences between models, with the alternative hypothesis being that the alternative model is better than the null model. The likelihood ratio test is outlined in the following equation (Eq.7)

$$LR = -2LN(\frac{likelihood\ for\ null\ model}{likekelihood\ for\ alternative\ model}) \qquad (7)$$

The log likelihood for the model with only the four contextual factors – the null model – is 188.882, while the log likelihood for the model including the two demographic variables – the alternative model – is 185.326. The likelihood ratio test indicates a chi-square test statistic of 0.038. With 2 degrees of freedom and at a significance level of $\alpha = 0.05$ the critical chi-square statistic value is 5.99. The chi-square test value of 0.038 is smaller than the critical chi-square statistic of 5.99 and therefore the null hypothesis is not rejected. Thus it follows that the alternative model is not a significantly better model than the null model. Therefore, the null model is used as a basis when running additional models and interpreting results.

In order to conclude this co-chapter, it is necessary to derive results from the model with four contextual factors, the null-model. In order to do this the significant variables are examined and the *B*-parameter needs to be interpreted. This entails that the increase in the odds of acting more along the lines of the PRRM model over the RUM model needs to be calculated for a one-unit increase in the *B*-parameter. Since the variables are standardized, one unit refers to one standard deviation. Thus, a one-unit increase represents the fact that the respondent scores one standard deviation higher than the status quo. Transforming the log-odds to odds is mathematically done by the following equation (Eq.8):

$$Logit(p) = log\ (odds)\ = log\ (\frac{p}{q}) \quad (8)$$

$$Log\ (\frac{p}{q})\ = a + bX$$

$$\frac{p}{q} = e^{a+bx}$$

Holding the other variables equal, a one unit increase in Decision Time accounts for the increase in the odds of being a regret minimizer by exp(0.372) = 1.450633. This indicates a 45.1% increase in the chance of the Pure-Random Regret Minimization model better explaining choice behaviour than the Random Utility Maximization model when someone deviates one standard deviation from the status quo in terms of Decision Time. The same applies to the Subjective Knowledge variable, a one unit increase in Subjective Knowledge accounts for the increase in the odds of being a regret minimizer by exp(-0.425) = 0.65377. This indicates a 34.6% decrease in the chance of the Pure-Random Regret Minimization model better explaining choice behaviour than the Random Utility Maximization model when someone deviates one standard deviation from the status quo in terms of Decision Time.

With regards to the results it is important to mention that the total sample consisted of 220 respondents, of which 37 belonged to the PRRM group and 183 belonged to the RUM group. Van der Ploeg et al (2014) report that, as a guideline, a valid sample for logistic regression should have a minimum of 10 values per predictor variable in either of the dichotomous endpoints. In the analysis there are four predictor variables and so respectively, 9.25 values per predictor variable. This implies that caution is necessary when interpreting the results as the amount of values used in the analysis falls short of the suggested requirement.

4.5.3 Estimation of additional models

In accordance with co-chapter 4.4.5 an additional model is run on the Decision Time variable to better outline the effects of removing the maximum decision-time parameters has on the structure of the decision-time data in general. This is done by plotting an additional model with the full nine-time data variable, see Table 23. Lastly, a correlation matrix is run to further outline the possible overlap in data structure, see Table 24.

Table 23

Logistic regression with the average of the (full) nine-Decision Time intervals variable

	B	*S.E.*	*Wald*	*Sig.*	*Exp(B)*
Decision Time (9)	,323	,164	3,877	,049**	1,381
Perceived Difficulty	,016	,191	,007	,934	1,016
Susceptibility	-,044	,188	,054	,817	,957
Subjective Knowledge	-,424	,193	4,838	,028**	,654
Constant	-1,692	,194	76,078	,000	,184
Descriptive					
Chi-square	.046**				
Cox & Snell R Square	.043				
Nagelkerke R Square	.072				
Box-Tidwell test	0.593				

Note. Decision Time (9), Perceived Difficulty, Susceptibility and Subjective Knowledge are standardized regression coefficients. Results are from the first step (method Enter). **, p < .05. The report of the Box-Tidwell test is the sig. value of the LNDecisionTime9*DecisionTime9 parameter.

Table 23 shows that using the full nine-time data variable brings out a very similar *B*-parameter and significance level than the eight-time data variable. Respectively, a *B*-parameter of 0.356 for the eight-time data model, versus a *B*-parameter of 0.321 for the nine-time data model. The significance level changes from 0.033 of the null model to 0.049 of the alternative model with Decision Time (9) as a variable. Which at a significance level of $\alpha = 0.05$ means both the Decision Time (8) variable and the Decision Time (9) variables are significant.

A correlation matrix is plotted to further assess how much of the data structure remains intact between these two types of decision-times. This is presented in Table 24.

Table 24

Correlation Matrix between the (full) nine-time data, eight-time data and omitted time data variables.

	Decision Time (9)	*Decision Time (8)*
Decision Time (9)	1	.768**
Decision Time (8)	.768**	1

The correlation matrix shows that there is multicollinearity between Decision Time (9) and Decision Time (8) for the correlation is 0.768. this indicates that for both these variables it can be said that one variable can to an extent be predicted by the other variable. These variables thus look very much alike. This could mean that the extreme time values, that are omitted from the data in the null-model, do not significantly steer the Decision Time variable to be a significant predictor. This could further indicate that the Decision Time variable could in fact be regarded as a valid measurement for Decision Time since for both the Decision Time (9) and Decision Time (8) variable a significant fit is reported.

To summarize this chapter: exploratory analysis of the data indicated various outliers. These were deleted and the remaining data from the 220 respondents was used in the subsequent analysis. The data for the variables was ordered and further explored, indicating the variable that denotes the Decision Time variable required additional attention, and could be constructed in a variety of ways. A logistic regression was run that indicated that respondents who take more time to make their decision are more likely to minimize regret, while respondents who have a lot of Subjective Knowledge are more likely to maximize utility. Additional models were run, the first including interaction variables and demographic variables, this model did not perform better than the model without these variables. And secondly, additional models with alternating Decision Time variables were run. These models indicated that the omitted outliers did not significantly contribute to a bias in the results derived from the Decision Time variable.

5. Discussion

The RRM paradigm is a very recently developed paradigm, that performs equally well as the RUM paradigm in a lot of situations (Chorus, 2008; Chorus, 2010). However, since it is a new paradigm, it is also not as popular as the RUM paradigm, and therefore not yet a readily available option in most of the off-the-shelf programmes. The fact that the RRM model often performs equally well, or sometimes even better than the RUM model, makes it very interesting to explore in which choice situations these differences between models are largest, and how this knowledge can be used to better interpret consumer behaviour.

Recent research has extensively compared RUM and RRM by estimating models on the full data set and then comparing model fit, out-of-model predictability and other metrics used to compare models (Beck et al, 2013; Chorus et al, 2014). The goal of this sort of research often appears to be to determine if the newer paradigm, RRM, is a worthy competitor of the decision-rule that holds the status quo, which is to be expected, so long as the usage of a homogenous decision-rule approach is common practice. However, without a doubt the future will steer towards models that allow for heterogeneity in decision-rules, such that the strengths of the individual decision-rules are able to complement each other, which ultimately enables the researcher to predict consumer behaviour more accurately. The Probabilistic Decision Process models (PDP-models) are one of the first models that aim to do this, by allowing for heterogeneity in decision-rules. However, research that use such models usually cannot find differences in contextual factors, but can only look at practical measures such as the amount of alternatives of the design, or the general subject of the survey (Chorus et al, 2014). This is due to the fact that to find differences, readily available data-sets are used, to which no particular variables of interest can be added. The study of Beck et al, 2013 is the only study I could find that links contextual factors directly to the respondent level, and they find that those respondents that bear the most responsibility in their household are more likely to act along the lines of the RRM paradigm.

In respect to the above, this thesis is unique by specifically searching for the link between contextual factors and the propensity of consumers to act along the lines of the RUM or PRRM model.

The results of the analysis indicate that there is a significant relation between the independent variables Decision Time and Subjective Knowledge and the dependent variable that denotes the propensity of acting more along the lines of the PRRM or the RUM model. The results indicate that respondents who take longer to make a decision are more likely to act along the lines of the Pure-Random Regret Minimization model, while respondents who have a lot of Subjective Knowledge are more likely to act along the lines of the Random Utility Maximization model.

These results provide a very promising finding, as Decision Time is very easy to measure in a stated preference research design. The practical implication of this finding is that researchers who include a timer in their study have better grounds to justify the use of the Pure-Random Regret Minimization model. However, it is worth noting that care must be taken when segmenting respondents, since it cannot be said that respondents that have high Decision Times are actual regret minimizers. Instead increased Decision Time only provides an indication that it is more likely that these respondents act more along the lines of the PRRM paradigm.

5.1. Future research

The future research co-chapter entails two subjects. The first subject relates to possible improvements to the research design used in this research paper and possible biases that may arise from it. Secondly, recommendations are made for future research.

Due to a lack of expertise in running state-of-the-art mathematical models, this research paper did not utilize a model that takes into account freedom in the taste parameter. Future research into the predictive power of contextual factors on when one decision-rule outperforms the other, should entail more complex models that allow for freedom in the taste parameter. This ensures that there is no specification bias in the results. Furthermore, the recommendation is to use state-of-the-art models to make the research design more relevant and realistic to the respondent. A first example of a more recent approach is the so-called tournament-mode choice-set, that drafts a specific research concept for each respondent. This entails that respondents can themselves include the attributes of a product that they actively take into account, and omit those that are not of interest to them. A second practical example could be to implement a 'none' option as a choice alternative, so that respondents who do not wish to make a decision are not forced to do so, but instead can opt-out. The latter idea would be of particular interest to studies relating to regret-minimization paradigms, since the literature reports that it can be expected that respondents who anticipate regret prefer to delay their choices, or avoid it altogether in some situations.

Taking a closer look at the research design-level, it could also be worthwhile to investigate for what sizes of choice-sets respondents become more likely to act more along the lines of the

PRRM paradigm. Since the mathematical PRRM paradigm postulates that regret arises when the chosen alternative is outperformed on any level, it is thus more likely that differences are found when choice sets have many alternatives, attributes and levels.

6. Conclusion

This study was set out to explore whether contextual factors have predictive value on when the Random Regret Minimization model structurally outperforms the Random Utility Maximization model. The contextual factors that are under investigation are derived from the theory of anticipated regret and consumer expertise. The theoretical literature on this subject has brought forth strong indications that a link exists between contextual factors and the mathematical decision-rule that best fits one's' decision-making. These indications are found in (meta-) studies where multiple, homogenous, decision-rules are applied to a full-data set and a comparison is made in terms of model fit. In this research paper, a unique approach, based on the PDP-model, is used that allows to look at the decisions, and drivers of decisions, of each respondent by allowing decision-rules to vary per respondent.

Thus, the aim of this research paper is to investigate the indications found in the literature and focuses on the respondent level in order to find differences. This line of research can yield significant contributions to industries such as marketing, transportation, and healthcare, that rely on estimation practices derived from conjoint analysis. The question that is central in this research paper is: do contextual factors have any predictive value on when the Random Regret Minimization model structurally outperforms the Random Utility Maximization model?

This question was investigated by having constructed four hypotheses that relate to the contextual factors under investigation, which are presented in table 24.

Table 24

Alternative hypothesis, including results and conclusions

	Alternative Hypothesis	Results	Conclusions
H1	Consumers who take more time to decide are more likely to choose in line with the Random Regret Minimization model than the Random Utility Maximization model	At a significance level of $\alpha = 0.05$ the null hypothesis is rejected for p-value = 0.033.	Consumers who take more Decision Time are more likely to minimize regret.
H2	Consumers who perceive decision-making as difficult are more likely to choose in line with the Random Regret Minimization model than the Random Utility Maximization model.	At a significance level of $\alpha = 0.05$ the null hypothesis is accepted for p-value = 0.759.	There is no relationship found between Perceived Difficulty and assumed decision-heuristic.
H3	Consumers who are susceptible to interpersonal influence are more likely to choose in line with the Random Regret Minimization model than the Random Utility Maximization model.	At a significance level of $\alpha = 0.05$ the null hypothesis is accepted for p-value = 0.736.	There is no relationship found between Susceptibility to interpersonal influence and assumed decision-heuristic.
H4	Consumers who have a lot of Subjective Knowledge are less likely to choose in line with the Random Regret Minimization model than the Random Utility Maximization model.	At a significance level of $\alpha = 0.05$ the null hypothesis is rejected for p-value = 0.027.	Consumers who have a lot of Subjective Knowledge are more likely to maximize utility.

The hypotheses shown in table 24 were evaluated to answer the research question. This was done by testing the four contextual factors, Decision Time, Perceived Difficulty, Susceptibility and Subjective Knowledge against the dependent variable that denotes whether respondents act more along the lines of the PRRM model or the RUM model.

As is reported in the Discussion chapter, the model used in this research paper lacks freedom in the taste parameter, and is heavily reliant on one continuous parameter in the choice-set, which may lead to a specification bias. Furthermore, according to research of Van der Ploeg et al (2014) the size of the P-RRM group borders on being an insufficiently large sample. Additionally, it is noted that the construction of the Decision Time variable is not done under ideal circumstances; firstly, it is assumed that completion time per page accurately measures the Decision Time property, however there is a possibility that reading times between respondents vary a lot, which could interfere with reliably measuring the Decision Time variable. Secondly, the situation under which the time variable is constructed is far from ideal because it was impossible to check if the outliers were experimental errors or in fact a correct measurement of Decision Time. To get better insights into the validity of the results a study that aims to replicate these findings would be highly valuable.

Taking into account the assumptions and restrictions of this research as outlined above, the remainder of this chapter provides an interpretation of the analysis output and an evaluation of the hypotheses.

The results from the logistic regression indicate that hypothesis 1 and 4 can be accepted, while hypothesis 2 and 3 are rejected. This means that respondents with a longer Decision Time are more likely to act along the lines of the Pure-Random Regret Minimization model, while respondents who have a lot of Subjective Knowledge are more likely to act along the lines of the Random Utility Maximization model.

The magnitude of these results are further examined to provide an answer to the research question if contextual factors have any predictive value on when the Random Regret Minimization model structurally outperforms the Random Utility Maximization model. Whether the factors that explain the relation to the dependent variable have enough predictive power is best described by the statistic of a R-square test, or in the case of the logistic regression, a Pseudo R-Square test.

Based on the Nagelkerke R-square and Cox & Snell R-square test, the conclusion is made that even though there are two significant variables in the model, the variability that they explain is very small (between 4.6% and 7.8%). The answer to the research question if contextual factors have any predictive value on when the Random Regret Minimization model structurally outperforms the Random Utility Maximization model is thus: the variables Decision Time and Subjective Knowledge do in fact indicate to some extent when it becomes more likely for a consumer to act more along the lines of the Random Regret Minimization model or the Random Utility Maximization model; but it is not possible to indicate where the line can be drawn and from what point on we can speak of structural outperformance. Therefore, the formal answer is 'no', contextual factors do not have any predictive value on when the Random Regret Minimization model structurally outperforms the Random Utility maximization model.

Contrarily, there is also no indication found for when there is structural outperformance of the Random Utility Maximization model over the Random Regret Minimization model.

Lastly, it is noted that this thesis has attributed to the way decision-rules are viewed. Models such as RUM have been viewed as simply describing the relation of explanatory variables to the outcome of a choice, without reference to exactly how the choice is made (Train, 2002). In terms of its added value to the literature, it therefore can be said that this thesis contributes to the understanding of the complexity of consumer decision-making by providing unique insights into possible drivers of individual's decision making.

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