PHD

The Impact of Consumer and Product Characteristics on Change in Attribute- Weights over Time and its Implications for New Product Sales Forecasting Using Choice-based Conjoint Analysis

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The Impact of Consumer and Product Characteristics on Change in Attribute-Weights over Time and its Implications for New Product Sales Forecasting Using Choice-based Conjoint Analysis

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Abstract

One of the major demand related risks for companies that produce consumer electronics goods is change in consumer preferences over time as reflected in the weights they attach to the attributes of products. This contributes to the difficulty of predicting whether consumers will purchase a new product or not and the accuracy of such forecasts can have significant ramifications for companies' strategies, profitability and even their chances of survival. Knowledge of attribute-weights and accurate forecasts of new products can give companies better insights during the product development stages, inform go-no-go decisions on whether to launch a developed product and also support decisions on whether a recently launched product should be withdrawn or not due to poor early stage sales. Despite the important implications of change in attribute-weights, no research has investigated the extent to which such changes occur and impact on the accuracy of forecasts of the future market share of these products. Prior to the current research, it was assumed that the weights are constant over time – even when the nature of the attributes was assumed to change.

To investigate these concerns choice based conjoint (CBC) was applied to data gathered in a longitudinal survey of consumer choices relating a range of consumer electronic products, where innovation has different rates and the product life cycles are various. This allowed an assessment of the extent to which the weights of attributes of choice-based conjoint models change over a six months period for consumer durable products and the degree to which this variability is dependent on the nature of the product. It demonstrates that the change in weights is greater for products that have high technological complexity and shorter life-cycles and also links the changeability of weights to the characteristics of potential consumers. The results of thesis demonstrate that the assumption of constant weights can potentially lead to inaccurate market share forecast for high-tech, short life-cycle products that are launched several months after the choice-based modelling has been conducted.

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Publications and Presentations

The work contained within this PhD has given rise to the following publications and presentations:

1. Jahanbin, S., Goodwin, P. and Meeran, S., 2013. New Product Sales Forecasting in the Mobile Phone Industry: an evaluation of current methods. Proceeding 33rd International Symposium of Forecasting, 23-26 June, Seoul, Korea.
2. Jahanbin, S., Goodwin, P. and Meeran, S., 2013. New Product Sales Forecasting in the Mobile Phone Industry. Operations Research Society Conference (OR-55), 3-5 September, Exeter, UK.
3. Jahanbin, S., 2013. New Product Sales Forecasting in the Mobile Phone Industry Annual Conference. IDO 2nd Annual Conference, 11 November, Bath, UK.
4. Jahanbin, S., Goodwin, P. and Meeran, S., 2014. How Change of the Relative Importance of Product Attributes to Consumers can Influence Sales Forecasting Methods in Consumer Electronic Goods. Operations Research Society Conference (OR-55), 3-5 September, London, UK.
5. Jahanbin, S., Goodwin, P. and Meeran, S., 2014. How Change of the Relative Importance of Product Attributes to Consumers can Influence Sales Forecasting Methods in Consumer Electronic Goods. INFORMS Annual Meeting, 9-12 November, San Francisco, US.
6. Jahanbin, S., Goodwin, P., Meeran, S. and Quariguasi Frota, J. 2015. How Change of the Relative Importance of Product Attributes to Consumers can Influence Sales Forecasting Methods in Consumer Electronic Goods. International Symposium on Forecasting, 22-24 June, Riverside, US.
7. Jahanbin, S., Goodwin, P. and Meeran, S., 2015. Does lability in consumer preferences make forecasts from choice-based conjoint models unreliable? Working Paper.
8. Jahanbin, S., Goodwin, P. and Meeran, S., 2015. Establishing Demographic Differential Changes in Consumer Preferences. Working Paper.

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1. Introduction

1.1. Research Background

One of the major demand related risks for companies that produce consumer electronics goods is change in consumer preferences over time. In this particular market, it is often not clear which technology is on the rise and which is on its way out. It is also difficult to predict whether consumers will purchase a new product or not, which has significant ramifications for company sales forecasts and overall business strategy (Sodhi and Lee, 2007). Change in consumer preferences is manifested by changes in weights of attributes (attribute-weights) which reflect the relative importance of features to consumers. Changes in attribute-weights over time been widely observed and several reasons have been put forward to explain this, including: cognitive biases and limitations, changing familiarity and knowledge of products, as well as external factors (Simon, 1955; Bettman et al., 1998; Amir and Levav, 2008; Payne et al., 1992; Kahn, 1995; Coupey, Irwin and Payne, 1998; March, 1978; Pollak, 1978; Fader and Lattin, 1993; Hledik, 2012; Davis, 1989; Briley et al., 2000). Despite the important implications of change in attribute-weights, no research has investigated the extent to which change in attribute-weights impacts on the accuracy of forecasts of the future market share of these products. Prior to the current research, it was assumed that the weights are constant over time – even when the nature of the attributes was assumed to change.

One of the potential reasons for changes in attribute-weights over time, especially in relation to consumer electronics goods, is technological advances, which have shortened the life cycle for many products (Kurawarawala and Matsuop, 1996; 1998). The increasing complexity of combinations of product features could be another reason for changes in attribute-weights. For example, Bettman, Luce and Payne (1998) believe that consumer preferences become more unstable where a consumer needs to make a complex or unfamiliar decision. This is, to some extent, connected with the theory of bounded rationality, which asserts that decision-makers have a limited capability to process information (Simon, 1955). Simon suggested that due to their limited capacity to process information, consumers use or recall only a certain subset of attributes during the decision-making process. If the subset changes over time, perhaps because some attributes become more or less salient, then clearly attribute-weights in the decision making process will change as well (ibid).

Knowledge of attribute-weights and accurate forecasts of new products can give companies better insights during the product development stages, inform go-no-go decisions on whether to launch a developed product and also support decisions on whether a recently launched product should be withdrawn or not due to poor early stage sales. In consumer electronics, design decisions as well as production and procurement decisions need to be made well in advance of the product's introduction stage, and hence the need for accurate forecasting becomes an even more crucial and challenging task (Kurawarawala and Matsuop, 1996; 1998). In addition to product planning, firms need to have accurate sales forecasts to plan their activities, such as setting marketing budgets, HR planning and allocating R&D expenditure. Two scenarios are likely to happen when firms do not make accurate forecasts: first, they may forecast less than their realisable sales and hence, lose market share to their competitors. Second, they may forecast more than their actual sales and end up with a significant amount of obsolete stock, which is a costly scenario that can represent as much as 50% of total product cost in the worst cases (Reiner et al., 2009). However, forecasting is a challenging task per se, especially regarding new products for which no past data are available.

A popular method that is designed to yield these insights and forecasts is choice based conjoint analysis (CBC). Essentially, CBC is an approach that uses statistical methods to determine the probability that a consumer will choose a particular product, given its particular combination of features. It achieves this through a process of asking people to make choices between products with different combination of features in carefully designed surveys. From this it infers the weights that consumers are implicitly assigning to each of the features; the weights are assumed to reflect the importance of each feature in the product selection decision and hence its contribution to the probability that a product possessing this feature will be selected. CBC can give insights into attribute-weights at any stage of the product development and marketing process and can also be used in new product sales forecasting. In addition to simulating how consumers might react to changes in current products or to new ones as well as forecasting, this method has much wider applications, such as in the fields of: health care (Halme and Kallio, 2011), the hospitality and service industry (Victorino et al., 2005), the tourism industry (Grigolon et al., 2014), economics (Keane and Wolpin, 2009), transport (Lapparent and Cernicchiaro, 2012) and pharmaceutical suppliers (Li et al., 2006). In fact, CBC can be used whenever somebody is required to make a choice or trade-off. As contended above, the attribute-weights are not stable over time, but CBC takes a snapshot of preferences at a particular moment. If the speed of changes in attribute-weights is quite slow then this snapshot can be considered a fairly reliable gauge of what is happening in the market. However, if their pace of change is highly volatile then the estimated weights obtained in a CBC analysis rapidly become obsolete. Prior to explaining how the current research investigates these issues as well as presenting the structure of the thesis, an overview and history of the consumer electronics in the UK market is provided in the next section.

1.2. Consumer Electronics in the UK-Market: Overview and History

Consumer electronics is one of the largest segments of the manufacturing industry with an estimated total global value of $211.3 billion in 2014, which is expected to grow to $214 billion in 2015 (PWC Technology Sector Scorecard, 2014). This rapid growth is due to increases in household income levels, local manufacturing, the launch of innovative technological products and rising awareness according to a Marketwatch Report (2014) on the ‘Global Consumer Electronics Market’. According to Euro Monitor (2014), the year 2012 witnessed a massive influx of newer and upgraded devices with increased features. In particular, it has been observed that new generations of mobile phones and personal computers (PC) are among the few products that are witnessing high growth rates and hold immense potential for the future. Accenture (2014) conducted a market research survey on consumer electronics for 11 countries with 11,000 participants in 2013, from which it emerged that 50% of the participants were planning to purchase a new consumer electronics product, with 41% wanting to buy a smart phone, 36% a PC, 33% a TV and 23% a tablet. In the 12 months prior to the Accenture survey, the participants, on average, had spent between $850 in the UK (lowest) and $1250 in China (highest) on such products. They also reported that they were planning to spend between $960 in the UK and $1490 in the China, on average, over the next 12 months. Based on their previous purchases and plans for the future, smartphones, PCs (including laptops), TVs and tablets comprise the highest percentage demand among consumer electronic goods. The large markets and significant projected growth for these goods provides justification for researching the chosen consumer electronics items in the current study, namely, mobile phones, laptops and PCs.

Additionally, the UK consumer electronics market is well-established and is mainly driven by the public desire for new technology, with the manufacturing industry being expected to generate revenue of £1.9 billion in 2014-15, (0.5% higher than the previous year). Exports are projected to amount to £1.8 billion and imports approximately £6 billion in the same year (Ibis World, 2014). The UK consumer electronics market is going to be the focal context market for the current study.

Mobile Phones

Mobile phones have become an essential part of daily life for the majority of people in the UK, starting their journey with an inaugural phone call on 1 January 1985 by the comedian Ernie Wise, a time when coverage was restricted to London as well as cost was prohibitive. Britain's mobile phone users were either very rich or used one for the purpose of their work, but: "When digital technology arrived in 1992 and two new networks, One2One and Orange, launched their first products a year later, the market opened up to consumers for the first time" (Mobile Phone History Website, 2012). The UK mobile phones market had total revenues of $3.1 billion by 2010, representing a compound annual growth rate (CAGR) of 4.5% between 2006 and 2010.

Currently, the UK mobile market is mainly served by five network providers, i.e. O2, Orange, Vodafone, 3 and T-mobile (Orange and T-mobile have recently merged as Everything Everywhere), which provide both network services and handsets from different manufacturing suppliers (e.g. Apple, Nokia and HTC) (Telecom Market Research Website, 2011). In total, there is a penetration rate of 134% in the market with more than 83 million subscribers in the UK (Forbes, 2013).

Televisions

In September 1929, the first British television broadcast was made by Baird Television's electromechanical system over the BBC radio transmitter (bairdtelevision website, 2015). Today in the UK, there is a range of free and subscription services over a variety of distribution media, comprising over 480 channels for consumers as well as on-demand content. There are 27,000 hours of domestic content produced a year at a cost of £2.6 billion. All television broadcasts in the United Kingdom have been in digital format since 24 October 2012, after the cessation of the analogue transmissions in Northern Ireland. They are delivered via terrestrial, satellite and cable as well as over IP platforms (The Communication Market Report, 2015).

Personal Computers (PC)

In 1955, there were only 250 computers in use globally with the number rising to more than one million by 1980, and this had reached 30 million by the mid-1980s. Nowadays, PCs in the forms of desktops, laptops and netbooks are common items in most homes. In 1955, a computer could not have fitted into a room in the typical house due to its large size. However, the development of much smaller transistors in the late 1950s made them far more reliable and therefore businesses took a much greater interest in them. Firms, such as IBM, could sell a mainframe computer for just under half a million pounds in today's money. Replacing the transistors with microchips made the machine smaller and more accessible in 1970 and a home PC with around a 1000 transistors would have cost nearly £70,000 in today's money. The first 'hobby' PC was the Altair 8800 in 1975, which would have cost just under £900 today and had the same power as a computer of the 1950s costing $1 million (History Learning site, 2014). In 2013, 316 million PCs were sold globally (Gartner website, 2014).

1.3. Scope of Thesis, Contributions and Managerial Implications

The above discussion has demonstrated the economic importance of the consumer electronics industry and the importance of forecasting as a tool for planning in that industry. However, it has also questioned the validity of demand forecasts based on CBC when there are rapid changes in attribute-weights for particular product features, which means that the weights associated with these features quickly become outdated.

To investigate these concerns CBC was applied to data gathered in a longitudinal survey of consumer choices relating a range of products including both consumer electronic products and other products where innovation has been less rapid and the product life cycles are longer. This allowed an assessment of the extent to which the weights of attributes of choice-based joint models change over a six months period for consumer durable products and the degree to which this variability is dependent on the nature of the product. Attribute-weights were measured on three occasions at three months intervals so changes over longer periods or within shorter periods of time were not considered. Nevertheless, it was considered that these time scales were appropriate given the rapid evolution of many electronic goods (this will be discussed in more detail in the methodology chapter). The implications of the results were only considered for point forecasts (rather than interval or density forecasts) in the consumer electronic goods market in the UK.

The research demonstrated that the change in weights is greater for products that have high technological complexity and shorter life-cycles and it also links the changeability of weights to the characteristics of potential consumers. Prior to this research, models in the literature had assumed that the weights do not change over time – even when the nature of the attributes was assumed to change. The finding of this thesis demonstrated that the assumption of constant weights can potentially lead to inaccurate market share forecasts for high-tech, short life-cycle products that are launched several months after the choice-based modelling has been conducted.

The results of the research have a number of important implications. When market share forecasts for high-tech, short life-cycle products are based on choice-based conjoint models the models should, ideally, be based on data that is collected as close as possible to the launch date of these products, otherwise the attribute-weights inherent in these models will be out-of-date. This is particularly the case where the potential consumers being surveyed demonstrate high levels of usage of products in the relevant category. Where surveying close to the launch data is not possible forecasts need to be based on methods that can estimate and extrapolate changes in weights over time. For low tech consumer durables, where the weights are unlikely to change significantly over time, surveys conducted at least six months ahead of the launch should produce reliable forecasts.

1.4. Outline of the thesis

In chapter 2, the reasons for changes in attribute-weights that were found in the previous literature are discussed as well as challenges posed by the need to measure weights of attributes. Afterwards, the literature on the product life cycle is reviewed and its importance, as one of the factors that influences the accuracy of forecasts. This is followed by a definition of product newness which is another factor that affects changes in attribute-weights. Next conjoint analysis and choice models are explained as they are the main methods used in this research. Finally, the research objectives and research questions are defined.

In chapter 3, the methodology of the study and the reasoning behind it are discussed in detail. Prior to explaining and justifying the proposed methodologies employed, the various types of research philosophies and methods available are described. Next, the research design and data collection methods are covered along with discussion of the relevant ethical issues. Subsequently, three trial studies using different conjoint analysis methodologies employing different software are presented with the aim of informing the main experiment design. This is followed by qualitative research data collection to establish the features and levels attributed by the participants regarding certain products. Finally, there is discussion on the most appropriate quantitative research design and data collection technique to fulfil this research objectives.

In chapter 4, the primary data analysis is covered with aim being to investigate the changes in attribute-weights for different types of consumer electronics products using CBC. This is in order to elicit whether the type of products significantly affects the speed of changes in attribute-weights and hence, has an impact on CBC outcomes. First, the demographics of the participants who completed all three rounds of the experiment and survey are presented, which is followed by data analysis using logit model estimations for each round and product. Once the attribute-weight estimations have been computed, the attribute-weights for each product for the three rounds are compared. In the following section, the changes in attribute-weights across products are presented and the reasoning behind the outcomes given. Subsequently, the internal consistency of the sample in the logit model estimation is examined using bootstrapping. Finally, Hierarchical Bayesian analysis is applied using Sawtooth software as an alternative estimation method to compare the changes in attribute-weights across products in different rounds with those from the logit model estimations.

In chapter 5, the individual characteristic differences that could influence the speed of changes in attribute-weights over time when using CBC are investigated. First, the chapter begins with a review of previous studies on different aspects of individual characteristics, which is followed by discussion of how individual variance can affect choices within a product. Specifically, the possibility of there being effects of demographics and technological competency on participant choices is studied. In addition to the characteristics examined so far, there is investigation into other characteristics that are specific to a certain product. Finally, change in attribute-weights over time is investigated for various user-characteristics of participants.

In chapter 6, the analysis focuses on whether changes in attribute-weights affect the accuracy of forecasting when using CBC and to what extent. First, the challenges of sales forecasting for products with short life cycles are considered, which is followed by a review of new product forecasting methods and dimensions, in particular, in terms of their pros and cons. Subsequently, new product sales forecasting using CBC is discussed, in relation to the chosen products investigated in this thesis. Finally, the results are presented and some conclusions drawn.

The last chapter is the conclusion chapter of the thesis, which contains a summary of the results, responses to research questions, key contributions, and consideration of the possible generalisation of the results, the research limitations as well as suggestions for future research.

2. Literature Review and Problem Definition

2.1. Introduction

In this chapter, the reasons for changes in attribute-weights found in the previous literature are considered as well as the challenges posed by the need to measure attribute-weights. Afterwards, product life cycle is discussed as one of the factors that influence forecasts and changes in attribute-weights. This is followed by a definition of product newness, which is another factor. Next, conjoint analysis and choice models are explained as they are the main methods used in this research. Finally, the research objectives and research questions are defined.

2.2. Possible Reasons for a Change in Attribute-Weights

Coupey, Irwin and Payne (1998) pointed out that measuring attribute-weights has been used to guide decision making in a variety of areas, such as medicine, law, public policy and marketing. For example, marketers often make strategic decisions about their products based on the results of research designed to gather information about attribute-weights. However, attribute-weights are not stable as Hlédik (2012) has stated, especially where a consumer needs to make a complex or unfamiliar decision (Bettman, Luce, Payne, 1998), which could be the case for consumer electronics goods and new products.

One of the major demand related risks for companies that produce consumer electronics goods is changes in the attribute-weights by consumers over time. In the consumer electronics goods market, it is not clear which technology is on the rise and which is on its way out. It is also difficult to predict whether consumers will adopt a new technology or not, which has significant ramifications for company sales forecasts and overall business strategy. Consequently, firms adopt various strategies to track and address the change in attribute-weights. For example, Samsung Electronics Europe continually monitors change in attribute-weights through customer data from its European customer care call centre as well as campaign management data and sales data (Sodhi and Lee, 2007). The criteria that might influence change in attribute-weights, the key ones being: cognitive factors, familiarity and knowledge of products, and external factors.

2.2.1. Cognitive factors

Five cognitive factors discussed as reasons for changes in attribute-weights in literature are:

First, bounded rationality: Simon (1955) put forward his bounded rationality theory believing that human beings have computational and informational limits regarding their rational decision making. In a later publication, Simon (1957) sharply criticised the assumption of maximisation in utility theory, arguing that a bounded rational decision maker attempts to attain some satisfactory, although not necessarily maximal, level of achievement. Simon's conceptualisation highlighted the role of perception, cognition, and learning in decision making and directed researchers to examine the psychological processes by which decision problems are represented and information is processed. The theory of bounded rationality asserts that decision-makers have a limited capability to process information (Simon, 1955). As mentioned earlier, Simon (1955) suggested that due to their limited capacity to process information, consumers use or recall only a certain subset of attributes during the decision-making process. If such a subset changes over time, perhaps because some attributes become more or less salient due to the external or internal stimuli they have recently been subject to, then clearly the attribute-weights in the decision making process will also change.

Second, constructing a choice during the decision process: The notions of bounded rationality and limited processing capacity are consistent with the growing belief among decision researchers that preferences for options involving complex and novel situations are often constructed, not merely revealed, when making a decision (Bettman et al., 1998). People often do not have well-defined preferences; instead, they may construct them on the spot when needed, such as when they must make a choice. Therefore, it has a degree of context specificity, which could also justify why people make decisions differently when dealing with different kind of products as well as possibly changing their preferences over time as they construct different choices during the process, especially when there are more features as in a complex product and some of these might become more or less important over time.

Amir and Levav (2008) carried out a study on changes in attribute-weights, looking into how people learn to become more consistent in their choices by repeating the process of choosing. These authors pointed out, that, “the prevailing view on the psychology of preference is that people hold subjective values only for basic attribute combination that define an option and that preferences for most other attribute combinations are constructed during the decision process”, which means participants might have some subjective values about a product and through the process of choosing, these subjective values becomes less subjective, thus leading to more objective decisions being taken. Consequently, repeating the process of choosing supposedly reveals peoples' subjective attribute values, because it enables them to learn how they prefer to resolve trade-offs between conflicting attributes in a choice set. If participants make more choices in a domain, they became more confident in their subjective value for the levels of each attribute and more internally consistent in their choices.

Amir and Levav's (2008) study shows that the type of learning depends on repeated decisions is highly sensitive to the structure of the choice set, which influences the degree of preference consistency that people subsequently exhibit. In their longitudinal study, the participants were required to trade-off between two attributes in a choice set experiment to meet the aim of the study (i.e. the goal was to pair trade-off learning so as to evoke choice construction and hence enhance trade-off learning that stimulates preference construction). However, the experiment is probably not a true reflection of how in reality consumer choices are made, as in reality the trade-off comprises a larger number of attributes than two, even for simple products, and consumer trading-off among alternatives (products) is as a whole rather than between only two attributes. Despite some of the argument in this paper being in the line with the bounded rationality theory perspective that the unfamiliarity of a consumer about a product can cause change in attribute-weights, Amir and Levav's (2008) work cannot explain the behavioural differences among consumers for various types of products and why the attribute-weights to participants for some type of products changes over time, whereas for certain others it does not.

Third, trading off among various features: explicit trading-off among various features for consumers is the most difficult and uncomfortable aspect of the decision making regarding a product. Payne et al. (1992) contended that one response to this is to adopt simplifying heuristics to make a decision, which may be an explanation for change in attribute-weights to consumers over time in the case of complex products with more features than with simple products. It should be noted that Payne et al. (1992) did not look into the reasons behind changes in attribute-weights.

Fourth, variety seeking: Kahn (1995) investigated the key reasons that lead to consumers choosing different options over time in his review paper. These reasons are defined as:

A. Internal desire: consumers seek variety due to some internal or personal motivation, which is called satiation/stimulation, to make precise exactly the desire to seek variety. Once a consumer has reached an optimal level of an attribute that is provided by a brand, he or she feels satiated and may choose to consume a different attribute that might be provided by another brand on the next occasion. It could happen because a specific product or brand does not satisfy all of the attributes to an ideal point, or because consumers seek a balance of attributes to maximise utility. Additionally, consumers may be satisfied with their current choices, but may be looking to try something new or different for fun of it, or for the thrill of it, or just for curiosity.
B. External situation: consumers seek variety due to external constraints rather than due to an immediate internally derived need for variety. It could happen primarily due to a change in their situation or environment, not just due to internal desire, such as price, promotions, brand perceptions, or the economic situation.
C. Future preference uncertainty: consumers seek variety so that they will have a portfolio of options as a hedge against future uncertainties or as a means to protect their continued interest in favourite options. Variety in a choice set is sought not because of the utility for diversity per se, but rather, because of the uncertainty about what future preferences will be. There are a few reasons for future uncertainty such as tastes may depend upon what was consumed immediately prior to the decision, or future moods may affects preferences.

Kahn's (1995) discussion on variety seeking is of a general nature and it does not address why there are different levels of variety seeking for different types of products. In addition, it cannot explain why the attribute-weights can be changed more often for a specific type of product, whilst for others this is not the case. Moreover, some of the explanations for variety seeking depend on the physical consumption of a product and hence, it cannot explain why mere expressions of preferences, in the absence of consumption, may be liable to change over time.

Fifth, delays in decision making: Dhar (1997) went beyond the traditional approach that focuses on the choosing of alternatives by consumers in the marketplace. His approach considers delay in purchasing decisions due to the difficulty in selecting a single alternative over other alternatives. Based on this perspective, he argued that the more difficult it becomes to choose a product (because of factors like the risk associated with the product, pricing, unfamiliarity, newness and the presence of more features), the more problematic the choice process will be; therefore consumers will postpone their purchasing decision by not choosing any product (in an experiment this would be manifested by choosing the 'none-of-them' option) leading to a source of changes in their attribute-weights over time.

2.2.2. Familiarity and knowledge of products

Two factors have been identified in the literature in relation to familiarity and knowledge of products as reasons for changes in attribute-weights. These are prior knowledge of the product and the risk arising from a purchase as a result of incomplete knowledge of a product.

First, prior knowledge: Coupey, Irwin and Payne (1998) took the view that consumers' prior knowledge of a product may affect two aspects of their expression of preferences:

A. The information about the product itself (i.e. its features' specifications) forms the basis for preferences or choosing the product by consumers.
B. The way in which this information is used by consumers to acquire or search for more information. For example, familiarity with products may involve the use of prior product–related knowledge when acquiring or searching for more information.

Whether a product is familiar or not, consumers may search their memory for some information to help guide preferences construction. With familiar products, choice is likely to be an easily performed task, as consumers are likely to know which attributes are most important, whereas for unfamiliar products they have less information in their memories to guide them. Consequently, there will be more changes in attribute-weights over time as they learn more about them. Unfamiliarity of consumers about a product is usual when it is new, has added new features and/or is a high tech product with many complex features, which leads to change in attribute-weights over time. As a product and its features become familiar to consumers over time, it is most likely that attribute-weights become more stable and consistent, particularly if it and its features stay the same after multiple purchases.

Second, associated risk: March (1978) claimed that every rational choice involves two concerns in terms of associated risks, first, consumers will be concerned about the consequences of a particular choice in the future, and second, they might not be certain about their future preferences as it might be different from the current preferences. March (1978) said "individual preferences often appear to be fussy and inconsistent, and preferences appear to change over time, at least in part as a consequence of actions taken". High tech consumer electronics products with complex features could be considered as being risky choices due to the complexity of their features and high cost, whereas simple low technology products might not be considered as risky.

2.2.3. External factors

Six external factors have been discussed in the literature as reasons for changes in consumer preferences.

First, the current economic situation: Pollak (1978), taking an economic perspective, contended that changes in attribute-weights happen for two main reasons:

A. Preferences and tastes shift due to changes in the demographic characteristics or economic circumstances of a household (e.g. their household budget), which occurs at the individual level. For example, Anderson (1984) carried out research on how a change in lifestyle or social status can alter consumer preference for a particular brand of a product.
B. Preferences and tastes can also be changed due to changes in the economic situation of the state, which requires understanding of the bigger picture through macro level investigation of the economy or welfare analysis.

Second, brand: some of choice studies between 1980 and 1998 focused on brand choices rather than product attributes, based on the assumption that non-brand product attribute-weights to consumers are stable over time. Fader and Lattin (1993) were of the opinion that most prior research was useful in explaining the brand preferences across households rather than explaining changes in attribute-weights for a brand over time. Therefore, they tried to use exponential smoothing to extrapolate consumer brand loyalty from univariate time-series data. Guadagni and Little (1983) measured the changes in households' tastes for brands over time using exponential smoothing weighted averages of past choice behaviour in which the recent choices were weighted more heavily. Keane

(1997) compared different models to figure out dependency of brand choice over time by applying a probit model to secondary panel data of consumer goods (ketchup). He concluded that choosing a brand in t-1 correlated with a choice in t; however, he ignored the effect of other underlying factors and features in the choice of a product. Erdem (1996) modelled brand choice by using panel secondary data based on habit persistence on consumer packaged goods. He found that consumers' choices of brand were based on previous purchases and hence, were habit persistent, which could explain persistency in the choice relating to simple product. Erdem and Keane (1996) carried out studies based on the effect of usage experience and advertising exposure on brand choice in relation to consumer packaged goods. They derived two models from Bayesian learning, which fitted the data very well, and performed better at out of sample in comparison to exponential smoothing. They found that consumers were risk-averse with respect to variation in brand attributes, which discouraged them from buying unfamiliar brands. However, they did not consider other factors, and could not account for changes in preferences over time for familiar brands. Chintagunta, Jain and Vilcassim (1991) conducted research on brand choice preference to show the dynamics of choice by applying logit models to panel data. Kamakura, Kim and Lee (1996) looked into consumer heterogeneity in terms of preference heterogeneity and structural heterogeneity in brand choice. The novelty of this research was in using nested logit instead of Multinomial logit, thereby giving more flexibility in the preference modelling and paying more attention to the hierarchy of consumer choices. However, they did not investigate how the attribute-weight to consumers might change over time. There are other studies on brand, such as Jain, Vilcassim and Pradeep (1994), who applied a choice model to panel data and Mela, Gupta and Lehmann (1997), who carried out a long term study for 8.25 years on the effects of price changes, advertising and promotion of the manufacturer on the brand choice of consumers, which focused mainly on advertising and brand perception.

Third, technological developments: Another reason for changes in attribute-weights over time is rapid technological development in consumer electronics products. Technological advances in communication and information technology have changed the nature of products and their capability as well as consumer demands and needs towards these products. As a result, some attributes have become more (sometimes less) important over relatively short periods of time (Jahanbin et al., 2013).

Fourth, mass customisations and complexity of products: The number of attributes has increased substantially in consumer electronics goods in recent years. For example, mobile phones that used be only for making phone calls in the 1990s, nowadays serve many functions, including emailing, social media, taking photos, and even banking and making payments.

A number of factors has led to the emergence of complex products, not least is the development of communications and information technology, which has changed the way companies operate as well as the structure of the economy of nation states. In today's globalised world, there are more multi-national firms than ever before and mass production of standardised products sold across the world have led to economies of scale, thus resulting in cheaper and more accessible products. On the other hand, there is huge pressure to differentiate products from competitors, which are no longer in a single local market. Consequently, a wide range of products has been created in response to demand in different segments in different markets. Additionally, firms try to differentiate their products by adding new features and functionality to the existing basic functions (Hledik, 2012). Referring to the mobile phone example, this is not only for talking anymore, it serves other purposes. Increases in number of features for certain products to such an extent have made it nigh on impossible for consumers to consider all of them when making a decision. Mass customisation strategies (Davis, 1989), mean that products can include a wide variety of features to satisfy greater numbers or segments of customers. The resulting high sales mean that mass produced standardised products cost less than a customised product, but each segment or consumer might buy it for their own reasons on the basis of a subset of the available features.

As retailers and manufacturers want to target as many consumers as possible in order to increase their sales, they use different combinations of features for the products so as to meet the requirements of a wide range of consumers with different tastes and demand. Hence, both customers and the producer can benefit from mass customisation by mass production or economies of scale. This decreases the costs of production due to the larger numbers of a product, which results in lower prices for customers and manufacturer consequently selling more items. This concept, known as the 'mass customised product', is one way to satisfy consumer needs on a segment level as well as to take into consideration individual preferences within a segment in a cost effective manner (Davis, 1989). In general, mass customisation become an ideal solution for keeping both marginal and fixed costs as low as possible (Cox and Alm, 1998).

Fifth, cultural differences: Briley, Morris and Simonson (2000) looked into consumer choices in terms of a cultural differences perspective with a static view point. Thus, it remains to be seen whether cultural differences shifting over time could change the attribute-weights to consumers or whether some cultures exhibit greater stability of these than others.

Sixth, framing the choice: Slovic (1995) highlighted that changes in attribute-weights to consumers appear to be remarkably labile; being sensitive to the way a choice problem is described or "framed". By designing an experiment that is consistent over time, a researcher can control this factor.

2.2.4. Other factors

In addition to the above discussed reasons, change in attribute-weights have been studied considering other factors in the literature. Basmann, was one of the pioneers, who started the discussions on the change in attribute-weights to consumers and elasticity of demand in 1956. Hoch and Loewenstein (1991) considered change in attribute-weights over time from the perspective of self-control and impulsivity, while Costley and Brucks (1992) approached the phenomenon taking a recall and information use stance. Finally, Yang and Allenby (2003) looked into the attribute-weights from the perspective of other consumers' choices within a network and found that consumer taste in a social setting could be influenced by the taste of others.

2.3. Challenges of Previous Studies to Measure Attribute-Weights

The increased complexity of products and technological advances pose new challenges to researchers in the exploration of attribute-weights. This is partly due to the fact that the methods used earlier to measure those of products were unable to address their changes in relation to complex products comprehensively. For this reason, in recent years much effort has been put into improving these methods so as to make them more suitable for measuring attribute-weights pertaining to a large number of complex products with many complex features (Netzer and Srinivasan, 2011; Scholz, Meissner and Decker, 2010).

The two common approaches to measuring consumer preferences or attribute-weights, conjoint analysis and the self-explicated method, are based on the assumption of classical utility theory that consumers have stable and coherent preferences. On the other hand, many studies conducted in the past decades on economic, psychology, marketing have confirmed that attribute-weights are not stable. Research has shown that change in attribute-weights is influenced by a number of factors, such as the context (Tversky and Kahneman, 1981), the goals (Bettman et al., 1998), and the experience (Hoeffler and Ariely, 1999) of making a choice.

Heldik (2012) looked into the instability of preferences over time by conducting a two-phase experiment for mobile phones (complex product) and yogurt (simple product); obviously they are not from the same category of products. The instabilities of preferences were examined with regards to each product attribute to see for which attributes the consumer had primary preference, secondary preference or non-preference, and whether there was instability in the preferences of the participants (who were only aged 18 to 23). Heldik (2012) did not find a significant relation between complexity of product and instability of preferences. This could be due to a number of reasons. First, it was only a two phase study; second, the experiment was not well designed to measure systematic inconsistency and hence, it only uncovered random inconsistency in both products; and third, there was a one year gap between the two times of data collection so consumers might have changed preferences for simple products as well as complex ones as this is quite a long period. The study also had a few other limitations. First, it involved using a narrow age range, which potentially decreased the generalizability of the findings; second, only two products were compared; third, these products were from different categories so other factors besides product complexity may have influenced the relative stability of preferences; fourth, the study did not look into the relative importance of the features to consumers; and fifth it only considered primary, secondary, and non-preferences.

Baltas and Doyle (2001) contended that individual differences and taste variations influence participants' choices, especially when they are participating in a repeated choice experiment with panel data. According to this study, if effects of individual differences are not taken into account, the model may just yield biased estimates of aggregate market response. Therefore, it is necessary to consider factors that could potentially affect and drive changes in individual's taste over time.

Sometimes, when choosing complex products not all participants consider all attributes. Scholz et al. (2010) used a modified version of Analytical Hierarchy Process (AHP) that involved applying peer comparison (trade-off between two variables) to make sure participants took into account all the features in their study. However, although it sounds very useful to make participants pay attention to all aspects and features, this does not reflect the reality of consumer choice. For, in most cases, consumers will not pay attention to all aspects of a certain product and will not be interested in all of its features. Additionally, in reality consumers choose or see a whole product with all its features and specification together rather than considering these aspects separately or comparing them in a two-by-two trade-off manner.

2.4. Product Life Cycle

The Product Life Cycle (PLC) concept was introduced in 1950, as "The evolution of product attributes and market characteristics through time.... [the PLC concept can be]....used prescriptively in selection of marketing actions and planning" (Rink and Swan, 1979). Kotler, Wong, Saunders and Armstrong (2005) define PLC as the course of a product's sales and profits over its lifetime, which includes four distinct stages: introduction, growth, maturity and decline; however, some authors add an initial stage of development and others add a final phase of cancellation (Tibben-Lembke, 2002) to these four stages.

According to Everett (1962) (cited by Rink and Swan (1979)), the theoretical rationale behind the PLC concept derives from the *adoption and diffusion theory of innovations.* In the introduction stage for a product, there are low sales as few consumers are aware of the new product or service. Subsequent increased consumer awareness and acceptance of the product or service raises the amount of sales, thereby signalling the beginning of the growth stage. However, the growth rate shrinks for the product or service as more competitors enter the industry and the market becomes smaller. In the maturity stage, sales become more stable when most of the mass market has already purchased the item and this is followed by the decline stage as most consumers begin to look for newer counterparts.

Although a product may go through all of the aforementioned stages, not all follow the PLC, for instance, some products never reach their intended customers and fail to reach the growth phase (Tibben-Lembke, 2002). According to Gallo (1992), the failure rate of new products is approximately 85 to 90 percent in the grocery industry and here products do not follow the usual shape of the PLC curve. In this industry, steep growth is followed by stable maturity and sharp decline (Jensen, 1982). There are other products that die quickly soon after their introduction and hence they do not have all the distinct stages, such as fashion apparel, PCs and mobile phones, which are called products with short life cycles. In fact, the PLC can be as short as a few months (a season) in fashion apparel (Kurawarwala and Matsuo, 1998) and PCs (Angelus and Porteus, 2002).

Although a company does not know how sales will change in the future from one period to the next for a particular product, its sales, to some extent, will follow the PLC curve from the initial stage to the termination of the product’s life through several distinct phases, according to a wide body of literature (Cox, 1967; Rink and Swan, 1979; Day, 1981; Gardner, 1987). The length of the product life cycle is one of the factors that potentially impacts on the stability of consumers’ choices and in turn the forecasts of demand for products. Short life cycles mean consumers will be unfamiliar with a rapid stream of new products, while constant changes and innovation in the features available mean that the relative importance of these features is likely to change over a short period of time.

Wu and Chu (2010) pointed out that life cycles are shortening for many products. Similarly, Kurawarawala and Matsuop (1996; 1998) remarked that “products with short life cycles of one or two years are becoming increasingly common in several industries”. Bilir (2014) categorised electronic components and accessories as well as computer equipment as products with the shortest life cycles (e.g. mobile phones and laptops), while household appliances (e.g. fan heaters) are categorised as having intermediate length life cycles.

In the context of this research, laptops and mobile phones are consumer electronic goods that have a slightly shorter life cycle (2 to 3 years) than TVs (4 to 6 years) and fan heaters (5 to 10 years) due to the speed of innovation, which makes mobile phones and laptops out of date more quickly in terms of both capability and features.

2.5. Definitions of a Product’s Newness

Product newness has been defined differently by scholars. One definition by McDade, Terence, Pirsche (2002) as well as McDade, Terence, and Thomas (2010) relates to the ‘radicalness’ of an innovation, which can be divided into three categories: A. incremental: innovations that make a marginal improvement in existing technology, such as improvements in the camera, display resolution, and the processor in an iphone 5 compared to that of an iphone 4 (apple UK website, 2012); B. semi-radical: innovations that represent a significant improvement in existing technology, such as the cordless phone; and C. radical: innovations that represent a major or revolutionary technological advance, such as the concept of the smartphone by Ericsson introduced for the first time in 2000 (Teardown Report, 2001). Regarding the last category, the Ericsson R380 smartphone combined the functions of a mobile phone and a personal digital assistant (PDA).

Another definition by Parker (1994) considers the newness of the product through its impact on consumer behaviour: products with continuous innovations will not disrupt behavioural patterns (e.g. an improved version of the iphone), products with dynamically continuous innovation will lead to small changes in behaviour, (e.g. a camera phone), and products with discontinuous innovation will lead to significant changes in consumer behaviour and substantial learning will be required on the part of consumers (e.g. the ipad as a new generation of PDAs). The launch of the ipad created new demands for the consumers in using tablets, thereby representing a discontinuous innovation that led to a significant change in consumer behaviour.

All levels of radicalness and continuousness are common in consumer electronics products, especially in the high tech sector. Therefore, launching new products with different specifications is common in this market. Although there are other products in the high tech sector that have short life cycles, such as tablets and smart watches, for this research mobile phones and laptops are investigated, because they are more generic products for the UK population and fulfil the research question's requirements.

2.6. Conjoint Analysis and Choice based Conjoint Analysis

2.6.1. History

Green, Krieger and Wind (2001) in their paper "Thirty Years of Conjoint Analysis: Reflections and Prospects", cited conjoint analysis (CA) as one of the most widely used marketing research methods for analysing consumers' trade-offs between two or more products with different profiles, and how their product preferences are related to the attributes of the products themselves. Simon (1957), Hoffman (1960, 1968) and Churchman (1961) were among the first people who suggested that researchers can infer, or "capture", decision makers' reasoning and values by observing their decisions over certain number of circumstances. Lancaster (1966) proposed that a consumer's utility for a product could be understood as a function of the utility for components, or attributes of that product (part-worths). Since the introduction of CA in the early 1970s, it has been used not only to analyse consumer preferences or intentions to buy existing products, but also for how consumers may react to potential changes in the existing product or to a new product being introduced into an existing competitive array (Qian, 2012).

2.6.2. What is conjoint analysis?

According to Malhotra and Birks (2007), CA "…attempts to determine the relative importance consumers attach to salient attributes and the utilities they attach to the level of attributes". CA also can be defined as a technique that determines the reasons behind the day-to-day decisions of consumers' preferences based on their trade-off among various attributes of a specific product. CA determines which attributes influence a customer's decision and to what extent. For instance, it helps researchers to understand on an individual basis why and how a consumer prefers mobile handset A over handset B.

In the situation where a product is in competition with others, choice-based conjoint (CBC) analysis (different types of CA are discussed in further detail later on) provides estimates of the probability that consumers will purchase that product, given its attributes relative to those of the competing ones. The probability of the consumer refraining from purchasing any of the products can also be estimated and when the size of the potential market is known these probabilities can be easily converted into a forecast of market shares. So far, CA has been used in many different ways by many researchers for different purposes, such as forecasting, market research, product development, transport, health care etc.

2.6.3. Why should conjoint analysis be chosen over other methods?

There are two common approaches to measuring consumer preferences or attribute-weights: conjoint analysis and the self-explicated method. According to Orme (2010), although conjoint analysis (or choice based conjoint analysis that was used in this study) involves more sophisticated survey design and analysis as well as more effort by participants, it delivers much more accurate, realistic and reliable results in comparison to the self-explicit method. In a self-explicit survey question, participants might be asked to evaluate or determine the importance of a feature, which on the face of it might appear to be a simpler and more direct method of eliciting the weights; however, in CBC is arguably more realistic in that it reflects the actual choice process that consumers engage in. Consumers need to make real trade-offs among features and levels to choose the profile that maximises their utility and, based on their choices, researchers or practitioners can infer the importance of a feature or an attribute-weight. The project by Orme tried to compare the self-explicit approach with conjoint analysis to find the weights of attributes for participants. It found that they spent, on average, only five seconds responding to each question in the self-explicit method. Moreover, the majority of the participants responded with high ratings for most attributes, while the bottom half of the scale was largely ignored. These results created a problem for the statistical analysis, such as skewed distributions, with typically little differentiation between attributes, as well as revealing little information on the reality of consumer preferences. This was especially the case for complex products, which in this project were laptops computers. The author also believed that the self-explicit method does not give participants a chance of trading-off among features to determine consumer preferences or attribute-weights. For example, how much battery life will participants trade-off for a given increase in processor speed? Additionally, he believed that asking about the importance of features often does not reflect true attribute-weights to participants. Hence when using self-explicit methods, participants' answers might be totally different from the reality of their choice behaviour. For example, "It may be socially desirable to say price is unimportant, as respondents do not want to appear to be miserly. Yet in the real-world laptop of purchases, price may become a critical factor". Finally, although it might be seem much easier to ask participants to rate attributes in a self-explicit questionnaire, the task of rating attributes' importance is not reflective of real world decisions, because the participants cannot always get the best of everything in reality and they must make difficult trade-offs and concessions. Having the participants make difficult trade-offs gives the researcher a greater opportunity to learn about their true (implicit and explicit) preferences. CBC even offers greater realism than traditional CA and extends the idea of side-by-side comparisons (Louviere and Woodworth 1983; Raghavarao et al., 2011). Hence, the reason that researchers have chosen CA over other methods is because it addresses three key questions: Do consumers prefer one attribute of a product over other? What attributes are they looking for? How do they make trade-offs between these attributes?

For example, it is potentially useful if a marketer in the mobile phone industry wishes to examine the possibility of modifying its current line of services. One of the first steps in designing a conjoint study is to develop a set of attributes and corresponding attribute levels to characterise the competitive domain (Raghavarao et al., 2011). Understanding how changes in the characteristics of alternatives affect the preferences of consumers can be used as follows:

I. Identify the weights of attributes or relative importance of attributes to consumers
II. Determine what combination of attributes are most appealing to consumers
III. Forecasting individuals' preferences and market share forecasts, which could be translated into sales forecasts.

2.6.4. Conjoint analysis steps

According to Hauser and Rao (2004), there are a number of steps required when designing a conjoint study, which are as follows:

I. <u>Decomposing:</u> one of the earliest steps in designing a conjoint study is to develop a set of attributes and corresponding attribute levels to characterise the competitive domain. From a theoretical standpoint, decomposing the alternative (product or service) into a set of attributes (factors) should be based on salient factors that are important in influencing consumer preference and choice (Malhotra and Birks, 2007). This can be done through qualitative methods, such as focus groups, in-depth consumer interviews, or an internal expertise brain storming. This stage is one of the most important parts of a conjoint study, which needs careful consideration as it influences the rest of the study (Green et al., 2001). Mobile phones can be decomposed into features such as brand, price, camera resolution, keyboard type, internet, battery, application etc and each feature can have a few levels, such as brand (Apple, Samsung, Nokia, HTC, LG, Sony, BB, others), price (low, medium, high), camera resolution (high, medium, low), keyboard type (finger touch, complete keypad, numerical keypad, combination F&K) etc. Keeping the right balance between having more features and facing problems of massive data collection along with possible respondent burden is crucial.
II. <u>Representation of alternatives (profiles):</u> refers to the way a researcher introduces a product or service and its attributes in order to be understandable to participants in a conjoint research endeavour. Profiles are, in general, described through verbal and written communication. However, sometimes additional visual tools, such as a physical mock-up, graphical design, a picture and/or a video (if applicable) can provide a better understanding of the product (Raghavarao et al, 2011).

III. Fractional design of experiments: a complete factorial design is usually impractical for CA except for some cases with limited attributes and levels owning to the large number of combinations. If the mobile experiment in Trial Study 1 (Appendix 1) is taken as an example, the complete factorial design will be a total of 6972 combinations (6972= brand (8)*price (3)*camera resolution (3)*keyboard type (4)*internet (2)*battery (3)*application (4)). Fractional factorial designs are experimental designs consisting of a carefully chosen subset (fraction) of the experimental runs of a full factorial design. The subset is chosen so as to exploit the sparsity-of-effects principle (sparsity-of-effects principle states that a system is usually dominated by main effects and low-order interactions) to expose information about the most important aspects of the problem studied, while using a fraction of the effort of a full factorial design in terms of experimental runs and resources (Raghavarao et al, 2011). In the Trial Study 1 example, IBM SPSS 20 was used to generate the fractional factorial design (orthogonal design), which produce 32 profile (Appendix1).

IV. Conjoint data collection: a few different methods of data collection have been developed since CA's introduction for conducting conjoint experiment surveys. Here, the pros and cons of three of them, Ranking CA, Rating CA and Choice Based Conjoint (CBC) are discussed.

Ranking CA

The ranking method used to be quite popular in early applications of CA and involves asking participants to rank various profiles of products. The problem with this method is the difficulty of participants capturing the competition or trade-off between various products. For example, in the mobile example in Trial Study 1, ranking 32 profiles would be a difficult task and cause substantial confusion for the participants. In reality, not all customers rank different products prior to their purchase, preferring to choose between options. That is, in the ranking data collection method, participants face too much information. However, one of the advantages of this method is that respondents provide rich data and hence, the parameters may be estimated at the individual level, which means that fewer participants need to be involved when compared to choice based conjoint analysis (CBC) (Raghavarao et al, 2011; Orme, B., 2002).

Rating CA

In later applications in industry and academia, researchers used scales in order to find consumers' preferences and this resulted in better analysis and fewer comparison difficulties in that it reduces the number of judgments each participant has to make (Hauser and Rao, 2004; Raghavarao et al., 2011). For example, participants are asked the likelihood of buying a mobile handset on a Likert scale between 1 and 7 (1=never buy, 4=neutral, 7=definitely buy), or they are asked to rate a mobile handset out of 100. In general, the rating method is a more participant friendly way of carrying out a CA experiment.

The rating and ranking methods have some common advantages; in particular, as mentioned earlier, respondents provide comparatively more information and richer data than with CBC, as they associate a value to every single profile. As a result, parameters may be estimated at the individual level and conducting experiments needs relatively fewer participants when compared to the requirements of CBC (Raghavarao et al., 2011; Orme, 2002). However, the rating method also has a few disadvantages. First, participants use the rating scales in different ways, in that some engage with all the available information for rating, whilst others do not. Moreover, some rate all options at one end of the scale, whereas others favour the opposite end. Second, traditional rating CA procedures do not ask customers to trade-off between profiles, just asking them to score a single profile by considering levels of attributes for that single profile in each stage of the experiment, which makes this method potentially weak with regards to capturing the competition or trade-offs made by the participants. In reality, customers choose from among a few products to make a purchase rather than rating them individually. Finally, referring back to the mobile example, although rating 32 profiles would be easier than ranking them as it needs fewer judgments, this is still not a straight forward task (Raghavarao et al, 2011; Orme, 2002) (Appendices 1 and 2).

Considering the purposes of current research, both the rating and ranking methods have some disadvantages in comparison to CBC, in particular regarding sales forecasting. The nature of the result and output of part-worth that will be generated from these methods are *interval data*, which only permit the simple operations of addition and subtraction. For example, the Celsius scale is an interval scale, with each degree of temperature representing an equal heat increment. The zero point is arbitrarily tied to the freezing point of distilled water and raising the temperature by 10 degrees from 10 to 20 needs the same amount of heat as 20 to 30. However, 60 degrees is not twice as hot as 30 degrees, and hence 60/30 does not represent a meaningful ratio. Therefore, having *interval data* outputs makes manipulating data for the purpose of this research difficult and subject to a few questionable mathematical assumptions. Additionally, translating the results from the total utility of a product to market share and choice probability for a specific product will not be a straightforward task using the aforementioned methods (Orme, 2010) (Trial Study1 and 2).

CBC

An alternative method to collect data for CA, which does not have the drawbacks of traditional CAs and can generate *ratio data,* is choice-based conjoint analysis (CBC), which also allows estimates to be made as probabilities of consumers buying a product. CBC involves trade-offs between competing profiles. The researcher organises these profiles into a certain number of systemically constructed choice sets with each set consisting of an equal number of profiles. A consumer chooses the option that maximises his/her utility to allocate his/her limited resources efficiently (Jun and Park, 1999).

CBC has some advantages over other CA methods. First, as aforementioned, the dependent variable is a choice, which is similar conceptually and practically to the process of purchasing and can be easily translated to market share and sales forecasting. Second, the participants take into account other available alternatives when they make a choice, which reflects the attractiveness of a product. Third, the outcome and results that will be generated for part-worth will be in *ratio scale,* which gives more freedom to manipulate data. That is, the *ratio scale* data permits all basic arithmetic operations, including division and multiplication. For example, weight, height, ratio and profit are data in ratio scale and in a typical distance measure, the zero point is meaningful. Moreover, the difference in value between 10 and 20 units of distance (e.g. kilometres) is the same as that between 20 and 30 units (kilometres), 60 km is twice as far as 30 km.

CBC has some disadvantages over traditional CA. First, as aforementioned, it does not provide rich enough data that might be analysed at the individual level, as participants just make a single choice from each choice set that they are presented with and consequently, such research needs relatively more participants. Second, in a CBC study different models, such as Multi-Nominal Logit and Nested Logit are used, which involve more complicated data analysis, compared to that of traditional CA that includes multiple regressions. Lee et al (2006) and Lee et al. (2008) used a rank-ordered logit model for a ranking conjoint survey, which had pretty much the same level of complication as multi-nominal logit and nested logit. Probability models provide a more detailed explanation of consumers' choices at different stages of the buying process. For example, they may include probabilities of a potential customer being aware of the product and of recognising a need for the product given that they are aware of it (Ozan et al., 2007). Alternatively, they can represent probabilities of a consumer being aware of the product, of considering it, of trialling it and of making a repeat purchase (Roberts et al., 2005). More details of discrete choice models are provided in the relevant section.

2.6.5. Previous conjoint analysis studies

Choice models and conjoint analysis have been applied in a wide range of areas and subjects, such as economic, transport, marketing, organisational studies, agriculture, the food industry, and health care (Vinety, Lancaster and Louviere, 2002) and generally, wherever there is choice, preferences, and a trade-off among two or more options it can be applied. For example, preferences for ethically labelled coffee, genetically modified agricultural food (Hu, Veeman, Adamowicz, 2005), and local versus organic foods (James and Burton, 2003).

There are many researchers who have used some sort of CA or CBC, especially in the forecasting literature in combination with a diffusion model. Jun and Park (1999) combined a diffusion model and a multi-nominal logit (MNL) choice model to forecast multi generation sales/demand of DRAM (dynamic random access memory). They believed that as time passes "…a consumer's valuation of a product's attributes usually increases when the product succeeds in the market". Although Jun et al. (2002) claimed this might be the case sometimes, from having reviewed the change of preferences literature, the belief here is that some attributes will lose their value over time or their value may be overlooked by consumers in favour of other attributes. Jun et al. (2002) used the same model for analogue and digital mobiles and PCs in Korea as Jun and Park (1999), who adopted a combined CA and diffusion model for generating substitutions in the telecommunication services in Korea. In 2006, Lee et al. combined a ranking-based choice model with the Bass model and estimates of price development over time to forecast the adoption of flat screen TVs in Korea. However, they relied on past data (analogy) for the estimation of the price function and used this to predict the probability that consumers would choose the product, rather than competing products, at time t. Lee et al. (2008) carried out another study with a combined diffusion and choice model, but this time on home networking in Korea. Eager and Eager

(2011) also used combined CBC with a Bass model through a MNL model in the context of the automobile industry to avoid the drawbacks of ranking models.

There is serious concern about all of the aforementioned research that tried to forecast over time by using CA and CBC, as these are static models that may not be able to replicate consumers' buying behaviour over time. Additionally, CA by itself does not take into consideration product evolution, changing competitor reactions, changing product awareness as well as availability and hence, changes in consumer preferred choices. There are some other downsides to previous studies, such as the lack of extensive testing of forecast accuracy for the periods following a product's launch. Kontzalis' (1992) study was completed before the launch of the product and hence, was unable to report forecast accuracy, whilst Roberts et al. (2005) tested their model only using six monthly observations and Ozan et al. (2007) provided a simulated model demonstration.

Some conjoint studies may yield inaccurate forecasts of market share, because they ignore the fact that particular product attributes will have different impacts on different individuals from different classes or segments of society. Some studies have also assumed that a new product will take customers from existing ones in the generic domain in proportion to their current share of the market. In reality, new products tend to gain share from an existing one that is similar to them. Finally, studies that have used CA and CBC in the area of forecasting, suffer from a lack of managerial or practical implications in the real business world. Next, discrete choice models will be discussed in more detail.

2.7. Discrete Choice Models

2.7.1. Introduction

Since the 1960s, discrete choice models have been widely applied due to the rapid growth of the use of survey data on individuals' behaviour and computers that can deliver complex data analysis (Train, 2009). Meanwhile, academics have been using them and they have also been used in many large scale commercial applications since the 1990s (Sawtooth Software, 2013). According to Manrai (1995), two major ways to study consumer preferences or choices are:

I. A choice model that uses secondary data to develop the model, such as check-out point data in a grocery store, which is called *"revealed preference (RP) data"*. RP could be used as an alternative to conducting choice based conjoint (CBC) as it offers the possibility of inferring the part-worth (or part-utility) of prospective attribute levels by regressing sales or market share on information about product attributes from secondary data.

II. Choice based conjoint analysis (CBC), which uses experiment based primary data from participants to determine the part-worth (or part-utility) of attribute levels and is called a *"Stated Preference (SP)"* study.

Calfee, Winston and Stempski (2001) conducted a study using SP (primary experiment data) rather than RP (secondary choice data) to estimate consumer preferences in an inner city transport context. According to their research using SP over RP has some advantages such as:

I. Market data (Secondary data) may not be available for a new product that has not been launched and consumers may react differently in term of preferences regarding new products;
II. SP has statistical advantages over RP; the explanatory variables in RP might have a little variation, which is not enough to develop a model or to make a feature significant in a model. Additionally, the explanatory variables might be highly correlated, which makes the effects unidentifiable;
III. RP data are limited as they only capture a single choice of a participant, while SP experiments contain several choices or non-choices for each participant.

SP also has its drawbacks, such as:

I. Preparation and conducting a survey is a difficult task and time consuming;
II. Finding a suitable number of participants might be difficult;
III. It could be the case that stated preference is different from what people do in reality.

Train (2009) proposed four characteristics that need to be exhibited by the set of alternatives, (called the choice set) in order to fulfil the requirements of a discrete choice model framework. First, the alternatives must be mutually exclusive from the participants' perspectives. Second, choosing one alternative definitely should indicate not choosing the other alternatives and participants only have to choose one alternative out of those presented. Third, the choice set must include all the possible alternatives, i.e. it must be *exhaustive.*

Fourth, the number of alternatives should be finite and countable. The first three of the above characteristics are not restrictive as the appropriate definition of alternatives and the proper design of experiments can always assure that the alternatives are mutually exclusive, the participants choose only one alternative and the choice set is exhaustive. For example, in the case of two alternatives not being mutually exclusive because the decision maker can choose both of them, the alternatives can be redefined as "*only A*", "*only B*" and "*both A and B*". There are always ways to satisfy the first three conditions; however the last condition is quite restrictive as it defines the characteristics of discrete choice models and distinguishes them from linear regression that has a continuous dependent variable.

2.7.2. Random utility maximisation (RUM)

The principle of utility maximisation postulates that a consumer uses all relevant available information and selects the choice that maximises his/her utility. The conceptual basis that underpins a discrete choice model is the assumption that consumers choose an alternative that maximises their utility according to random utility maximisation (RUM) (Train, 2009); and the word random is used because the model has a deterministic component which is common to all the participating consumers, given the same characteristics and constraints, and a random component, which reflects idiosyncratic tastes of individuals and unobserved attributes of choice. The RUM concept was developed by Thurstone in 1927 in relation to psychological stimulation and involved a binary probit model to see if participants could distinguish the level of the stimulus. Afterwards, other researchers referred to this as random utility maximisation (RUM).

As a conceptual definition, utility has no natural level or scale, which has important implications for the specification of discrete choice models. From a simple perspective, the models relate the explanatory variables to the outcome of a choice, without reference to exactly how the choice is made. However, the probability derived from the models can be translated into market share and sales forecasts (Train, 2009). According to Jun and Park (1999) and Lee et al (2008), RUM can be derived as a participant, labelled n, maximised utilities (U_n) for choosing a certain product. U_n cannot be seen by researchers per se, so it is decomposed into two components to be measured by researcher:

A. a deterministic utility (systematic component) that can be measured as V_n

B. a stochastic utility (random component) that cannot be measured ε_n

$$U_n = V_n + \varepsilon_n$$

Equation 2.1

The participant n, faces J choices that obtain a certain level of utility (profit) from each alternative, which can be written as U_{nj}, j=1, 2… J. As pointed out above, this utility cannot be seen by the researcher, but it is known to the participant and as a result, the participant chooses the alternative that provides the greatest utility to use his/her limited resources more efficiently. The behavioural model can be written as: choose alternative i if and only if $U_{ni}>U_{nj}\ \forall\ j \neq i$.

Consumers choose the particular product that maximises their utility and efficiently use their limited resources; they adopt new products whenever they can maximise their utility. Although researchers cannot observe the consumers' utility directly, they can observe some of the attributes of the product that they choose. As there are some aspects and features of utility that cannot be observed by a researcher then $U_{nj}\neq V_{nj}$ and therefore, the utility of choice j can be decomposed as:

$$U_{nj} = V_{nj} + \varepsilon_{nj}$$

Equation 2.2

The characteristics of ε_{nj}, such as its distribution, depend critically on the researcher's specification of V_{nj} and cannot be defined for a choice situation per se. When a researcher wants to evaluate which choice model is more appropriate for data from a specific experiment, the characteristics of ε_{nj} become important. As the $\varepsilon_{nj}\ \forall\ j$ is unknown, researchers treat it as random and the joint density of the random variable $f(\varepsilon_n)$ can be written as $\varepsilon'_n = \{ \varepsilon_{n1},\ldots\ldots,\varepsilon_{nj}\}$. Given the density, probabilistic statements can be written on the participants' choices, whereby the probability that participant n chooses alternative i is:

$$\begin{aligned} P_{in} &= \text{Prob}\ (U_{ni}>U_{nj}\ \forall\ j \neq i) \\ &= \text{Prob}\ (V_{ni} + \varepsilon_{ni}>V_{nj} + \varepsilon_{nj}\ \forall\ j \neq i) \\ &= \text{Prob}\ (\varepsilon_{nj} - \varepsilon_{ni}<V_{nj} - V_{ni}\ \forall\ j \neq i) \end{aligned}$$

Equation 2.3

The above probability equation (Equation 2.3) shows that each random term $\varepsilon_{nj} - \varepsilon_{ni}$ is below the observed quantity $V_{nj} - V_{ni}$, which is called the cumulative distribution and can be written by using the density $f(\varepsilon_n)$ as:

$$P_{in} = \text{Prob}\ (\varepsilon_{nj} - \varepsilon_{ni}<V_{nj} - V_{ni}\ \forall\ j \neq i)$$

$$=\int_{\varepsilon} I\,(\varepsilon_{nj} - \varepsilon_{ni} < V_{nj} - V_{ni}\ \forall\, j \neq i)\, f(\varepsilon_n)\, d\varepsilon_n$$

Equation 2.4

The above multidimensional integral (Equation 2.4) is over the density of the unobserved portion of utility, $f(\varepsilon_n)$, where I (.) can be defined as an indicator function, equalling 1 when the expression in parentheses is true and 0 when it is not (Train, 2009). From the various assumptions about the distribution of the unobserved portion of utility ε_n and different specifications of the cumulative distribution of density, various forms of discrete choice models can be obtained and the most common forms are: multi-nominal logit (MNL), nested logit (NL), multi-nominal probit (MNP) and mixed logit (NL). In the following sections, the MNL receives the most attention as it is to be used in the modelling for this research, whilst NL, MNP and ML are discussed only briefly.

2.7.3. Multi-nominal logit (MNL)

MNL is by far the most widely used discrete choice model and was proposed by McFadden in 1974. It was developed under the assumption that ε_n (the unobserved proportion of utility) is independently and identically distributed (iid). The iid assumption for MNL means that the unobserved factors (error term ε_n) are not correlated over various alternatives (profiles) and have the same variance for all alternatives. It can be derived from this assumption that the error for one alternative provides no information to the researcher about the error for another. As such, MNL provides a very simple and convenient model of choice probability, which has made it very popular (Train, 2009). However, the iid assumption is fairly restrictive and it was the main reason for the development of other models such as NL, MNP and ML with the aim of avoiding this assumption and allowing for correlated errors. Nevertheless, it is not as restrictive as it might at first seem, and in fact can be interpreted as the natural outcome of a well-specified model. This assumption is based on the fact that a researcher who obtains a well specified observed portion (V_n) will ensure that the remaining unobserved portion of utility is just random, which is the ultimate goal of any researcher. Such a goal for a researcher is more idealistic rather than a restriction (Train, 2009). From the integral in Equation 2.4, and after some algebraic manipulation the closed form expression can be written as:

$$P_{in} = \frac{e^{V_{ni}}}{\sum_j e^{V_{nj}}}$$

Equation 2.5

which is the MNL choice probability. V_{nj} is usually specified to be linear as $V_{nj}=\beta X_{nj}$, where X_{nj} is the vector of the observed variable, such that:

$$U_{nj} = V_{nj} + \varepsilon_{nj} = \beta X_{nj} + \varepsilon_{nj}$$

Equation 2.6

In CBC, X is an attribute of a product and β is a coefficient. Some attributes are associated with a numeric value, such as time (10_s, 15_s, 20_s), whilst others can be categorical (either ordinal or nominal) and these need to be defined as dummy variables in the CBC model (e.g. brand, colour etc). Some variables can be considered either way and it depends on the research design regarding such a matter as Price. For example, if a researcher assumes price is a numerical variable then β can be its coefficient and X can be any amount of Price (£10, 20, 30, 50, 70, 90, 100, 150, 200, 250). However, if a researcher assumes it is a categorical Price (low, medium, high) then a dummy variable is made so that β_1 can be the coefficient of Low Price (X_1), for which X_1 is either 0 or 1 (exists/does not exist), β_2 is the coefficient of Medium Price (X_2), either 0 or 1, and High Price will be eliminated from the model (it becomes part of the constant).

In the case of correlation among the unobserved portion of utility (ε_{nj}), according to Train (2009), there are three options available for a researcher: first, using another model that allows correlated error. Second, re-specifying the representative utility in order to capture the missing factors that are the source of correlation and consequently, the new error will satisfy the assumption. Finally, using the MNL model under the current situation by considering the model is an approximation. Prior to considering the limitations of MNL, the independence from irrelevant alternative (IIA) term needs to be discussed. Under this assumption for any alternatives, such as *i* and *k*, the ratio of the probabilities is:

$$\frac{P_{ni}}{P_{nk}} = \frac{e^{v_{ni}}/\sum_j e^{v_{nj}}}{e^{v_{nk}}/\sum_j e^{v_{nj}}} = \frac{e^{V_{ni}}}{e^{V_{nk}}} = e^{V_{ni}-V_{nk}}$$

Equation 2.7

The above ratio (Equation 2.7) does not depend on any alternatives other than *i* and *k*. Moreover, choosing *i* over *k* or vice versa does not depend on the availability of any other alternatives or their features. Since the ratio is independent from any alternative other than *i* and *k,* it is said to be independent from irrelevant alternatives (IIA). When it comes to dealing with similarity among alternatives, MNL has some limitations as a result of biases relating to the assumption of IIA, which can cause overestimation of the market shares of similar products. That is, in choice experiments, consumers are assumed to select deterministically the most preferred product, but in the case of similarity among products, the model overestimates the choice shares of the highest rated alternatives. Other alternative models such as NL, MNP and ML have been developed to deal with this limitation of MNL, which are discussed in the next subsections.

2.7.4. Nested logit (NL)

As quite often researchers are unable to capture all sources of correlation in observed factors (Vnj), explicitly in order to make the unobserved portion of utility (εnj) just random (white noise), other models have been developed to avoid the independence assumption within a MNL model. One of the most well-known extensions of the MNL is NL, which has been widely used (Train, 2009). A NL model is appropriate when a set of alternatives can be categorised into different subsets. Each subset is called a *nest* and needs to have the following criteria:

I. The ratio of the probability of any two alternatives in the *same nest* is independent of the attributes. This means independent from irrelevant alternatives (IIA), which implies proportional substitution across alternatives. Within a nest, there should not be any correlation in the error term and it should be only white noise.

II. The ratio of the probability of two alternatives in *different nests* can depend on the attributes of other alternatives in the different nests. In general, IIA does not hold for alternatives in different nests.

For example, a person has four transport choices to travel to work: driving in himself/herself, sharing his/her car with others, bus or train (as shown in the figure below). If that person's car breaks down, it influences his/her choice. As a result, transport choice can be divided into two nests, such as driving and public transport, in order to eliminate the effect of car break down on that person's choice by using an NL model. This example is called a two level nest and is derived under the assumption that the unobserved portion of utility is a generalised extreme value.

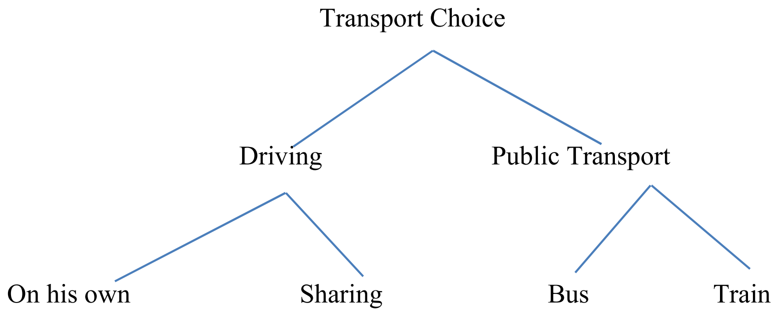


Figure 2.1. Nested logit example

2.7.5. Multi-nominal probit (MNP)

As mentioned in above section, the MNL model has some limitations, the two most important being:

A. It has a restriction regarding the iid assumption.
B. It cannot be used with panel data, when unobserved factors are correlated over time for each decision maker.

MNP addresses both drawbacks associated with MNL and is derived under the assumption that the unobserved portion of utility in equation 2.4 follows a joint normal distribution with a mean of zero and covariance matrix Ω as $\varepsilon'_n = \{\varepsilon_{n1},\ldots\ldots,\varepsilon_{nj}\} \sim N(0, \Omega)$. With a full covariance matrix Ω, any pattern of correlation and heteroskedasticity can be addressed. The main advantage of MNP is handling correlation over alternatives and time; however the functional limitation due to its normal distribution causes some drawbacks. For instance, the desirable attributes of products for customers who want to buy a phone are necessarily positive and that contradicts the normal distribution assumption as the normal distribution has density on both sides of zero. Unlike the MNL and NL models, the choice probability of the MNP model cannot be expressed as closed form, and thus it has major drawbacks regarding the numerical simulation of the estimated results.

2.7.6. Mixed logit (ML)

ML allows the unobserved factors to follow any distribution. It is based on the assumption that the unobserved portion of utility consists of a first part that follows any distribution specified by the researcher that includes all the correlation and heteroskedasticity, and a second part that is the iid extreme value. The first part of ML being allowed to have any kind of distribution, even non-normal, gives it an advantages when modelling any discrete choice situation (McFadden and Train, 2000). As the ML model needs be defined by the researcher and this involves a very complicated process, unless there is no other model that can be fitted, it is not recommended. Moreover, ML, like MNP cannot be expressed in closed form; as a result estimation relies on high-cost numerical simulation for evaluation, which is a major drawback.

2.7.7. Previous choice model studies

Gowrisankaran and Rysman (2012) developed a dynamic model of consumer preferences for a new durable product based on persistent heterogeneous consumer tastes, rational expectations of consumer and consumers repeat purchase over time. The model was estimated for the digital camcorder industry using panel data on prices, characteristics and sales. These authors looked into the trade-off between the price and time in their model as there is a general belief among consumers that later purchases are most likely have a lower price and better technology specifications. They also analysed price elasticity for a short period (one month) and a long one (12 months).

In order to deal with the static nature of CBC, Vag (2007) combined it with multi agent simulation, for which CBC provided the behavioural (preferences) data to the simulation, which offered a dynamic solution to the static issues of CBC. According to him, all consumer survey methods do not take into account changing conditions and motivations of buyers in the future, which is the usual problem with static methods as they cannot consider future changes in consumer choice, relative products important, and features utility (weights). In order to address this matter, he studied the effects of sales promotion and word of mouth on future market share or sales so as to find an explanation for tackling the reality of changes in preference as an aggregate matter. He addressed the effects of these factors through using multi-agent simulation to analyse social interaction in a way that imitated social processes. In addition to this, he used the method to analyse social networks to anticipate and model society as sets of people and linked groups by simulating these social factors. This researcher concluded that changes in preferences are due to social interaction and influence from social communications among people in society. The CA designed was based on the characteristics of the most relevant behavioural and social attributes when purchasing a mobile phone in Hungary, such as talking to friends about the products, satisfaction with service or product, habit and selecting products according to others' opinions, rather than directly considering the features and attributes. In sum, the design of CA characteristics were based on social interaction and totally ignored the importance of product features and specification in the process of decision making and changing of preferences.

Sultan and Henrichs (2000) undertook a study on consumer preference for choosing the internet by trading-off between price and purchase time (as technological product faces marked down prices over time). They combined CA and a diffusion model to estimate the effect of purchase time on the diffusion of internet service against price. Liechty, Fong and DeSarbo (2005), in their study, questioned the standard general assumption in conjoint analysis that a consumer's utility remains constant over the course of a conjoint study (for a single study, in which a consumer has to make multiple choices), which underlines most normative theories of value maximisation. They concluded that individuals have a global set of utility that is revealed at certain points in time.

The majority of choice studies that have been discussed so far are about changes in preferences, Severin, Louviere and Finn (2001), taking the opposite approach conducted research to assess the stability of preferences over time on retail shopping. Their results show no differences at all in retailing preferences, i.e. both random component variances and weights were unchanged over the four-year period studied. Specifically, the data were collected three times over four years in Canada, using different participants each time, in order to compare models of shopping centre choice based on perceived centre attributes. They used two waves of panel data to check generalisability of their research findings. They conducted surveys to study shopping centre or supermarket choice by consumers, which thus was not about a product or across different products and the research was not about a complex or unfamiliar task. Therefore, their findings are not generalisable about complex products or any type of product in the consumer electronics context. Moreover, they used different participants in each round of their survey for the same shopping malls. Shoppers in a same shopping mall location would be expected to be relatively consistent in their preferences of location, which brought them to the same place as there is not much of complexity to this decision and it is a geographical location based decision as well as location accessibility. Notably, if these researchers had surveyed the same participants that were in first round in the next rounds, the same participants might response differently to the location preferences or not, which is one of the limitations of their research.

A number of reasons have been put forward for randomness or changes of individuals preferences (as opposed to systematic changes in preferences) when conjoint experiments are being conducted and when participants have to make multiple choices:

I. Payne et al. (1992) and Slovic (1995) argued that human beings make decisions and judgments by employing a simplification strategy;
II. Individuals learn through the process of their decision making on how to make a decision, so this might be another reason for changes and randomness in the choices participants make;
III. Fatigue, boredom or changing moods might be other reasons (Bijmolt and Wedel, 1995).

A choice model, as a static model for simulating the current attitudes of consumers, giving a researcher a snapshot of the current situation, is one of the major concerns about all previous research using conjoint analysis (CA) or choice based conjoint (CBC) analysis, especially in the consumer electronic goods context, as these are complex products with short life cycles and high level technology. Some of these studies have tried to make dynamic models to address this concern. However, they have all been based on the assumption that the coefficients of the attributes (β) stay constant, which means their attribute-weighting for customers will not change over time and only the amount of the attribute (price) or the existence of attributes (internet connection) will (see Equation 2.8). Moreover, under this assumption attributes will never become more or less important over time and hence, the trade-offs that the customer is prepared to make between them will remain constant (Jun and Park, 1999; Jun et al. 2002; Lee et al. 2006, 2008; Eager and Eager, 2011). For example the weight attached to the value of a camera's pixels on a mobile phone stays the same in mind of customers and the model only reflects increases in the amount of pixels over time. It can be seen that this assumption does not consider changes in the taste of consumers that might happen over time; for instance, they might value their phone camera less compared to the speed of connection in their future choices. This is likely to be especially true in the mobile phone industry, where the novelty of a new proposed product may change consumer attitudes, as a feature might become more or even less important in relatively short periods of time. With consumer electronic goods, consumers' attitudes sometimes depend on their observations of others' experiences of the product or they may be initially unaware of the benefits that novel features can bring to them.

$U_{nit} \neq V_{njt}$, $U_{njt} = V_{njt} + \varepsilon_{njt} = \beta X_{njt} + \varepsilon_{njt}$

Equation 2.8

The current research involves looking at impact of products and consumer characteristics on change in attribute-weights (coefficient β) over time and how this might affect using CBC as a forecasting tool. There has only been one study that this researcher is aware of, namely that of Mellers et al. (1995), which has connected the changes in attribute-weights (differential weighting of attributes) with riskless decision contexts. In their study, they examined changes in human choice or judgment (preferences reversals) from a risk associated with the choices perspective in both risky and riskless domains. They contended that changes in preferences are due to various strategies adopted by consumers in order to deal with risks. In the next section, the research problem, objectives and questions are defined.

2.8. Problem definition, research questions and objectives

None of the previous studies have considered the changes in attribute-weights over time for different products and therefore, the first and the second research questions are:

RQ1: To what extent do the attribute-weights that consumers attach to a product change over time?

RQ2: Are the changes in attribute-weights associated with the complexity and life-cycle of products?

In this research, the above research questions for a purposive sample of electronics products will be examined and compared from different angles as follows.

Complex Product ⟷ Simple Product

Product with a Short Life Cycle ⟷ Product with a Long Life Cycle

High Tech Product ⟷ Low Tech Product

Moreau et al. (2001) contended that although the diffusion literature in marketing has provided numerous insights into the aggregate adoption patterns regarding new technologies, which has implications for sales forecasting, pricing, advertising strategy and launching of successive generations of new products, how individual consumers learn about and develop preferences for new products has not been extensively researched. From their argument, it can be concluded that the factors that influence consumer preferences in relation to new products from both the consumer behaviour and psychology perspective are: knowledge of existing products, consumer perception regarding the product advantages that could be translated into the importance of a product to consumer, consumer comprehension on product that could be translated into the level of technology competency of the consumer. Pollak (1978) believed that preferences and taste of individuals might change due to change in the demographic characteristics and in line with this, the third research question is:

RQ3: How do the characteristics of individual consumers relate to the stability of the attribute-weights of specific products?

If evidence of changes in the attribute-weights is found through this comparison, it means that a static choice based model based on consumer responses made prior to the launch of a product may soon become out of date and hence any forecasts based on such models may have large errors. If not, it reassures the usage of a static CBC model for forecasting products with short life cycles. Therefore, the fourth research question is:

RQ4: When using choice-based conjoint models, are forecasts for some types of new products likely to be more accurate over longer lead times than others?

In the next chapter, the methodology of the current study adopted to respond to the above research questions will be discussed.

3. Methods, Preliminary Studies and Data Collection

3.1. Introduction

In this chapter the methodology of this study and the reasoning behind it is discussed in detail. Prior to explaining and justifying the proposed methodologies of this study, different kinds of research philosophies and methods are described, which is followed by an explanation of the research design and data collection methods as well as discussion of ethical issues. Subsequently, three trial studies using different conjoint analysis methodologies employing different software are presented with the aim of informing the main experiment design. This is followed by qualitative research data collection to establish the features and levels attributed by the participants regarding certain products. Finally, there is discussion on the most appropriate quantitative research design and data collection technique to fulfil this research objectives.

3.2. Type of Investigation

The diverse nature of management and business scholars has led to considerable disagreement on how research findings in this field should be evaluated and investigated. The type of investigation in a research endeavour depends on: first, different visions regarding how social reality should be studied. Methods are not simply neutral tools, they are linked with the ways in which social scientists envision the connection between different viewpoints about the nature of social reality and how it should be examined. Second, there is the question of how research methods and practice connect with the wider social scientific enterprise. Research data are invariably collected in relation to either a business/management matter or a theory. Prior to discussion of what should be considered as acceptable knowledge (epistemological considerations) and the nature of reality in the social context (ontological considerations), the link between theory and research as well as the deductive or inductive approach will be discussed.

3.2.1. The link between theory and research

Characterising the nature of the link between theory and research is by no means a straightforward matter. The most important issues here is: whether the data are collected to test or build a theory. Theory is important to business and management research, because it provides a backcloth and rationale for the research that is being conducted. It also provides a framework within which social phenomena can be understood and the research findings interpreted. In the following section, the deductive and inductive research approaches as two general types of relationship between theory and research will be discussed (Bryman and Bell, 2011).

3.2.2. Deductive versus Inductive approach

Deductive theory represents the commonest view of the nature of the relationship between theory and social research. The researcher, on the basis of what is known about a particular domain and of theoretical considerations in relation to that domain, deduces a hypothesis (or hypotheses) that must then be subjected to empirical scrutiny. Embedded within the hypothesis will be concepts that will need to be translated into researchable entities. The social scientist must both skilfully deduce a hypothesis and then translate it into operational terms. This means that he/she needs to specify how data can be collected in relation to the concepts that make up the hypothesis. Based on the findings, the hypothesis can be tested in order to be confirmed or rejected. The confirmation or rejection of a hypothesis (or hypotheses) as well as interpretations of the findings can be generalised and used to revised the tested theory. Some researchers prefer an approach to the relationship between theory and research that is primarily inductive and with such stance, theory is the outcome of the research. In the other words, the process of induction involves drawing generalizable inferences out of observations.

Although inductive and deductive approaches can be distinguished as discussed, in reality it is not as clear-cut as a theory might go through many iterations in a cycle of induction and deduction. For example, after a theory is inducted from observation, it will be tested by deducting hypothesis, then from the findings and interpretation of these, the theory will be revised (this element of the deduction process is inductive, but it is typically deemed to be predominantly deductive, being called a “deductive approach”) (Bryman and Bell, 2011).

3.2.3. Ontological considerations

According to Bryman (2008), the ontological concern pertains to the nature of reality and the main point is “whether social entities can and should be considered objective entities that have a reality external to social actors or whether they can and should be considered social construct built up from perceptions and action of social actors”. The former position is known as *objectivism* and the latter *constructionism*. Objectivism is an ontological position that implies that social phenomena confront people as external facts, which have an external existence and they are beyond people's reach and influence (they are independent and separate from social actors). On the other hand, constructionism is an alternative ontological position, which challenges the suggestion of social actors as external realities. It holds that social phenomena and categories are not only produced through social interaction, but also are continuously under a state of revision and therefore, from a constructionist point of view, "the researchers always present a specific version of social reality rather than one that can be regarded as definitive" (Bryman, 2008).

3.2.4. Epistemological considerations

The epistemological concern in research is the question of, "what is or should be regarded as acceptable knowledge in a discipline". A central issue regarding epistemological considerations is whether the social world can and should be studied according to the same principles, procedures, and ethos as natural science, or rather, needs to be studied completely differently. The application of natural science methods in social science research positions the researcher as having an epistemological stance known as positivist (Saunders et al., 2007). Under the positivist lens, principles such as knowledge can be conceived by the senses and genuinely warranted. This knowledge is said to be value free (since it is objective) and the attitudes of the researcher should not have any influence on the reality being studied. However, there is a long-standing debate about the appropriateness of the natural science model for the study of society, which led to the introduction of a contrasting epistemological stance, called "*Interpretivism*". *Interpretivism* "respects the differences between people and objects of natural sciences and therefore requires the social scientist to grasp the subjective meaning of social action" (Bryman, 2008). Under the interpretivist lens, it is believed that the subject matter of the social science academic is fundamentally different from that of the natural scientist. Hence, study in this domain requires a different logic of research procedure; one that reflects the distinctiveness of human behaviour. That is, interpretivist proponents take the position that social reality has meaning, which needs to be interpreted from the actors' points of view (Bryman, 2008). Saunders et al. (2007) pointed out that research studies conducted based on the perspective of the natural sciences deduce a hypothesis (or hypotheses). Under this perspective, the researcher prepares his or her hypothesis (or hypotheses) by reviewing the literature and then tests it/them to confirm or to reject it/them.

At the other end of the spectrum, there is inductive enquiry, through which the researcher infers the implications of his or her findings regarding the theory that prompted the whole exercise. In other words, theory is built after collecting the data.

3.2.5. Research strategies

As for research strategies, there are two major forms, qualitative and quantitative, although it is difficult to draw a line between them by simply saying quantitative researchers employ numeric measurement and qualitative ones do not (Saunders et al., 2007). According to Bryman (2008), there are far more distinctions than just the presence or absence of quantification for these two research frames, such as a connection between theory and research (deductive versus inductive) as well as the epistemological and ontological stance of the research. Although the general tendency of a specific research method (e.g. questionnaire) toward particular ontological and epistemological stance can be determined, it is more of determining tendency toward a direction rather than absolute belonging to a particular ontological and epistemological stance in the social science research practice. For example, a self-completing questionnaire using a Likert scale of 1 (e.g. extremely unhappy) to 5 (e.g. extremely happy) is generally considered as a research method with positivist epistemological stance and objectivist ontological one. However, two different respondent with the same demographics, who responded with a 4 for the levels of happiness in their relationship might have different definitions and perceptions of happiness. As a result of this fuzzy and free-floating tendency, another research strategy that is widely acknowledged as being a third cluster, positioned in between the two major research strategies, has been developed: “the mixed methods research or approach” (Johnson et al., 2007). There are some arguments for and against integrating quantitative and qualitative methods as mixed methods, which will be discussed in the next section

3.2.6. Arguments for and against mixed method research

Mixed methods research attempts to respect the wisdom of both research strategies’ point of view (quantitative and qualitative research), while seeking workable solutions for many (research) problems of interest. Generally speaking, it is an approach that considers multiple positions and perspectives in order to give the researcher better solutions to the research problems. This has come about as a response to the long-lasting, circular, and remarkably unproductive debates discussing the advantages and disadvantages of quantitative versus qualitative research (Feilzer, 2010).

One argument against mixed methods holds that research methods are ineluctably rooted in epistemological and ontological commitments. Therefore, the decision to employ a certain method of data collection, such as questionnaire, is not simply about how to go about collecting data, but a commitment to an epistemological stance, which in questionnaire case is positivism, and ontological position is objectivism. That is inimical to opposite stances, which is in this example constructionism and subjectivism. However, as stated in the previous sub-section, research methods in social science does not have fixed and clear-cut epistemological and ontological stance (Bryman, 2011).

Another argument against mixed method is that regarding the incompatibility of different paradigms. Prior to discussing this, the term paradigm needs to be considered, as it is frequently used in social science and is defined in various ways by different authors. However, the influential usage of the concept paradigm derives from Kuhn in 1970 for his analysis regarding revolutions in science. A paradigm is a cluster of beliefs and dictates in a discipline, which affect "what should be studied, how research should be done, [and] how results should be interpreted" (Bryman, 2008). Paradigms have one common main feature in that they are incommensurable or incompatible; they are inconsistent with each other because of their divergent assumptions and methods. Incommensurability of paradigm raised some related concerns in mixed methods researches.

There are two different ways to define and consider the nature of quantitative and qualitative research methods. As result of these ways of perspectives, the grounds for mixed methods research can be determined. First, quantitative and qualitative research methods can be defined as two separate paradigms that are different and incompatible. According to this definition, their epistemological and ontological stances are totally separate and incompatible, so it is not possible to integrate these methods. Under the second lens, quantitative and qualitative research methods are two different research strategies, which could be defined as techniques for collecting and analysing data. Despite each research strategy being associated with distinctive epistemological and ontological assumptions, these associations are not viewed in these definition as fixed and ineluctable. Consequently, the research method from one strategy is capable of being pressed into the service of another, as was the case in previous section regarding the self-completing example (Bryman, 2011). This definition allows for mixed quantitative and qualitative research to coexist peacefully with strong logical justifications as well as terminating the antagonism between the two paradigms definitions, which is very unproductive and basically, a circular discussion

(Feilzer, 2010) and Johnson et al. (2007). Additionally, mixed methods research has proven to be a more effective approach in many fields (e.g. sociology, education, evaluation, health sciences) in that it has had a higher impact in terms of citations than non–mixed methods studies. In particular, mixed methods research in the business and management context has delivered comparatively have highest citation counts and added more value than the others type of research (Molina-Azorin, 2011).

3.2.7. The current Study

For this research, it was deemed that in order to eradicate the limitations of using a single method (e.g. only qualitative or quantitative methods) to tackle the research problems and objectives, conducting effective CBC studies required a mixed method, to be deployed. Specifically, this researcher decided to conduct a sequential mixed methods approach. By way of explanation, the current research initially involved using qualitative research to find the key attributes when choosing consumer electronic goods in the UK. Qualitative research that involved group interviewing both consumers and retailers prior to designing and conducting the quantitative part was a very effective method for providing insights into what these attributes are. For the subsequent inquiry, the hypotheses were deducted on the basis of what was known in the literature about the topic in order to contribute in a wider spectrum of both theory and practice. The quantitative investigation consisted of collecting data for CBC experiments as well as conducting a questionnaire. In sum, a sequential mixed methods approach was adopted, regarding which the qualitative parts with interpretivist epistemological and subjectivist ontological stances helped to develop the necessary instrument for the subsequent quantitative part of the research. The quantitative research involved adopting positivist epistemological and objectivist ontological stances and constituted the main part of the study.

3.3. Research Design and Data Collection Methods

As discussed before, research problems and objectives play a significant role in determining the research design and its philosophical foundation. As the current research involved using a mixed methods approach with a pragmatic philosophical foundation, the researcher collected both qualitative and quantitative data to achieve the research aims and objectives. Before covering sampling and data collection, first, it is necessary to explain and justify the data sources. According to Malhorta and Birks (2007), picking the most suitable data sources is one of the important stages in a successful research project. There are a wide variety of data sources that can be used separately or together; however, all of these can be classified as either primary or secondary data.

Secondary data have been previously gathered for different purposes, with their key advantage being that they provide the researcher with economic and rapid access resources regarding the research background; however, they carry certain disadvantages, such as often being out of date for research purposes or not having all the details that a researcher needs for conducting a study (Sekaran, 2003). Malhorta and Birks (2007) defined primary data as those collected by the researcher for the aim of solving particular research problems and there are various types of collection methods for obtaining these, such as: experiments, questionnaires, observations, interviews and focus groups. For the current study primary data were mainly used due to the unavailability and inaccessibility of suitable secondary data as well as the nature of the research per se.

It is possible to generalise survey/experimental findings from a sample in a study to the population as a whole in order to predict behaviour patterns that are more or less true for large groups of people (Saunders et al., 2007). Hence, since it is impossible to collect data from the entire population of consumer electronic goods users in the UK due to limited financial resources and time constraints, it was essential to select a sample to fulfil the research objectives.

In this research, a number of focus groups and desktop research were conducted to determine the key attributes and levels of the focal consumer electronic goods and a baseline product. More specifically, fan heaters, as simple durable baseline products that are not high tech and have a long life cycle were chosen for comparison with mobile phones, laptops and TVs, which are comparatively more complex, high technology products with short PLCs. As there is bound to be a natural variation in the weights assigned to the product attributes across the three CBC models caused by factors, such as respondents' random inconsistency over time, a comparison of the variation observed for the baseline product with that for other products allows for the estimation of any non-random variation which is specific to fast evolving short-life cycle products.

Three focus groups with mixed genders were conducted in September 2013. The participants for two of them were UK mobile phone customers aged from 18 to 48 years old, located in the south and west of the UK. The third group comprised sales personnel from Everything

Everywhere (T-mobile) sales teams from four different stores in the south and east of the UK in order to provide wider perspectives on mobile phone customers. A few trial studies were conducted in order to determine that the best data collection methods, analysis and software were adopted for achieving the research objectives. Moreover, there was a pilot study in February 2014, prior to the launch of the online experiment to ensure the quality of the experiments. Once the quality had been assured, there were three rounds of online experiments/surveys data collection on a quarterly basis in March 2014, June 2014, and September 2014 for all products, and Qualtrics was used as an online platform to conduct these. There are a few reasons for choosing quarterly based data collection. As stated earlier, changes in attribute-weights over time is an accepted reality in the literature (Simon, 1955; Bettman et al., 1998; Amir and Levav, 2008; Payne et al., 1992; Kahn, 1995; Coupey, Irwin and Payne, 1998; March, 1978; Pollak, 1978; Fader and Lattin, 1993; Hledik, 2012; Davis, 1989; Briley et al., 2000). However, one of the key points of this research is to see whether or not changes in attribute-weights have different rates for products with different levels of complexity and life cycle. If the CBC experiment data collection were conducted in less than three months periods, say every months, the change in attribute-weights might not be noticeable for any type of products and the researcher would not be able to trace any changes in such a short period of time. On the other hand, if the CBC is conducted over a longer period, such as six months or one year, there might be changes in attribute-weights for both high technology products with short life cycles and low technology products with long ones. Consequently, the researcher would not be able to trace a variation in rate of change in attribute-weights for different products. Hledik's (2012) research is an example of this problem, for he had a year gap between his two experiments and found change in consumer preferences happens for both mobile phones and yogurt. That is, he discovered that there is not much different between these two types of product in terms of changes in consumer preferences over a one year period. Another problem with using a longer period is the time constraints of a PhD project. For instance, a longer gap such as six months or one year, could extend the total data collection length for three rounds from six months to a year or even two years.

According to Curwin and Slater (2007), a well-conducted non-random survey can produce acceptable results more quickly, and at a lower cost, than a random sample; for this reason it is often preferred in marketing and psychology. One of the forms of non-random sampling is convenience sampling, which was used for this research. There are many researches that rely on convenience sampling in psychology and marketing (Chiu et al., 2005; Maringe, 2006; Yu and Cooper, 1983). Although convenience sampling generally might be subject to some biases, here the aim of the study was to uncover variation in preferences and hence, it was critically important that as many as of the same participants took part in all three rounds of the experiment. Over time the same 161 participants took part in all three rounds, which helped the primary aim of the research as this research is less about drawing general inferences about a population than it is about exploring the extent to which a given group of potential consumers can manifest change in attribute-weights for different consumer electronic products over time (it will be discussed in more detail later on).

3.4. Ethical Issues

Ethical issues pertain to human relationships and hence, are pertinent only when an individual interacts with other people. As this research involved contacting people to collect both qualitative and quantitative data some concerns regarding this needed to be addressed. In particular, before conducting any fieldwork, maintaining privacy and confidentiality should be taken into account (Nagy, 2011) and should be rigorously enforced throughout all stages of the research; in this work, all of which were complied with. Another ethical concern is in relation to the survey/experiment and the focus-group parts regarding informed consent (Appendix 8), which refers to researchers not conducting any sort of research covertly or without the permission of the participants (Nagy 2011). Moreover, participants took part in the current research on a voluntary basis.

3.5. Trial Studies

Three trial studies were conducted prior to the main qualitative and quantitative data collection in May 2013 so as to give the researcher better understanding of the potential issues/challenges that might occur during the main data collection as well as familiarising him with the pros and cons of various methods.

3.5.1. Trial Study 1

The first trial study was conducted by a single participant using the rating conjoint analysis (CA) method for mobile phones to investigate the experimental environment, participation experience, methods, software and to see the potential issues/challenges that might occur during the main data collection (Please find the details of the study in Appendix 1). A few points can be concluded from Trial Study 1 as follows:

I. The participant was asked to score a product from 0 to 100 by looking into its features. The scoring task was a difficult task to complete, for it took the participant more than 10 minutes to score 32 profiles. In reality, shoppers do not score products prior to their purchase.

II. Although the scoring was going to be a potentially difficult and frustrating task for future participants, it was easier than ranking 32 profiles as this researcher found when he tried to do so. That is, ranking emerged as being a very confusing and difficult task to complete. In reality, not all customers rank different products prior to their purchase, but rather, choose between options. In sum, it became apparent that with the ranking data collection method the participants would face too much information.

III. A visual aid such as a photo from real cases could be appealing.

IV. Internet and mobile application were each treated as a separate feature in the experiment. However, they could be treated as one feature (without the internet having mobile application is meaningless) or the internet could be eliminated as an attribute as all phones have it.

V. Carrying out scaling calculations of parts-worth by hand is a difficult and frustrating task in which there is a high potential for mistakes being made.

3.5.2. Trial Study 2

The second trial study was conducted with eight participants from the University of Bath for mobile phones using two different ways of analysing rating CA (the two methods are explained below) to familiarise the researcher with these two methods and to weigh up the pros and cons of each. Additionally, the potential issues that might occur during the main data collection were assessed. First, the data was analysed by using the IBM SPSS conjoint function syntax for rating conjoint analysis, which was an automated process. Second, the data was analysed using dummy variables and then multiple regressions (same method as Trial Study 1) (Please find the details of the study in appendix 2). A few points were elicited from Trial Study 2 as follows:

I. From the results of both the studies, it was found that eliciting sales forecasts from the utility of a product out of 100 was not a straight forward and meaningful task as it could not be translated into market share or probability of purchase.

II. The numerical values of the experimental result i.e. output of parts-worth, generated from these two studies were of *interval data*, which only permitted simple operations of addition and subtraction and hence, did not give the freedom of data manipulation. In addition to this, the relationship between parts-worth of the different features that are in the *interval scale* might not be linear.

III. One of the advantages of this method is that the respondents provided rich data, such that parameters could be estimated at the individual level and thus, relatively fewer participants would be needed as compared to CBC.

IV. The results from the SPSS syntax, which is an automated process and easier to conduct for large datasets, were the same as for the dummy variable regression. Additionally, the former provided the average importance of each feature.

V. Again, all the participants found the process of scoring was extremely difficult and time consuming.

VI. Some of the participants asked for visual aids or further explanation as they were not familiar with some of the mobile phones.

VII. As noted above, the internet did not need to be considered as an option as most phones have it by default.

3.5.3. Trial Study 3

The third trial study was conducted with five participants from the University of Bath by using CBC methods which avoids the drawbacks of CA. As SPSS could not be used for CBC, Sawtooth was used in this trial study, which is a specific software designed for such research (Please find the details of the study in appendix 3). A few points were derived from Trial Study 3, as follows:

I. The dependent variable is a binary value (either 1 for choice or 0 for non-choice), which is similar conceptually and practically to the process of purchasing, as consumers choose one among the available alternatives when engaging in buying.

II. The participants took into account other available alternatives when they made a choice, which reflected the attractiveness of a product when there was the availability of alternatives.

III. CBC generates the probability of purchasing, which is much easier to use for the purpose of forecasting.

IV. CBC generates *ratio scale* data, which is much easier to manipulate than CA.

V. Comparatively, CBC provides less rich data than CA and so it needs more participants.
VI. The process involves much more complicated data analysis than traditional CA.
VII. Sawtooth is user friendly software, but the researcher does not have control over the process.

3.6. Qualitative Research

As stated in the Research Design and Data Collection Methods section, qualitative research conducted in September 2013 enabled identification of the key features and the levels relating to choosing mobile phones. It comprised two stages: desktop research and focus groups.

3.6.1. Mobile phones

The desktop research activities were conducted to see what key features and levels had been introduced to customers by retailers in online mobile shops. This research was followed by research based on focus groups.

3.6.1.1. Desktop research

Three online retails shops of major service providers in the UK were investigated, i.e. Vodafone, 3 and Everything Everywhere (EE) and details of about a total of 45 different phones relating to their features and levels were extracted. 23 features were found, such as brand, price, processor, and memory, each of which had different levels, e.g. brand included Apple, BlackBerry, Nokia, etc. Subsequently, it was decided to run focus groups to find the key influencers in customers' decision making as the numbers of features and levels were quite high. Additionally, some features that are commonly available in most of the phones were eliminated due to their less distinguishable characteristics.

3.6.1.2. Focus groups

The focus group is one of the most popular qualitative research methods in consumer studies for exploring what individuals believe or feel as well as why they behave in the way they do. The main aim is to understand and explain the criteria that influence the attitudes and behaviours of individuals (Rabiee, 2004). Focus groups comprise in depth group interviews in which the participants are selected because they are a purposive, although not necessarily representative, sampling of a specific population (Rabiee, 2004).

For this research, three focus groups were conducted to find out the key attributes and levels that influence the purchasing decisions of mobile phone users in the UK. The first two groups' participants were mobile phone consumers covering different genders, age and backgrounds, which will be called the '*First customer focus group*' and '*Second customer focus group*'. In the first customer focus group, there were seven participants and in the second one, six. In the last focus group, there were four sales associates from an Everything Everywhere (T-mobile) store in the UK, which will be called '*Sales people focus group*'. Each lasted around half an hour and involved two parts: mobile phone features and change of features over time. They were conducted in the form of semi-structured group interviews, with the interviewer facilitating the participants to lead and drive the discussion. The interviewer also asked the participants some targeted questions, as shown in appendixes 6 and 7.

Rabbie (2004) proposed that the main aim of data analysis from a focus group is to reduce data in order to reach the initial goal of study. The process began during the data collection with the researcher facilitating the discussion to generate rich data, taking supplementary notes from observation of the process and considering non-verbal communication (body language). This was further followed by listening to data from a recording made during the focus group. However, the researcher did not transcribe the recording as the aim was to identify key features, levels and changes of features over time, rather than extracting any relationship, mapping or theoretical model development.

3.6.1.3. Key attributes and features

In order to conduct the CBC surveys, some of the features and levels that were common to most of the phones, such as internet connection, connectivity, IM and Email, were eliminated as it was discussed in subsection 3.6.1.1. In all the focus groups, the participants believed that price, camera, brand and memory of the phone were main criteria, but they were not that concerned about the type of the keypad. In both the 'First customer focus group' and the 'Second customer focus group', the participants expressed the view that design and physical appearance are the most important criteria. However, according to the 'Sales people focus group', the most important features are screen size, phone size, weight and brand. Moreover, in both the ‘First customer focus group’ and the ‘Second customer focus group’, the participants’ emphasis on the ease of use, functionality and compatibility with their other devices were also important factors. In the ‘Sales people focus group’, the participants contended that it was basically the operating system that determines the compatibility with other devices, such as Android and Windows being compatible with outlook and iOS being so with other Apple devices and iTunes.

Despite one of the participants in the ‘First customer focus group’ raising the issue of the switching cost from one phone to another, the participants in the ‘Sales people focus group’ believed this should not be a concern anymore as they have a special application for transferring the information from one phone to another or even from one operating system to another (except for transferring data from the BlackBerry operating system to another operating system). Therefore, in their view this is more about the wrong perception of some of the customers. Another misunderstanding among some of the participants in both customer focus groups was regarding the build of the phone or the quality in that the participants in the ‘Sales people focus group’ said that manufacturers use the same screen, processor and have pretty much the same quality, claiming that the real differences are brand perception (that comes from word of mouth) and the operating system. One of the concerns also raised by some participants in both the customer focus groups was battery life, but not for the majority as charging the phone every night had become part of their lifestyle.

Considering the outcomes from the desktop research, focus groups, and previous experience from trial studies, keeping a right balance between the numbers of features and levels in order to capture their influence on customers’ choices and avoiding an overcomplicated experiment with too many features and levels were crucial. For instance, Alcatel, Acer and Huwaei were considered as a generic brand as they were not as popular as the rest, in particular, according to the focus group. In addition, weight and display size were considered as proxies for phone size in the interest of experimental simplification. The results from the both customers focus groups discussions also revealed that the majority of consumers do not have enough technical knowledge and technological competency to know whether a specific feature is sufficient for fulfilling their usage requirement or not. For example, they might not know whether they need 8 GB or 64 GB of memory for their particular appliance or they probably do not know the range of available hours of battery duration in the market. Consequently, the decision was made to categorise the feature levels ordinally, using such terms as low, medium, high, rather than numerically. Moreover, care was taken to avoid using words with negative connotations, such as calling a mobile phone heavy, so as to prevent possible biases.

The current study considers the overall variation of the relative importance of features over time as well as how this variation influences the forecasting accuracy, when CBC is used as a tool for new product sales forecasting. Therefore, using categories and simplifying technical terms make the experiment design much more appealing to the general population in the UK. Initially, price had been labelled (e.g. low, medium, high); however it was realised that the participants were capable of making evaluations on the price based on their judgment without such labels, which could have introduced biased. The participants were given a range of prices rather than using a certain point for three reasons: first, according to the pilot study, it is easier to make decisions or choices when given a range; second, this researcher was not looking for the utility of a specific price such as £300 or £400, as other researchers might do when they conduct conjoint analysis for other purposes; and finally, from design perspective it is a less complex to model as well as being more consistent with the rest of the features in the experiment. Another point regarding technical features is that unlike price, they do have set limitations owning to the level of advancement of technology. For example, there is no phone with more than 18 hours of battery life available to the general population in today's market. The features and levels can be written as:

Brand *(Apple, Samsung, Nokia, HTC, Sony, BlackBerry, Generic Brand)*

Price (£) *('Less than 150', '150 to 299', '300 to 450', 'More than 450')*

Camera Resolution (Mpix) *(No, Normal '5 or Less', High 'More than 5')*

Memory Size (GB) *(Small 'Less than 16', Medium '16 to 32', High 'More than 32')*

Display Size (inch) *(Small 'Less than 4', Medium '4 to 5', Large 'More than 5')*

Battery Life (Talking Hours) *(Short 'Less than 8', Medium '8 to 12', High '12 to 15', Very High 'More than 15')*

Weight (g) *(Very Light 'Less than 120', Light '120 to150', Medium 'More than 150')*

3.6.1.4. Changes in the importance of features over time

According to all the participants in the three focus groups, the main change over time in terms of relative importance of features is the functionality of mobile phones from a phone and messaging device to a platform that is integrated with all aspects of their daily lives. Nowadays, phones have become a much more important component of each individual's life, which has led to a change in the importance of the features and levels of their characteristics. For example, customers are prepared to pay comparatively higher prices than before, given that mobile phones now play a more important role in their lives. Additionally, the sales people were of the view that customers have become relatively more features sensitive over the time as phones have, to some extent, become replacements for PCs and laptops.

In both customer focus groups, the participants highlighted that the design, size and battery duration have changed considerably. Specifically, they pointed out that when mobile phones were introduced, they had less battery life duration, and were large and ugly, but subsequently had longer hours of battery power, were smaller and were more beautifully designed. Nowadays, they again have less hours of battery power than what is desirable, have become larger in terms of size and are less beautifully designed.

3.6.2. Laptops

Laptops have been chosen as the second complex and high level technology with a short life cycle. However, they generally have a longer life cycle and less complexity when compared to mobile phones. Their features and levels were extracted and decided upon based on a desktop research of major online retailers (e.g. Comet, and PC world), manufacturers' main websites, and brain storming sessions between well informed researchers in the field. In addition to these, the experiences from the trial studies and focus groups were taken into account, with the features and levels being identified through these processes being as follows:

Brand *(Apple, Samsung, HP, Sony, Dell, Lenovo, Toshiba, Generic Brand)*

Price (£) *('Less than 400', '400 to 699', '700 to 1000', 'More than 1000')*

Display Size (inch) *(Small 'Less than 12.9', Medium '13 to 16', Large 'More than 16')*

Processor *(Normal, Fast, High performance)*

Memory Size (GB) *(Small 'Less than 4', Medium '4 to 8', High 'More than 8')*

Hard Drive *(Medium 'Less than 499GB', High '500 GB to 1 TB', Very High 'More than 1 TB')*

Weight *(Ultra-Light 'Less than 2 Kg', Light 'More than 2 Kg')*

3.6.3. TV

TVs have longer life cycles and are less complex in comparison to laptops and mobile phones. Their features and levels were extracted and decided based on a desktop research from major online retails, such as Comet, Currys and Argos as well as brain storming sessions. In addition, the experiences from mobile trial studies and focus group were taken into account, resulting in features and levels as follows:

Brand *(JVC, Sony, Panasonic, Samsung, LG, Toshiba, Generic Brand)*

Price (£) *('Less than 200', '200 to 400', 'More than 400')*

Screen Size (inch) *(Medium 'Less than 25', Large '25 to 42', Very Large 'More than 42')*

Smart *(Yes, No)*

3D *(Active, Passive, No)*

Freeview *(Yes, No)*

3.6.4. Fan heaters

In general, there should be two types of change in participants' choices when measured over time: first, there is inevitable randomness in any longitudinal experimental research and this would be the case for any kind of product. However, there is also systematic change of choices over time due to life cycle effects, level of complexity of a product and changes in technology. Consequently, to measure this aspect of change it was deemed necessary to have a baseline for comparison with the three chosen electrical appliances. Although mobile phones, laptops and TVs have different life cycle lengths, technological features and levels of complexity, all of them have relatively similar properties when compared with basic consumer electronic goods, such as fan heaters. Therefore, these were chosen as a baseline product in order to time-track changes in attribute-weights to customers across the focal products. This would allow for the measurement of the systematic change highlighted above.

Desktop research was conducted on the Argos website, which is one of the major catalogue retailers in the UK, and the features and levels of fan heaters were extracted. Based on prior experience from the trial studies and a pilot study, the following features and levels for fan heaters were included:

Brand *(Challenge, Dimplex, DeLonghi, Dyson, Generic Brand)*

Price (£) *(less than 25, 25-49, 50-75, More than 75)*

Power (KW) *(Less than 2, 2 to 2.9, 3 or more)*

Type *(Upright, Flat, Down Flow)*

Oscillating *(Yes, No)*

3.7. Quantitative Research

3.7.1. CBC Experiment Design

Based on the key attributes and levels determined from the focus group and desktop research, it was hypothesised that the Random Utility Model (RUM) equation below applies to mobile phones, which is also suggested general form of the RUM, rather than a mathematical representation of it. Here is the RUM equation for mobile phones:

RUM= Brand*(Apple, Samsung, Nokia, HTC, Sony, BlackBerry, Generic Brand)+****Price(£)*** *('Less than 150', '150 to 299', '300 to 450', 'More than 450')+****Camera Resolution(Mpix)****(No, Normal '5 or Less', High 'More than 5') +****Memory Size (GB)*** *(Small 'Less than 16', Medium '16 to 32', High 'More than 32')+****Display Size (inch)*** *(Small 'Less than 4', Medium '4 to 5', Large 'More than 5')+****Battery Life (Talking Hours)*** *(Short 'Less than 8', Medium '8 to 12', High '12 to 15', Very High 'More than 15') +* ***Weight (g)*** *(Very Light 'Less than 120', Light '120 to150', Medium 'More than 150')*

Here is the RUM equation for TVs:

RUM= Brand *(JVC, Sony, Panasonic, Samsung, LG, Toshiba, Generic Brand) +* ***Price (£)*** *('Less than 200', '200 to 400', 'More than 400') +* ***Screen Size (inch)*** *(Medium 'Less than 25', Large '25 to 42', Very Large 'More than 42') +* ***Smart*** *(Yes, No) +****3D*** *(Active, Passive, No) +* ***Freeview*** *(Yes, No)*

Here is the RUM equation for laptops:

RUM= Brand *(Apple, Samsung, HP, Sony, Dell, Lenovo, Toshiba, Generic Brand)+****Price (£)*** *('Less than 400', '400 to 699' , '700 to 1000', 'More than 1000') +* ***Display Size (inch)*** *(Small 'Less than 12.9', Medium '13 to 16', Large 'More than 16')+* ***Processor*** *(Normal, Fast, High* *performance)+* ***Memory Size (GB)*** *(Small 'Less than 4', Medium '4 to 8', High 'More than 8')+* ***Hard Drive*** *(Medium 'Less than 499GB', High '500 GB to 1 TB', Very High 'More than 1 TB')+* ***Weight*** *(Ultra-Light 'Less than 2 Kg', Light 'More than 2 Kg')*

Here is the RUM equation for fan heaters:

RUM= Brand *(Challenge, Dimplex, DeLonghi, Dyson, Generic Brand) +* ***Price (£)*** *(less than 25, 25-49, 50-75, More than 75) +* ***Power (KW)*** *(Less than 2, 2 to 2.9, 3 or more) +* ***Type*** *(Upright, Flat, Down Flow) +* ***Oscillating*** *(Yes, No)*

The features and levels extracted and used to write the RUM are real specifications of the focal products from the 2013 to 2014 consumer electronic market. The number of possible representative alternatives for the mentioned features and levels for mobile phones is 7*4*3*3*3*3*4*3=9,072, for laptops it is 9*4*3*3*3*3*2=5,832, for TVs it is 7*4*3*2*3*2=1,008 and for fan heaters it is 5*2*3*3*3=270. It can be seen that there are way too many alternatives for designing an experiment and hence, a fractional factorial design (orthogonal design) was used. It is a feasible solution to select a subset of the complete design based on a sample, while tracing the main effects and the magnitude of each feature and level in an experiment (Raghavarao et al., 2011). IBM SPSS 22 was employed to generate the fractional factorial design (orthogonal design), which resulted in 32 alternative profiles for mobile phones, 24 for fan heaters, 32 for laptops and 28 for TVs (appendix 9). Some of the determined profiles from the fractional factorial design are a hypothetical combination of real features and levels in the consumer electronics goods market (there might not be a product in the market with such combinations of features and levels). These combinations of features and levels are necessary in CBC experimental design in order to be able to trace their effect and the magnitude for various consumers as well as characterising and simulating the market for the chosen product. They also give the possibility of generating enough controlled variations in the design to be able to understand variations in the participants' choices based on changes in specific features and levels for a certain product, which is one of the strengths of a CBC experiment when compared to choice models based on secondary data. Additionally, a CBC experiment owing to its better design has less violation of assumptions during modelling compared to a choice model with secondary data. However, there might be some concerns about the generalizability of CBC experiment design and how well these methods and profiles might reflect the reality of a market, which will be discussed later on in this chapter.

The number of possible alternatives for each of the selected products obtained in the fractional factorial design is still quite large, which might have affected results of the conducted experiment. For example, if the participants had 32 and 28 choices for mobile phones and TVs respectively, this would increase confusion among them when aiming to make their best choice to maximise their utility. Therefore, the decision was taken to follow a suggestion by Kuhfeld (2010) to subset the choice design into smaller sets. This author believed that doing so is more economical and practical in an experiment, whilst it does not change the expected utilities. Moreover, he believes that is the reason for most researchers, who conduct discrete choice model experiment or choice based conjoint analysis to show their participants multiple choice subset as this makes it more user-friendly (ibid). However, having small choice subsets could be problematic, if the attributes are highly correlated over the entire design, but this is not the case with the current study as this researcher used fractional factorial design to eliminate such an effect. This design also delivers much better results than ranking and rating CA. There are other researchers who have also taken this course of action, such as Hansen (1987), Woodward (1992) and Friedman, et al. (1992) (cited in Chen et al., 2005). Further, in this research a non-choice option (or not purchasing) was included in each choice set, based on a suggestion by Dhar (1997), so as to reflect the world reality much better in the experiment for the participants. In the analyses in chapter four, selecting the non-choice option in a choice-set means that the participants did not choose any of profiles in that choice-set and the non-choice option was not considered as a variable to prevent any biases or inconsistency in the result. There is an exception for Hierarchical Bayesian analysis by Sawtooth that automatically includes non-choice as a variable in the model (The researcher did not have any control over the Sawtooth analysis process). As was explained in sub-section 4.8, considering the non-choice option as a variable potentially created some inconsistency in the results. From the orthogonal design for the mobile phone (32 profiles), a random combination of profiles was presented to the participants in eight sets, with each set including five choices (four profile choices and one non-choice option). For the fan heaters (24 profiles) and TVs (28 profiles), a random combination of profiles was presented to the participants in six sets and seven sets, respectively, each of which included five choices (four profile choices and one non-choice option). For laptops, as with mobile phones, there were eight sets, each of which included five choices. The aggregation of the chosen alternatives for each participant was collected in a dataset which was used in identifying the parameters of the model.

3.7.2. Pilot Study

In February 2013, a pilot study were conducted, prior to the launch of the online survey, to ensure the quality of the surveys, in which eight experienced researchers participated and gave feedback on each scenario so that the final design could be reached. In general, they reported that they found the survey very interesting, well presented and engaging.

3.7.2.1. First experiment design scenario

In the first experiment design scenario, different colours were used for each product to distinguish them. Almost all of the profiles were hypothetical, with there being no real product in the market matching the same specification for the majority of them. Therefore, photographs of similar products in the market were placed on the top of the profiles to give the participants a visual aid and hence, to improve their experience (appendix 10). However, according to the participants of the pilot study, these pictures caused a huge distraction from the written features and they made their decisions only based on the pictures and design of the mobile phones, for instance, rather than its real features, which could potentially have been a large source of bias for the main experiment.

3.7.2.2. Second experiment design scenario

In the second experiment design scenario, everything was kept same as of the first; however, the pictures of similar products were replaced by the brand logo so as to reduce this potential bias whilst keeping some form of visual aid that would improve participant engagement with the experiment (appendix 10) rather than just presenting the written word. However, according to the feedback from participants during the testing of the second design, using brand logos as visual aids could also potentially create bias towards those that had stronger brand image among participants.

3.7.2.3. Third experiment design scenario

In the third scenario, the decision was taken to remove the visual aids and only leave the features descriptions in the experiment (appendix 10). According to the participants, although there were colour differences, written messages, and features specifications to give them sufficient information on what the product was and what was its specification, they would have still preferred to have some form of visual aid during decision making. They also recommended to using the term the ‘Generic Brand’ instead of ‘Others’, and to eliminate the price level indicators: low, high, very high.

3.7.3. Data collection

The final design of the experiment was approved by all the participants in the pilot study and was used for data collection. A black and white sketch for all products was used as a visual aid, which did not create any biases in the participants’ responses (appendix 11). The first round of online experiments was launched in March 2014 and 327 participants managed to complete it. There was an incentive for all participants who completed all three rounds with a donation being made to a charity. The participants were asked to provide a username instead of their real name to protect their identity, and they were asked to give an email address so that the researcher could email them the link to enable them to take part in the second and third rounds of data collection. They were also asked to provide demographic data, including gender, employment status, education level and age. In the second round, 215 participants out of the 327 people who had managed to complete the first round also finished this one in full. At the end of third and final round, 161 participants had completed the entire experiment. In the second and third rounds, in addition to a charity donation, Amazon vouchers were also offered to the participants, if they took part in all three rounds, which proved a successful strategy for keeping them on board. The reason for this was because, some participants mentioned that personal reward would be a better incentive than a charity donation for them to remain involved.

3.7.4. Generalizability and research design

Based on the discussions pertaining to Bryman and Bell (2011) and Saunders (2007) about the generalizability as well as experiment design, there are a few concerns about this study, which will be discussed as follows:

1. **Sampling:** this relates to how well the sample in this experiment represents the entire population of potential consumers and hence whether the findings would be true for the entire population (this has been discussed in section 3.3 of this chapter).
2. **Reliability of the method:** this relates to how reliable the CBC experiment is as a method and whether the results from this method are replicable or not. As stated in the literature chapter in sections 2.6 and 2.7, conjoint analysis and choice models are one of the most widely used marketing research methods for analysing consumers’

trade-offs between two or more products with different profiles, and how their product preferences are related to the attributes of the products themselves (Green, Krieger and Wind, 2001). They have been used not only to analyse consumer preferences or intentions to buy existing products, but also, for how consumers may react to potential changes in the existing product or to a new product being introduced into an existing competitive array (Qian, 2012). According to Sawtooth Software (2013), a CBC experiment is a reliable and acceptable method in both academia and the commercial world with many different applications, which can simulate the trade-off and choice between two or more products in the best possible way. That is, the reliability and credibility of the method to reflect the reality of choice task or trade-off of consumer in the real world is widely accepted, although this method might have some shortcomings, which will be discussed later on in this section.

3. **Revealed Preference vs. Stated Preference:** As stated earlier in the literature review chapter in section 2.7, two major ways to study consumer preferences are Revealed Preferences (RP) and Stated Preferences (SP) (Manrai, 1995). Each of these methods has its own advantages and disadvantages. RP has a few drawbacks, such as:
    i. Unavailability of market data (secondary data) for a new product that has not been launched and consumers might react differently in terms of preferences regarding new products with different combinations of features and levels. Additionally, there were no secondary data available or accessible to this researcher.
    ii. RP has some statistical drawbacks in terms of data analysis and modelling. The explanatory variables in RP might have only a little variation, which is not enough to develop a model or to make a feature significant in a model. Additionally, these variables might be highly correlated, which will make the effects unidentifiable.
    iii. RP data are limited as they only capture a single choice of a participant, while SP experiments contain several choices or non-choices for each.

    SP also has some drawbacks, such as:

    i. Preparation and conducting a survey is a difficult task and time consuming.
    ii. Finding a suitable number of participants might be difficult.

iii. It could be the case that stated preference is different from what people do in reality.

Taking into account the unavailability of secondary data for this research and other limitations of RP, SP was adopted, given that it is regarded as very reliable and accepted method in the literature.

4. **Simulations of reality of purchasing:** how well can this CBC experiment design reflect the reality of purchasing and can it generate valid experiment results or not? Although this experiment might not simulate the reality of purchasing in a shop with a sales assistant, it gives the possibility to test hypothetical combinations of real features and levels in various consumer electronics goods, which would not have been possible in the real world. Additionally, this experiment could be regarded as being more similar to an online shopping experience for participants, if they were able to see the various features of few products side by side so as to be able to compare them and decide whether or not to make a purchase. Online shopping represents a large part of retailing in consumer electronics. In sum, not being able to simulate perfectly the same shopping experience in the store might be one of the drawbacks and limitations of the CBC experiment, and study; however it does not fundamentally affect the purpose of this study. In future, technology improvement might improve the CBC experiments experience for its participants by using advanced visualisation methods, such as 3D or virtual reality, (this will be discussed in the last chapter in the context of limitations of the study). However, as stated earlier, the CBC experiment is one of the most widely used and reliable methods for both academics and practitioners.
5. **Experiment measurement biases:** there were three rounds of pilot study and three rounds of trial research as well as careful consideration of previous studies in the literature to eliminate any potential biases. The designed profiles and experiment stay constant over time to control for inconsistency in participants' preferences that might be caused by variations in these factors. Finally, no major launch of a product or radical innovation of features and levels happened during the experiment, which could potentially have been a source of bias.
6. **Participant biases:** very careful consideration was taken to reduce participants' biases through making the experimental environment more user friendly. Also, using

fractional factorial design (orthogonal design) relieved the burden for participants by creating a more reasonable length of experiment, thus avoiding potential fatigue.

7. **Participants' learning process:** another limitation of this longitudinal study might be the lack of a learning process from one round to another, as the participants cannot learn from the real experience of using a product when they purchased it so as to use this in their future decision making. However, most participants are probably familiar with the relevant features and levels as they are currently available in the consumer electronic goods market.

3.8. Summary

In this chapter, the research methodology and design, qualitative data collection and analysis, and quantitative data collection have been explained and justified. In the next chapters, the collected data from experiment and the surveys will be analysed and discussed.

4. Assessing the Change in Attribute-Weights

4.1. Introduction

In the previous chapters, the literature review, methodology and data collection for the current research were covered. Here, in this chapter, the primary analysis of data is discussed with the aim being to respond to RQ1 and RQ2 as well as testing hypothesis H_1 that is drawn from RQ2 and literature, which are as follows:

RQ1: To what extent do the attribute-weights that consumers attach to a product change over time?

RQ2: Are the changes in attribute-weights associated with the complexity and life-cycle of products?

H_1: Attribute-weights change much quicker over time for products with more complex features and shorter life cycles when compared with less complex products with longer life cycles.

First, the demographics of the participants who completed all three rounds of the experiment and survey are presented. This is followed by the results from significance testing of their choices for various type of products and data analysis using logit model estimations for each round as well as product. Next, having provided the computed weight estimations, the weights of the attributes for each product for the three rounds are compared. In the following section, the weight variations among the products are presented and the reasoning behind the outcomes given. Subsequently, the internal consistency of the sample analysed using the logit model estimation is examined using bootstrapping. Finally, Hierarchical Bayesian analysis is carried out using *Sawtooth* software as an alternative estimation method to compare the trends in weight variation among products across the rounds with those from the logit model estimations.

4.2. Demographics

The first round of online experiments was launched in March 2014 and 327 participants managed to complete this round. In the second round, 215 participants out of the 327 people who had managed to complete the first round also finished this one in full. After the third and final round, there were 161 participants who had completed all three rounds of survey.

The data from participants, who dropped out and did not complete the second and third rounds were eliminated in the analysis in order to prevent any potential biases in the results. That is, only data from participants who had completed all three rounds were considered and analysed. As data from dropped-out participants was not included at any stages of analysis, it is believed they did not have any influence on the experiment outcomes.

The participants, who completed all three rounds of the survey comprised 82 males (50.9%) and 79 females (49.1%), as shown in Table 4.1. The participants were divided into four age categories. The category 18 to 30 years old represents the highest proportion of the participants with 81 out of the 161 (50.3%) total, while the over 60 years old participants represented the lowest at 3 (1.9%) respondents. The participants' education level was divided into three categories. Education up to secondary level is compulsory in the UK and therefore, none received only a primary level of education, so this category was eliminated from the results. 107 of the participants (66.5%) out of 161 had a postgraduate degree, that is, the majority, while 13 (8.1%) had only completed secondary school education. The employment status of the participants was divided into six categories. The majority of the participants had full-time jobs, 83 out of 161 (51.6%), while only one participant was retired (0.6%).

Demographics		**Frequency**	**Percent**
Gender	**Male**	82	50.9
	Female	79	49.1
Age	**18-30**	81	50.3
	31-45	50	31.1
	46-60	27	16.8
	Over 60	3	1.9
Education	**Secondary School**	13	8.1
	Undergraduate	41	25.5
	Postgraduate	107	66.5
Occupation	**Unemployed**	3	1.9
	Student	59	36.6
	Full-time employee	83	51.6
	Part-time employee	4	2.5
	Self-employed	11	6.8
	Retired	1	0.6

Table 4.1.Participants' demographics

4.3. Significance Testing of Participants Choices for Various Products

Prior to estimating the CBC weights for each features of the products in the later sections of this chapter in order to response to RQ1 and RQ2, each participant's choices in each round were compared to those in the other rounds to find out how many choices were different (mismatch) with aim of testing H_1. Hence, the consistency of choices of products between each of the different rounds was calculated. Specifically, the number of mismatches in choice between each round for all four products (called the 'number of mismatch choice variable') was compared using repeated measures one way ANOVA (General Linear Model) in order to investigate if there was a greater change in product choice for some types of product than for others. Given the size of the sample, 161, and after examining normal distribution histograms and Q-Q plots, it was assumed that the number of mismatch choice variables for each product was at least approximately normally distributed. As also shown below, the data met the necessary sphericity conditions and consequently, the application of repeated one way ANOVA was judged to be appropriate (Fields, 2013).

4.3.1. Round 1 and Round 2

Table 4.2 provides the descriptive statistics for consumers' choice mismatches between Round 1 and Round 2 for the various products. According to Field (2013), the sphericity conditions are met based on non-significance (0.079) of the Mauchly test (0.940) (Table 4.3), and hence, the hypothesis of violation of sphericity condition was rejected. Since the sphericity conditions are met, the '*Sphericity assumed test*' value is used to investigate within subject effects that exhibits significance at the 5% level (P-value = 0.000<0.05) with F-test 7.414 (Table 4.4). The results show there is a significant difference between consumer choice in Round 1 and Round 2 among the various products. In the pairwise comparison, there is also a significant difference at the 5% level between fan heaters (as a baseline product) and mobile phones, with a mean difference of -0.770 mismatches and a p-value 0.006, and between fan heaters and laptops, with a mean difference of -1.205 mismatches and p-value 0.000 as well as fan heaters and TV with a mean difference of -0.497 mismatches and p-value 0.040 (Table 4.5). The pairwise results demonstrate that there is significant difference in consumer choices of fan heaters in comparison to the other products. Based on this results H_1 is accepted.

Descriptive Statistics

Product Type	Mean	Std. Deviation	N
Mobile Phones	7.43	2.89	161
Fan heaters	6.66	2.49	161
Laptops	7.86	3.05	161
TVs	7.15	2.46	161

Table 4.2. Descriptive statistic for consumer mismatch choices between R1 and R2

Mauchly's Test of Sphericity

Within Subjects Effect	Mauchly's W	Approx. Chi-Square	df	Sig.	Epsilon
					Greenhouse-Geisser
Product Type	0.940	9.868	5	0.079	0.964

Table 4.3. Mauchly's test of Sphericity between R1 and R2 participants' mismatch choice data

Tests of Within-Subjects Effects

Source		Type III Sum of Squares	df	Mean Square	F	Sig.
Product Type	Sphericity Assumed	123.050	3	41.017	7.414	0.000
	Greenhouse-Geisser	123.050	2.891	42.565	7.414	0.000
	Huynh-Feldt	123.050	2.950	41.716	7.414	0.000

Table 4.4. One way ANOVA tests of within subject effects between R1 and R2

Pairwise Comparisons

Product Type		Mean Difference	Std. Error	Sig.	95% Confidence Interval for Difference	
					Lower Bound	Upper Bound
Fan heaters	Mobile Phones	-0.770*	0.276	0.006	-1.315	-.225
	Laptops	-1.205*	0.274	0.000	-1.747	-.663
	TV	-0.497*	0.240	0.040	-0.970	-.024

Table 4.5. Pairwise comparisons of products' choices mismatches between R1 and R2

4.3.2. Round 2 and Round 3

Table 4.6 illustrates the descriptive statistics for consumers' choice mismatches between Round 2 and Round 3 for the various products. As stated in sub-section 4.3.1, the sphericity conditions are met based on non-significance (0.070) of the Mauchly test (0.938) (Table 4.7). Hence, the '*Sphericity assumed test*' value is used to investigate within subject effects that exhibits the significance at the 5% level (P-value = 0.058) with F-test 2.511 (Table 4.8). Although the result is not significant, it shows there was still some small variation between consumers' choice mismatches in Round 2 and Round 3 among the various products, but comparatively less than between Round 1 and Round 2 as well as between Round 1 and Round 3. This is explored in more detail in a later section of this chapter. In the pairwise comparison, there is a significant different at the 5% level between fan heaters (as a baseline product) and TVs, with mean a difference of -0.764 mismatches and a p-value 0.010. However, between fan heaters and laptops as well as fan heaters and mobile phones are not significant differences in consumer choices (Table 4.9). Based on this results, there are not enough evidence to accept H_1.

Descriptive Statistics

Product Type	Mean	Std. Deviation	N
Mobile Phones	4.36	2.92	161
Fan heaters	4.19	2.63	161
Laptops	4.43	3.52	161
TVs	4.95	3.03	161

Table 4.6. Descriptive statistic for consumer mismatch choices between R2 and R3

Mauchly's Test of Sphericity[a]

					Epsilon
Within Subjects Effect	Mauchly's W	Approx. Chi-Square	df	Sig.	Greenhouse-Geisser
Product Type	0.938	10.183	5	0.070	0.960

Table 4.7. Mauchly's test of Sphericity between R2 and R3 participants' mismatch choice data

Tests of Within-Subjects Effects

Product Type	Type III Sum of Squares	df	Mean Square	F	Sig.
Sphericity Assumed	52.129	3	17.376	2.511	0.058
Greenhouse-Geisser	52.129	2.881	18.097	2.511	0.061
Huynh-Feldt	52.129	2.939	17.737	2.511	0.059

Table 4.8. One way ANOVA tests of within subject effects between R2 and R3

Pairwise Comparisons

Product Type		Mean Difference	Std. Error	Sig.	95% Confidence Interval for Difference	
					Lower Bound	Upper Bound
Fan heaters	Mobile Phones	-0.174	0.261	0.505	-0.689	0.341
	Laptops	-0.248	0.320	0.439	-0.880	0.383
	TVs	-0.764*	0.292	0.010	-1.340	-0.187

Table 4.9. Pairwise comparisons of products' choices mismatches between R2 and R3

4.3.3. Round 1 and Round 3

Table 4.10 demonstrates the descriptive statistics for consumers' choice mismatches between Round 1 and Round 3 for the various products. As stated in sub-section 4.3.1, the sphericity conditions are met based on non-significance p-value (0.629) of the Mauchly test (0.978) (Table 4.11). Hence, the '*sphericity assumed test*' value is used to investigate within subject effects that exhibits significance at the 5% level (P-value = 0.002<0.05) with F-test 5.036 (Table 4.12). The results show there exists a significant difference in consumer choice between Round 1 and Round 3 among various products. In the pairwise comparison, there are also significant difference at the 5% level between fan heaters (as a baseline product) and mobile phone with a mean difference of -0.683 mismatches and p-value 0.010, and between fan heaters and laptops with a mean difference of -0.994 mismatches and p-value 0.001 as well as fan heaters and TV with a mean difference of -0.516 mismatches and p-value 0.052 (this one is just above the 0.05) (Table 4.13). The pairwise results demonstrated that there is significant difference in consumer choices of fan heaters in comparison to other products. Based on this results H_1 is accepted.

Descriptive Statistics

Product Type	Mean	Std. Deviation	N
Mobile Phones	7.43	2.77	161
Fan heaters	6.75	2.59	161
Laptops	7.74	3.09	161
TVs	7.26	2.49	161

Table 4.10. Descriptive statistic for consumer mismatch choices between R1 and R3

Mauchly's Test of Sphericity[a]

Within Subjects Effect	Mauchly's W	Approx. Chi-Square	df	Sig.	Epsilon[b]
					Greenhouse-Geisser
Product Type	0.978	3.465	5	0.629	0.985

Table 4.11. Mauchly's test of Sphericity between R1 and R3 participants' mismatch choice data

Tests of Within-Subjects Effects

Product Type		Type III Sum of Squares	df	Mean Square	F	Sig.
	Sphericity Assumed	83.458	3	27.819	5.036	0.002
	Greenhouse-Geisser	83.458	2.955	28.241	5.036	0.002
	Huynh-Feldt	83.458	3.000	27.819	5.036	0.002

Table 4.12. One way ANOVA tests of within subject effects between R1 and R3

Pairwise Comparisons

Product Type		Mean Difference	Std. Error	Sig.	95% Confidence Interval for Difference	
					Lower Bound	Upper Bound
Fan heaters	Mobile Phones	-0.683*	.264	.010	-1.204	-0.163
	Laptops	-0.994*	.283	.001	-1.552	-0.435
	TVs	-0.516	.263	.052	-1.036	0.005

Table 4.13. Pairwise comparisons of products' choices mismatches between R1 and R3

4.4. Data Analysis using Logit Model Estimation

The data for the 161 participants who completed all three rounds of the survey were cleaned and manipulated. Uncompleted responses were eliminated, only the participants who completed all rounds were selected and the results were given participant ID as well as profile ID. The data from the profile and response tables were merged into one table and dummy variables were created using VBA and SPSS syntax in preparation for the model estimation. In order to estimate the model for the CBC experiment, the binary logit model was used to calculate the attribute-weights. As was explained in subsection 2.7.2, the logit model is derived to represent a participant labelled n who maximises his/her utility (U_n) when choosing certain products. As U_n cannot be seen by researchers per se, it has to be decomposed into two components that need to be measured:

A. a deterministic utility (systematic component) V_n
B. a stochastic utility (random component) ε_n

$$U_{nj} = V_{nj} + \varepsilon_{nj} = \beta X_{nj} + \varepsilon_{nj}$$

Equation 4.1

The participant n faces J choices that obtain a certain level of utility (profit) from each alternative, which can be written as U_{nj}, j=1, 2,…., J. As pointed out above, this utility cannot be seen by the researcher, but is assumed to be known by the participant and as a result, the latter chooses the alternative that provides the greatest utility so as to employ his/her limited resources most efficiently. V_{nj} were specified as being linear as $V_{nj}=\beta X_{nj}$, where X_{nj} is the vector of the observed or explanatory variable. When an alternative, say i, is chosen among a choice set j, the chosen alternative is assigned a value of 1 and the non-chosen, 0, which results in binary values, based on the choice of alternatives being attributed by the participant n, for the dependent variable. In the case where a participant chooses the 'none of them option', 0 values are assigned to all the choices in a choice-set. The explanatory variables in the equation are the alternative specifications (features and levels), which were fitted to the MNL choice probability model:

$$P_{in} = \frac{e^{V_{ni}}}{\sum_j e^{V_{nj}}}$$

Equation 4.2

When the random utility is assumed to follow logistic distributions, the model is a binary logit model (Greene, 2009), which can be written as:

$$P_{in} = \frac{1}{1+e^{-(\beta X ni)}}$$

Equation 4.3

Where, X is an attribute of a product and β is the coefficient. For example, participant number 121 chose profile 18 for fan heaters in round 1 of the experiment, i.e. chose this particular product from the choice-set. For this participant, the value of the dependent variable is 1 and the equation for the explanatory variables is:

β_{brand} Brand (Generic Brand) + β_{price} Price (Less than £25) + β_{power} Power (2 to 2.9) + β_{type} Type (Flat) + $\beta_{oscillating}$ Oscillating (No)

As all attributes are categorical variables, they need to be defined as dummy variables in the logit model (a detailed explanation is provided in subsections 2.7.2 and 2.7.3). Each participant for each of the products in every round generated multiple responses or observations by choosing or not choosing alternatives (profiles). As a result, the total number of observations in each round is as follows:

Total number of observations in each round	**Profiles numbers × Participants numbers**
Mobile phones	32×161 =5152
Fan heaters	24×161=3864
Laptops	32×161=5152
TVs	28×161=4508

Table 4.14. The total number of observations in each round

There were Total number of observation × Number of rounds=Total number of observations in three rounds for all the products (5152+3864+5152+4508 × 3 =56,028). The data for each product at each round were fitted into a logit model using SPSS 22.

4.5. Weights Comparison in the Different Rounds

Once the weights or coefficients (β) for each attribute of each product had been calculated, those for the different rounds within each product were compared. In order to improve the comparison of weight fluctuations, each attribute's mean weight was calculated as well as the Mean Absolute Deviation (MAD) of these weights. The MAD shows how much a attribute's weight deviated from its mean over the three rounds, which allows for the identification of attributes that have more fluctuations across rounds in comparison to other attributes.

4.5.1. Fan heaters

The results show (Table 4.15 and Figure 4.1) that price is the most important attribute for the participants as it received the highest weight. More specifically, the 'Price_Low' variable was in first place, followed by 'Price_Medium', and 'Price_Hi' was third in terms of weight importance, which is to be expected for fan heaters as they do not have complex technological attributes. This may be because it is a low technology product with a few simple attributes which do not vary much across different brands and therefore, price would be assumed to be the most important factor in consumer choice over time. The weights of other attributes for this product were within a similar range. Notably, there is not much change in the attribute-weights across three rounds, except for a slight variation in brand weight in R1 in comparison to R2 and R3. The MADs are generally small for the attributes of fan heaters: 0.18 or less for all attributes.

FH B	R1	R2	R3	Mean (R1, R2, R3)	Mean Absolute Deviation
Brand_Challenge	-0.95	-1.10	-.93	-0.99	0.07
Brand_Dimplex	0.03	0.19	0.33	0.18	0.10
Brand_DeLonghi	-0.02	0.35	0.30	0.21	0.15
Brand_Dyson	0.30	0.52	0.59	0.47	0.11
Price_Low	2.05	2.17	2.16	2.13	0.05
Price_Med	1.66	1.74	1.71	1.70	0.03
Price_Hi	0.58	0.37	0.18	0.38	0.14
Power_Hi	0.77	0.71	0.71	0.73	0.03
Power_VeryHi	0.55	0.81	0.55	0.64	0.12
Type_Upright	0.63	0.53	0.57	0.58	0.04
Type_Flat	0.21	0.08	0.03	0.11	0.07
Oscillating_Yes	0.61	0.95	1.06	0.87	0.18
Constant	-3.94	-4.22	-4.26	-4.14	0.13

Table 4.15. Fan heaters attribute-weights comparison over the three rounds

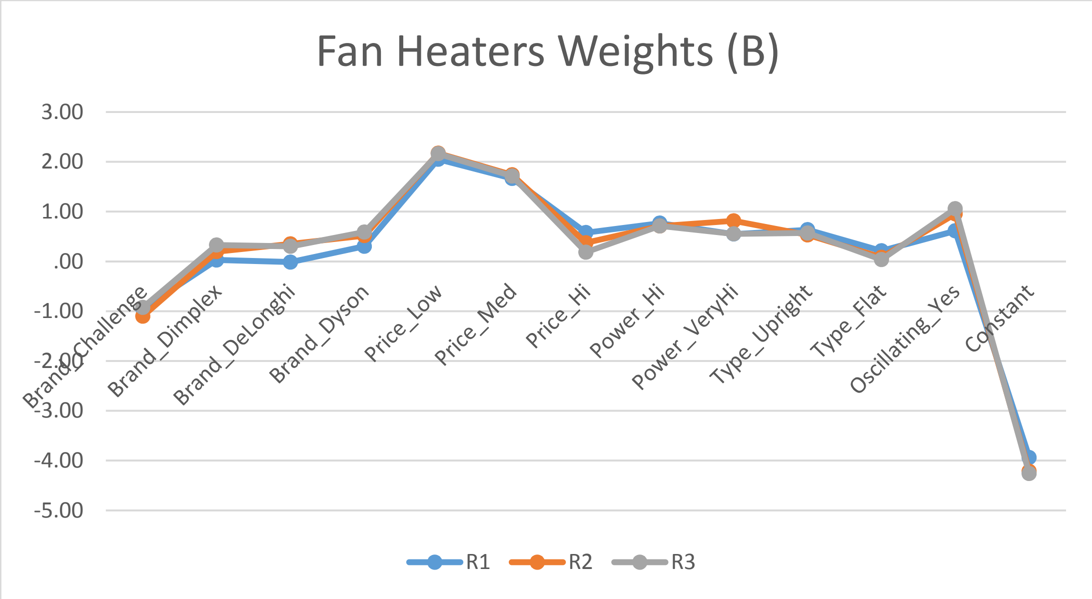


Figure 4.1. Fan heaters attribute-weights comparison over the three rounds

4.5.2. Laptops

The results for laptops show (see Table 4.16 and Figure 4.2) that brand is the most important attribute for the participants as it has the highest weight, especially Apple, which is the highest of all the brands. Apple is the most well-known brand in the market and therefore, it having the highest weight is no surprise. Other brands are pretty much in the same weight range, except for Lenovo which has slightly lower weights. Although brand weights have some variation across the different rounds, the trend and their ranking order remain the same, i.e. brand positions do not change over time. Price, processor specification and memory have the same weight range, while hard drive and display size have the lowest weights among the participants' choices. There are some notable changes in brand weights across the rounds, whereas there is a smaller range of changes in memory, processor, hard drive, product weight and price over time. The MADs are larger for the attributes of laptops in comparison to fan heaters, especially for brands, where they are between 0.18 and 0.31.

Laptop B	R1	R2	R3	Mean (R1, R2, R3)	Mean Absolute Deviation
Brand_Apple	1.79	2.26	2.12	2.06	0.18
Brand_Samsung	0.32	0.75	0.76	0.61	0.19
Brand_HP	0.45	0.85	1.04	0.78	0.22
Brand_Sony	0.46	0.93	0.91	0.77	0.20
Brand_Dell	0.37	0.89	1.03	0.76	0.26
Brand_Lenovo	-0.04	0.55	0.70	0.40	0.30
Brand_Toshiba	0.39	1.06	1.12	0.86	0.31
Price_Low	1.06	1.02	0.93	1.00	0.05
Price_Med	0.71	0.57	0.57	0.62	0.06
Price_Hi	0.59	0.47	0.35	0.47	0.08
Dis_S	-0.35	-0.48	-0.46	-0.43	0.05
Dis_M	0.08	0.18	0.15	0.14	0.04
Proc_Fas	0.59	0.35	0.48	0.47	0.08
Proc_Hi	0.76	0.45	0.50	0.57	0.13
Mem_M	0.49	0.62	0.68	0.60	0.07
Mem_H	0.71	0.86	0.83	0.80	0.06
HDD_Hi	0.54	0.41	0.24	0.40	0.10
HDD_VerHi	0.22	0.13	0.21	0.19	0.04
Weight_UltraL	0.63	0.46	0.45	0.51	0.08
Constant	-3.82	-4.01	-4.06	-3.96	0.10

Table 4.16. Laptops attribute-weight comparison over the three rounds

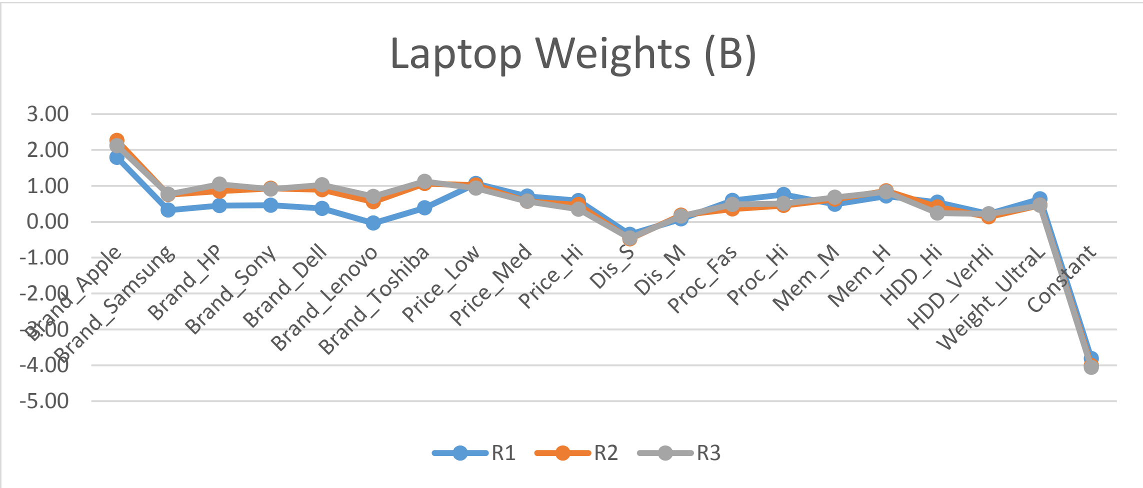


Figure 4.2. Laptops attribute-weight comparison the three rounds

4.5.3. Mobiles

The results for mobile phones show (see Table 4.17 and Figure 4.3) that camera resolution is the most important attribute for participants as it has the highest weights, which is in line with the findings from the focus groups. Length of mobile phones battery lives has the second highest weights in all the rounds, whilst the weights of brand varies significantly. That is, brands have generally less weights in round 1; however, over time they have higher weights, being more so in Round 2 and by Round 3, this reaches the same level of weight range as battery life. Apple and Samsung have first and second weight placing in all rounds, which reflects the reality of their positions in terms of market share. As can be seen, there is more change in brands than with other attributes. There are slight changes in memory, camera resolution, product weight, and display size across the different rounds. The MADs are largest for the attributes of mobile phones, especially for brands, where they are between 0.21 and 0.53.

Mobile B	R1	R2	R3	Mean (R1, R2, R3)	Mean Absolute Deviation
Brand_Apple	0.76	1.45	1.72	1.31	0.37
Brand_Samsung	0.46	0.81	1.04	0.77	0.21
Brand_Nokia	-0.11	0.57	0.62	0.36	0.31
Brand_HTC	0.01	0.47	0.97	0.48	0.32
Brand_Sony	-0.40	0.46	0.83	0.30	0.46
Brand_BB	-0.56	0.52	0.76	0.24	0.53
Price_Low	1.01	1.11	1.13	1.08	0.05
Price_Med	0.82	0.85	0.82	0.83	0.01
Price_Hi	0.44	0.40	0.27	0.37	0.07
Cam_Norm	1.55	1.28	1.48	1.44	0.10
Cam_Hi	2.20	1.96	2.13	2.10	0.09
Mem_M	0.40	0.60	0.57	0.52	0.08
Mem_H	0.41	0.64	0.62	0.56	0.10
Dis_S	-0.45	-0.20	-0.47	-0.37	0.12
Dis_M	0.21	0.00	0.01	0.07	0.09
Batt_M	0.54	0.85	0.61	0.67	0.12
Batt_H	1.06	1.05	0.80	0.97	0.11
Batt_VerHi	1.17	1.39	1.07	1.21	0.12
Weight_VerL	0.43	0.21	0.40	0.35	0.09
Weight_Li	0.35	0.01	0.05	0.14	0.14
Constant	-4.70	-5.25	-5.44	-5.13	0.29

Table 4.17. Mobile phones attribute-weights comparison over the three rounds

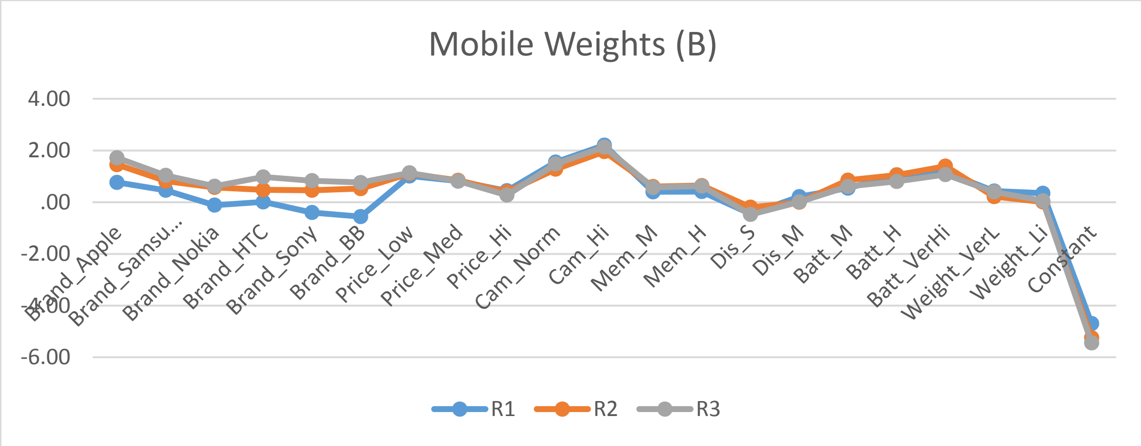


Figure 4.3. Mobile phones weight comparison over the three rounds

4.5.4. TVs

The results for TVs demonstrate (Table 4.18 and Figure 4.4) that there are no specific attributes that have the highest weights, as brands, price, screen size and smartness of TVs are all almost within the same range. However, it can confidently be contended that 3D attributes have the least weight to participants when compared with the others. Brands have the highest level of fluctuation over the different rounds, while both smart TV and screen size attributes have slight fluctuation in comparison to the rest of the attributes. The MADs for the attributes of TVs are larger than for fan heaters, but smaller than laptops and mobile.

TV B	R1	R2	R3	Mean (R1, R2, R3)	Mean Absolute Deviation
Brand_JVC	0.42	0.81	0.68	0.64	0.14
Brand_Sony	0.85	1.20	1.38	1.14	0.20
Brand_Panasonic	1.55	1.68	1.69	1.64	0.06
Brand_Samsung	0.99	1.32	1.34	1.22	0.15
Brand_LG	0.99	1.05	1.02	1.02	0.02
Brand_Toshiba	0.56	1.22	0.90	0.89	0.22
Price_Low	0.92	0.97	0.96	0.95	0.02
Price_Med	1.22	1.17	1.10	1.16	0.04
Screen_L	1.25	1.16	1.04	1.15	0.07
Screen_VeryL	0.86	0.91	0.71	0.83	0.08
Smart_Yes	0.93	1.04	0.79	0.92	0.09
ThreeD_Act	0.05	0.07	-0.07	0.02	0.06
ThreeD_Pass	-0.19	-0.02	-0.07	-0.09	0.06
FreeV_Yes	0.52	0.47	0.43	0.47	0.03
Constant	-4.81	-5.19	-4.75	-4.92	0.18

Table 4.18. TVs attribute-weights comparison over different rounds

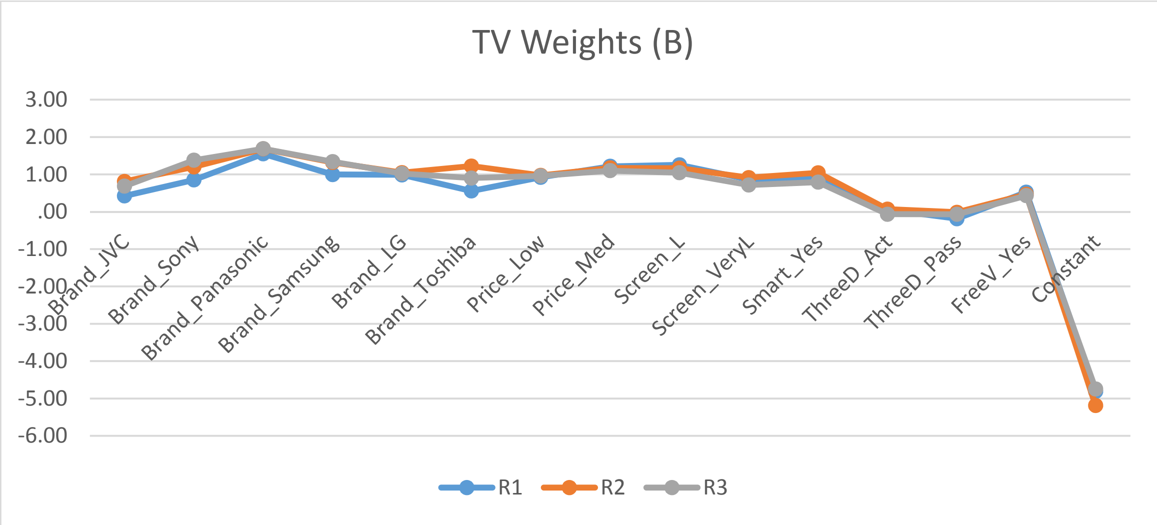


Figure 4.4. TVs attribute-weights comparison over different rounds

4.5.5. Discussion: Weights Comparison in the Different Rounds

In this section, there are discussions on the weight variations across different rounds for each product as well as which attributes show the most variations for a particular product in order to identify the attributes that are major drivers of changes in consumer preferences for a specific product. There is further discussion on cross product weight variation in the next section.

In terms of the most important attribute, for mobile phones, which have more complex attributes, more technological specifications, and generally have the shortest life cycle in comparison to the other products, camera resolution has the highest weight. For laptops, which are relatively less complex products in comparison to mobile phones with a relatively longer life cycle, brand has the highest weight. For TVs, which have relatively fewer technological specifications, less complexity, and a longer life cycle than the two aforementioned types of product, no feature exhibits significantly greater weights than any other. With fan heaters, which are simple low technology products with the longest life cycle of all the tested products, price has highest weight.

For mobile phones and TVs, although brand does not have the highest weights of all the attributes, it has the major fluctuations over time. As mentioned in chapter 2, there were many studies on the effects of brand on choices between 1980 and 1995 (Guadagni and Little, 1983; Fader and Lattin, 1993) that showed its relative importance in consumer preferences; however they did not investigate changes in attribute-weights over time. More change over time with regards to brand when compared to other attributes could be put down to the subjectivity and superficiality of brand. That is, this attribute is driven by people's perceptions that are shaped by marketers' adeptness at using advertisements, brand perception, brand identity, news, and lifestyle to promote their brand. According to Erdem and Keane's (1996) study, advertising could affect consumer preferences in the short term, which might explain the brand perception changes across the different rounds of the experiment.

In addition to brands, there are other changes in weights over time both in mobile phones and laptops that have a slight influence, i.e. memory and product weight. Yet other weights that slightly vary for mobile phones over time are camera resolution and display size, whilst in laptops such variations are found for the processor, hard drive, and price. With TVs, the smartness and screen size attributes have slight fluctuations in comparison to the rest. These changes could be due to technological advances that make some attributes more important (or less important) (Jahanbin et al., 2013) or usage experience (Erdem and Keane, 1996).

4.6. Cross-Product Weight Variation

In the section 4.5, the weights were calculated for each of the attributes of the products in each round, with the aim being to identify which attributes exhibit variations and to what extent, for each product over time. After the mean absolute deviations (MADs) were calculated for each attribute, the average MADs were calculated for all attributes of a given product to investigate whether they are different across products or not. The average MADs show that mobile phones have the highest value of 0.181, with laptops in second highest place with 0.130. Interestingly, the results for fan heaters and TVs are very close 0.093 and 0.095, respectively (Table 4.19). The higher average MADs shows the greater changes in attribute-weights of mobile phones and laptops in comparison to TVs and fan heaters, which could be due to more attributes complexity and technological advancements as well as a shorter life cycle.

	Fan heaters	**Laptops**	**Mobile phones**	**TVs**
Average MADs	0.093	0.130	0.181	0.095

Table 4.19. Average MADs for all products

As these products have different attributes and specifications, the decision was taken to investigate changes in attribute-weights by significance testing as well as by comparisons of the differences between each two rounds of each products to obtain more robust results and confirm previous findings in the following subsections.

4.6.1. Significance testing of weights variations

The attribute-weights from the three rounds show that those for the attributes of mobiles and laptops have the highest variation, and fan heaters and TVs, the lowest, as expected. Additionally, the MADs for fan heaters and TVs are very low and close indicating that both have small amounts of variations. The small MADs and changes in attribute-weights may therefore provide a measure of non-systematic inconsistency in consumer choice, i.e. people make different choices at different points in time for 'stable' products not because their fundamental preferences have changed, but because humans exhibit random inconsistency over time. For fan heaters and TVs, the deviation of the weight for each feature in each round from the mean of the three rounds' weights (Mean R1, R2, R3) were calculated, for instance:

Brand_Challenge $_{\text{weight in R1}}$ (-0.95) – Mean **Brand_Challenge** $_{\text{weights for all three rounds}}$ (-0.99) = 0.04

Price_Hi $_{\text{weight in R2}}$ (0.37) – Mean **Price_Hi** $_{\text{weights for all three rounds}}$ (0.38) = - 0.01

The deviations for the fan heaters were pooled yielding the following histogram of deviations of the weights from their means (Figure 4.5)

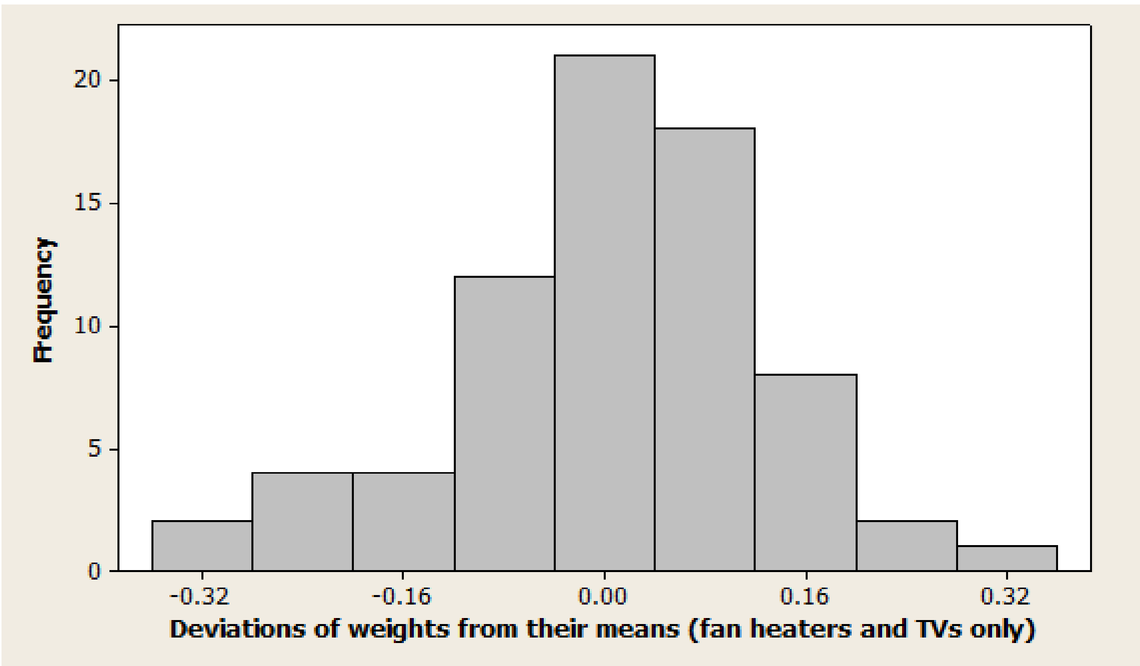


Figure 4.5. Deviation of attribute-weights from their means histogram (Fan heaters and TVs only)

This histogram appears to be close to a normal distribution which further support the idea that the attribute-weights for these two ‘stable’ product are simply varying randomly. Both the Kolmogorov-Smirnov and the Shapiro-Wilk test were used to test the null hypothesis that the distribution is normal. Neither test yielded a significant result so the null hypothesis could not be rejected and this provided further support for the idea that the attribute-weight deviations were normally distributed (Table 4.20). The distribution has a mean of 0 (it has to be given that MADs were used) and a standard deviation of 0.1239.

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Fan heaters and TVs	.064	78	.200	.975	78	.132

Table 4.20. Test of normality of data for variation from mean (Fan heaters and TVs only)

Based on the normal distribution assumption, it can now be used to test the hypothesis that individual weights for laptops and mobiles have the same variation as for ‘stable’ products because they also just reflect the participants’ random inconsistency. If they do, the probability of obtaining a deviation outside the range $0 \pm 1.96 * (0.1239)$, i.e. between -0.243 to + 0.243 is less than 0.05. For example, for laptops in round 1 ‘Brand_Apple’ has a deviation $|Y-\bar{Y}|$ of $|1.79 - 2.06| = 0.267$. If its distribution is the same as that for the stable products then there is only 0.016 probability of obtaining a deviation as big as this. For mobile phones in Round 1, ‘Brand_Samsung’ has a deviation $|Y-\bar{Y}|$ of $|0.46 - 0.77| = 0.31$. Based on hypothesis that its distribution is the same as that for the stable products then there is only 0.006 probability of obtaining a deviation at least as big as this. As shown in tables 4.21 and 4.22, the changes in the weights of brands deviate significantly from what would be expected if the hypothesis is true for both mobile phones and laptops (at the 5% level of significant). In R3, for mobile phones the weights for all brands show significant deviations, while for laptops the weights for four out of seven attributes are significant. In R2, only two brands significantly deviate from the variation observed in the ‘stable’ products. The results suggest that brands are the major driver of change in consumer preferences for mobile phones and laptops.

Laptop	R1			R2			R3		
	|Y-Ȳ|	z-score	Probability	|Y-Ȳ|	z-score	Probability	Y-Ȳ	z-score	Probability
Brand_Apple	0.267	2.152	0.016***	0.203	1.641	0.050***	0.063	0.511	0.305
Brand_Samsung	0.290	2.341	0.010***	0.140	1.130	0.129	0.150	1.211	0.113
Brand_HP	0.330	2.663	0.004***	0.070	0.565	0.286	0.260	2.098	0.018***
Brand_Sony	0.307	2.475	0.007***	0.163	1.318	0.094	0.143	1.157	0.124
Brand_Dell	0.393	3.175	0.001***	0.127	1.022	0.153	0.267	2.152	0.016***
Brand_Lenovo	0.443	3.578	0.000***	0.147	1.184	0.118	0.297	2.394	0.008***
Brand_Toshiba	0.467	3.766	0.000***	0.203	1.641	0.050***	0.263	2.125	0.017***
Price_Low	0.057	0.457	0.324	0.017	0.135	0.446	0.073	0.592	0.277
Price_Med	0.093	0.753	0.226	0.047	0.377	0.353	0.047	0.377	0.353
Price_Hi	0.120	0.969	0.166	0.000	0.000	0.500	0.120	0.969	0.166
Dis_S	0.080	0.646	0.259	0.050	0.404	0.343	0.030	0.242	0.404
Dis_M	0.057	0.457	0.324	0.043	0.350	0.363	0.013	0.108	0.457
Proc_Fas	0.117	0.942	0.173	0.123	0.995	0.160	0.007	0.054	0.479
Proc_Hi	0.190	1.533	0.063	0.120	0.969	0.166	0.070	0.565	0.286
Mem_M	0.107	0.861	0.195	0.023	0.188	0.425	0.083	0.673	0.251
Mem_H	0.090	0.726	0.234	0.060	0.484	0.314	0.030	0.242	0.404
HDD_Hi	0.143	1.157	0.124	0.013	0.108	0.457	0.157	1.264	0.103
HDD_VerHi	0.033	0.269	0.394	0.057	0.457	0.324	0.023	0.188	0.425
Weight_UltraL	0.117	0.942	0.173	0.053	0.430	0.333	0.063	0.511	0.305
Constant	0.143	1.157	0.124	0.047	0.377	0.353	0.097	0.780	0.218

Table 4.21. Significant testing of laptops attributes deviations

Mobile	R1			R2			R3		
	|Y-Ȳ|	z-score	Probability	|Y-Ȳ|	z-score	Probability	|Y-Ȳ|	z-score	Probability
Brand_Apple	0.550	4.439	0.000***	0.140	1.130	0.129	0.410	3.309	0.000***
Brand_Samsung	0.310	2.502	0.006***	0.040	0.323	0.373	0.270	2.179	0.015***
Brand_Nokia	0.470	3.793	0.000***	0.210	1.695	0.045***	0.260	2.098	0.018***
Brand_HTC	0.473	3.820	0.000***	0.013	0.108	0.457	0.487	3.928	0.000***
Brand_Sony	0.697	5.623	0.000***	0.163	1.318	0.094	0.533	4.305	0.000***
Brand_BB	0.800	6.457	0.000***	0.280	2.260	0.012***	0.520	4.197	0.000***
Price_Low	0.073	0.592	0.277	0.027	0.215	0.415	0.047	0.377	0.353
Price_Med	0.010	0.081	0.468	0.020	0.161	0.436	0.010	0.081	0.468
Price_Hi	0.070	0.565	0.286	0.030	0.242	0.404	0.100	0.807	0.210
Cam_Norm	0.113	0.915	0.180	0.157	1.264	0.103	0.043	0.350	0.363
Cam_Hi	0.103	0.834	0.202	0.137	1.103	0.135	0.033	0.269	0.394
Mem_M	0.123	0.995	0.160	0.077	0.619	0.268	0.047	0.377	0.353
Mem_H	0.147	1.184	0.118	0.083	0.673	0.251	0.063	0.511	0.305
Dis_S	0.077	0.619	0.268	0.173	1.399	0.081	0.097	0.780	0.218
Dis_M	0.137	1.103	0.135	0.073	0.592	0.277	0.063	0.511	0.305
Batt_M	0.127	1.022	0.153	0.183	1.480	0.069	0.057	0.457	0.324
Batt_H	0.090	0.726	0.234	0.080	0.646	0.259	0.170	1.372	0.085
Batt_VerHi	0.040	0.323	0.373	0.180	1.453	0.073	0.140	1.130	0.129
Weight_VerL	0.083	0.673	0.251	0.137	1.103	0.135	0.053	0.430	0.333
Weight_Li	0.213	1.722	0.043***	0.127	1.022	0.153	0.087	0.699	0.242
Constant	0.430	3.471	0.000***	0.120	0.969	0.166	0.310	2.502	0.006***

Table 4.22. Significant testing of mobile phones attributes deviations

4.6.2. Comparisons of the Attribute-Weights Differences between Each Two Rounds for Each Products

The decision was taken to investigate changes in attribute-weights by comparisons of the differences between each two rounds of each products to obtain more robust results and confirm previous findings in the following subsections. The differences, absolute differences, and squared differences between paired rounds for each feature were calculated (see appendix 12). Subsequently, the means of each of these differences were found for each product and their levels of variation were compared. These instruments for comparing the variations were adopted from instruments for forecasting accuracy measures (Ord and Fileds, 2013). These include, the Mean Error (ME), which was adapted to provide the mean differences of attribute-weights, the Mean Absolute Error (MAE), which was modified to give mean absolute differences of attribute-weights and the Mean Squared Error (MSE), which was slightly altered to get mean squared differences of attribute-weights. These three measures were employed as Hyndman et al. (2014) recommended using at least this number of measures for forecasting accuracy and bias measures.

4.6.2.1. Mean differences of the attribute-weights

The mean differences of attribute-weights were calculated for all the products and there were generally more variations between R1 and R2, and R1 and R3 in comparison to R2 to R3 (Table 4.23 and Figure 4.6). The results show that fan heaters have the smallest variation in comparison to other products between the paired rounds, while mobile phones have the greatest. Laptops come second and TVs third. However, the mean absolute differences, as presented in the next section, provide a much more precise view on changes in the relative importance of the features.

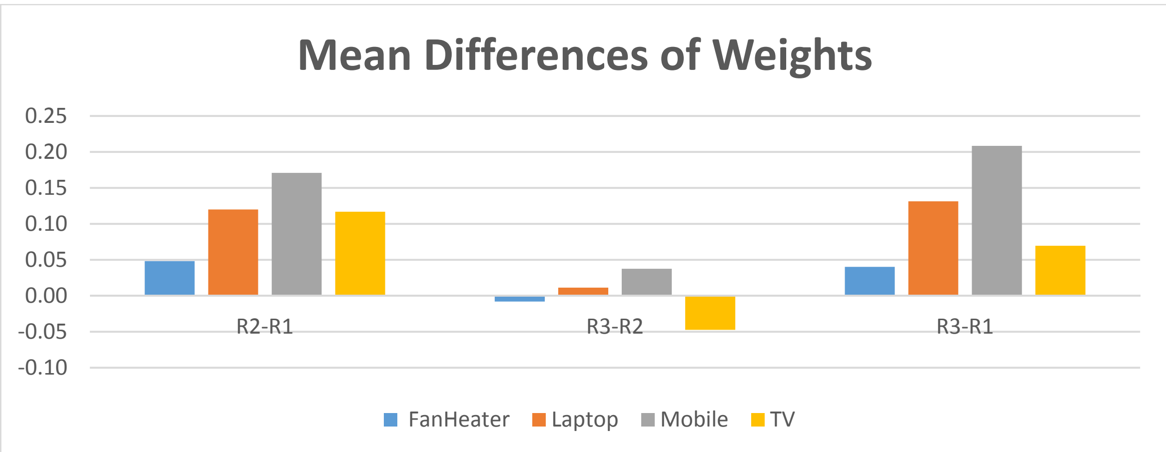


Figure 4.6. Mean differences of attribute-weights

Mean Difference B	R2-R1	R3-R2	R3-R1
Fan Heater	0.05	-0.01	0.04
Laptop	0.12	0.01	0.13
Mobile	0.17	0.04	0.21
TV	0.12	-0.05	0.07

Table 4.23. Mean differences of attribute-weights

4.6.2.2. Mean absolute differences of the attribute-weights

The numerical values of the mean absolute differences of the attribute-weights are different and they are slightly higher than those of the mean differences of attribute-weights, which is due less cancelling out of positive and negative values. However, the mean absolute differences of the attribute-weights generally show the same trend as the differences of attribute-weights (Table 4.24 and Figure 4.7). That is, mobile phones have the highest variation, with laptops and TVs occupying second and third places, respectively. Unsurprisingly, the fan heaters have the lowest variation of the mean absolute differences of attribute-weights. Additionally, there is more variation in between R1 and R2, and R1 and R3 than R2 and R3, which is the same outcome as that found regarding the features within each product across the different rounds (see section 4.5).

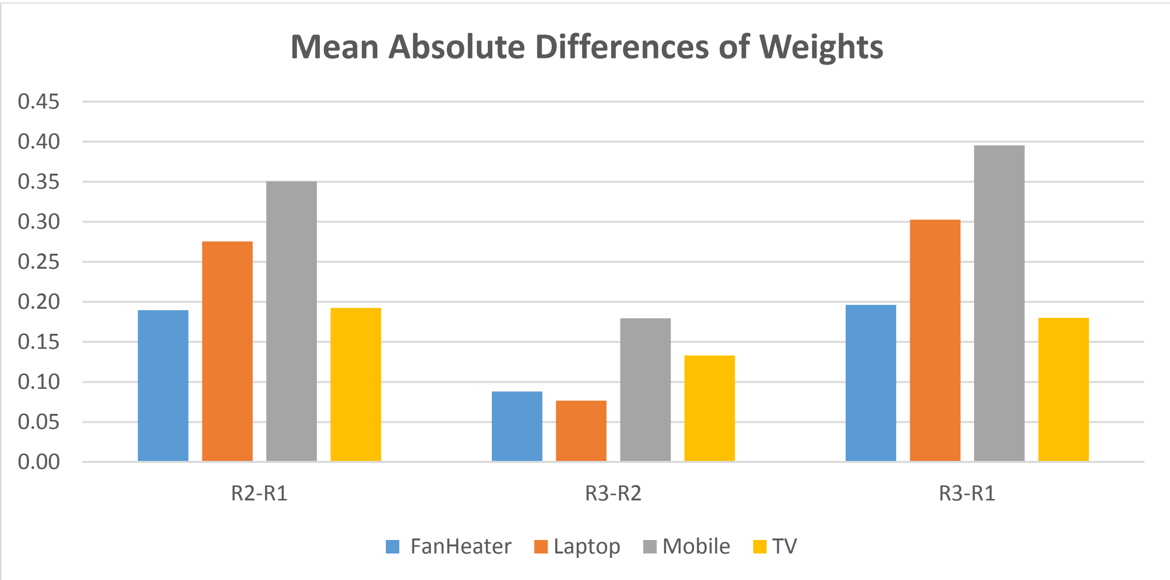


Figure 4.7. Mean absolute differences of attribute-weights

Mean Abs Difference B	R2-R1	R3-R2	R3-R1
FanHeater	0.19	0.09	0.20
Laptop	0.28	0.08	0.30
Mobile	0.35	0.18	0.40
TV	0.19	0.13	0.18

Table 4.24. Mean absolute differences of attribute-weights

4.6.2.3. Mean squared differences of attribute-weights

In general, the mean squared value has slightly lower numerical values than the mean absolute differences of attribute-weights, whereas it is higher than the mean differences of attribute-weights (Table 4.25). However, it shows the same trend as both of these previous measures, thus providing robust confirmation of the results as a whole (Figure 4.8).

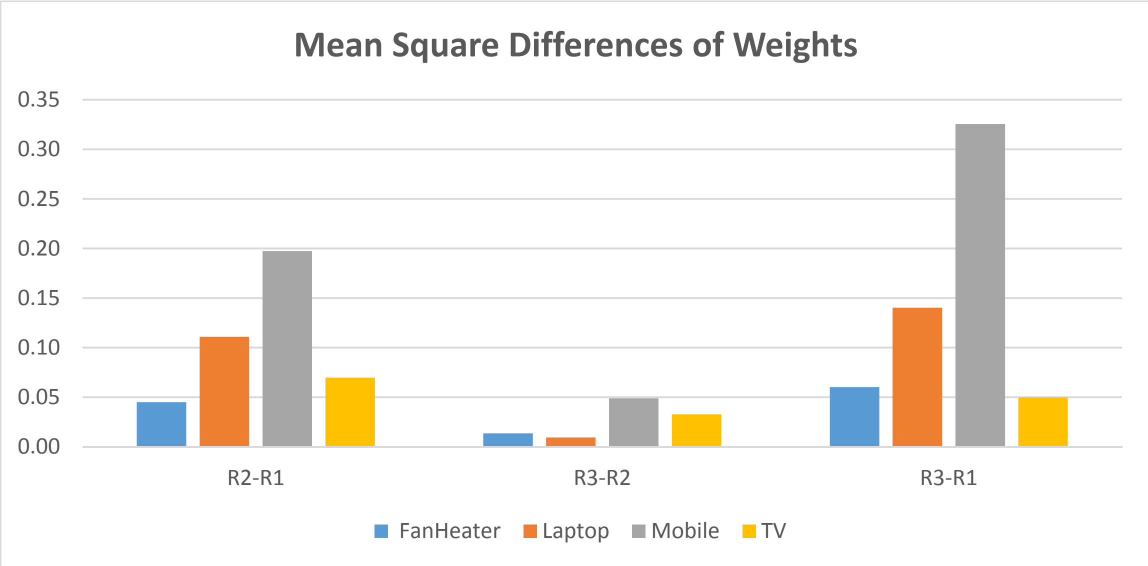


Figure 4.8. Mean square differences of attribute-weights

Mean Square Difference B	R2-R1	R3-R2	R3-R1
Fan Heater	0.05	0.01	0.06
Laptop	0.11	0.01	0.14
Mobile	0.20	0.05	0.33
TV	0.07	0.03	0.05

Table 4.25. Mean square differences of attribute-weights

4.6.3. Discussion: Cross-Product Attribute-Weight Variation

In addition to the significance testing results, all three measures of attribute-weight variation across the different products show the same trend. Mobile phones have the highest variations in the different rounds, which could be interpreted as being that the attribute-weights changed more frequently for the participants than for the other products. On the other hand, fan heaters demonstrate the lowest changes of weights in the different rounds, thus indicating less frequent changes in attribute-weight for the participants or they are more consistent over time in choosing fan heaters than mobile phones.

In reality, mobile phones are the most complex product of those surveyed, with the highest technological features, and the shortest life cycle as well as having the highest average MADs. Laptops are very close to mobile phones in terms of complexity of the product, sophistication of technological attributes, and the length of the life cycle, which their MADs has a second highest place. These two products have the two highest levels of changes in their attribute-weights, i.e. the participants showed more changes in their choices over time. TVs are less complicated products with lower technological complications than mobile phones and laptops and hence, unsurprisingly, came third in the results order. Finally, fan heaters have the longest life cycle and are simple products with little technological sophistication. Therefore, it can be concluded that the greater a product's technological advancements and complexity in terms of its attributes, the more changes in attribute-weights over time. In addition, the life cycle length has a reverse relationship with changes in the attribute-weights over time, i.e. the shorter the life cycle, the more changes over time.

Some of the identified changes in attribute-weights for complex and high tech products with short life cycles in comparison with simple ones with a long life cycle could be due to cognitive factors as discussed in the literature review chapter. Bounded rationality (Simon, 1955) is one of these cognitive factors, which refers to human beings having computational and informational limits regarding their rational decision making. Simon (1955) suggested that due to their limited capacity to process information, consumers use or recall only a certain subset of attributes during the decision-making process. If the subset changes over time, perhaps because some attributes become more or less salient due to the stimuli they have recently been subject to, then clearly the attribute-weights to consumer in the decision making process will also change. Hlédik (2012) has also supported the idea that customer preferences are not stable, especially where a consumer needs to make a complex or unfamiliar decision (Bettman et al., 1998). Another cognitive factor that could explain the greater variation in decision making for complex products is the construction of choice during the experiment process. People often do not have well-defined preferences; instead, they may construct them on the spot when needed, such as when they must make a choice (Bettman et al., 1998). Consequently, it can be concluded that to some degree decisions are underpinned by the context, i.e. people differ in their decision making process when considering different kinds of products.

When a product is more complex with more attributes, e.g. mobile phones and laptops in comparison to a simple product, e.g. fan heaters, explicit trading-off among the various attributes is the most difficult and uncomfortable aspect of the decision-making process for consumers. Payne et al. (1992) contended that one response to this is to adopt simplifying heuristics to make a decision, which may be an explanation for the greater changes in the attribute-weights to consumers over time, especially when a product is more complex than others. Technological advances in communication and information technology have changed the nature of products and their capability, which has meant that some attributes have become more or less important over relatively short periods of time for consumers (Jahanbin et al., 2013). This could explain the greater variations in choice regarding mobile phones and laptops. Although there are some changes in participants' choices between R2 and R3, they were more consistent between these two rounds with less changes in attribute-weights in comparison to R1. This could be related to familiarity with the products, whereby the participants became more knowledgeable about the hypothetical products with time. Regarding which, as discussed in the literature review chapter, Coupey et al. (1998) took a view that consumers' prior knowledge with a product may affect two aspects of preferences expression: First, the information about the product itself (i.e. its features' specifications) forms the basis for preferences or choosing the product by consumers. Second, the way in which this information is used by consumers to acquire or search for more information. For example, familiarity with products may involve the use of prior product–related knowledge when acquiring or searching for more information.

Both of the above perspectives are in line with the greater stability of attribute-weights between R2 and R3. During a decision making process, consumers often search their memory for some information to help guide preferences construction, regardless of whether a product is familiar or not. With familiar products, choice is likely to be an easily performed task, as consumers are likely to know which attributes are most important, whereas for unfamiliar products they have less information in their memories to guide them. Consequently, there will be more change in the attributes that are important over time as they learn more about them. Unfamiliarity of the consumer about a product is usual when it is new, has added new attributes and/or is a high tech product with many complex attributes. These factors can lead to more changes in attribute-weights over time. As a product and its attributes become familiar to consumers over time, it is most likely that preferences become more stable and consistent, particularly if it and its features stay the same after multiple purchases. Another consequence of familiarising participants with products, according to Coupey et al. (1998), is that change in attribute-weight happens due to a shift in the strategy of purchasing, whereby increasing the familiarity regarding the attributes of products increases the ability of consumers to take decision such that they have a more solid choosing strategy (or purchasing strategy). Finally, familiarity and knowledge of products by consumers over time decreases the associated risk of their decisions-making consequences for them (March, 1978).

Another reason for less variation over time between R2 and R3 in comparison to R1 could be due to the construction of decision making during the experiment process. This can be explained by the results of Amir and Levav's (2008) study on how people learn to become more consistent in their choices through repetition. More specifically, making repeated choices supposedly reveals peoples' subjective attribute values, which enables them to learn how they prefer to resolve trade-offs between conflicting attributes in a choice set. If participants make more choices in a domain, they became more confident in their subjective value for the levels of each attribute and more internally consistent in their choices.

4.7. Internal Consistency using Bootstrapping (BS)

In order to check the internal consistency of the sample, bootstrapping was conducted by taking a small random sample of 1,000 from the dataset to make sure that there was systematic variation over time and that the variation was not due to internal inconsistency or randomness in the sample. The bootstrapping results show very little difference in outcome in comparison to the logistic regression. In the subsequent subsections, the cross product attribute-weights variation for the bootstrapping results are illustrated and as is seen, the similar results were obtained as that of the logistic regression (Tables 4.26, 4.27, 4.28 and Figures 4.9, 4.10, 4.11).

4.7.1. Mean differences of attribute-weights using bootstrapping

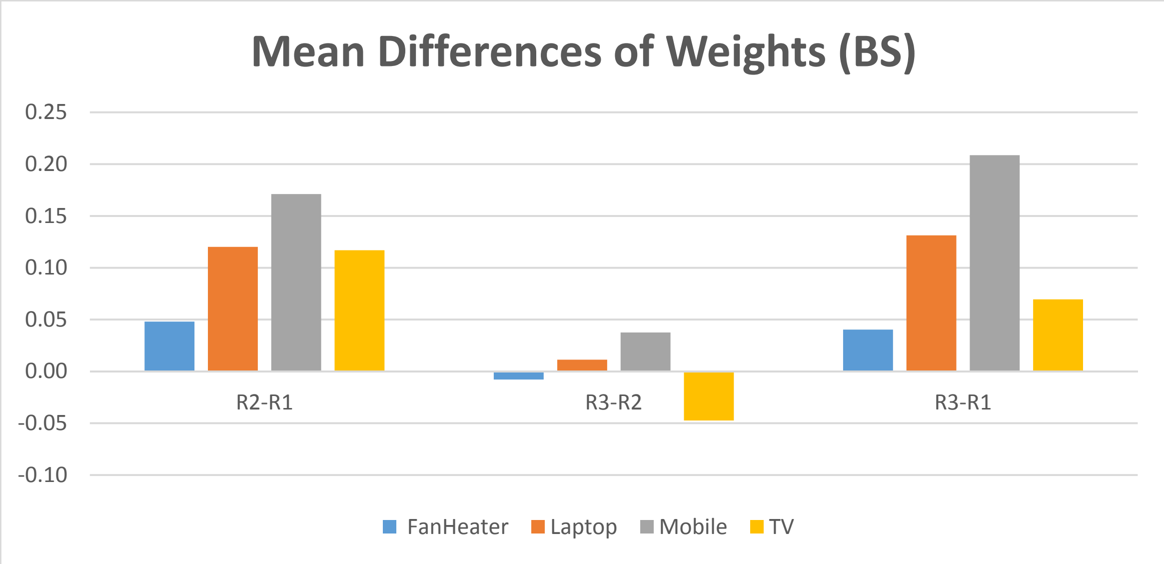


Figure 4.9. Mean differences of attribute-weights using bootstrapping

Mean Difference B	R2-R1	R3-R2	R3-R1
Fan Heater	0.05	-0.01	0.04
Laptop	0.12	0.01	0.13
Mobile	0.17	0.04	0.21
TV	0.12	-0.05	0.07

Table 4.26. Mean differences of attribute-weights using bootstrapping

4.7.2. Mean absolute differences of attribute-weights using bootstrapping

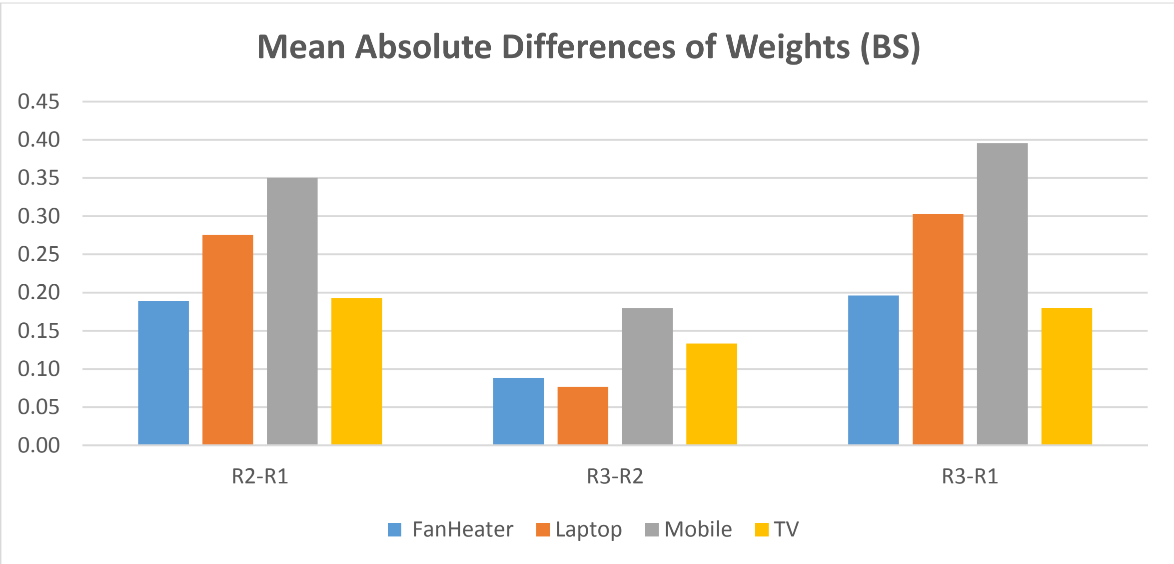


Figure 4.10. Mean absolute differences of attribute-weights using bootstrapping

Mean Abs Difference B	R2-R1	R3-R2	R3-R1
FanHeater	0.19	0.09	0.20
Laptop	0.28	0.08	0.30
Mobile	0.35	0.18	0.40
TV	0.19	0.13	0.18

Table 4.27. Mean absolute differences of attribute-weights using bootstrapping

4.7.3. Mean squared differences of attribute-weights using bootstrapping

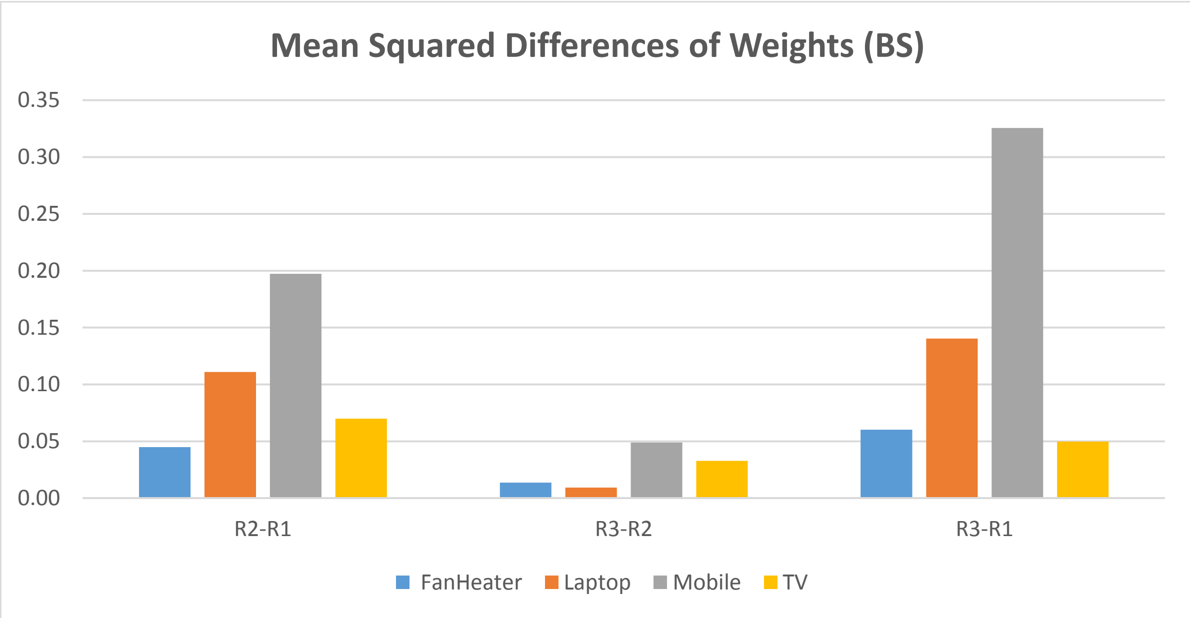


Figure 4.11. Mean squared differences of attribute-weights using bootstrapping

Mean Square Difference B	R2-R1	R3-R2	R3-R1
Fan Heater	0.04	0.01	0.06
Laptop	0.11	0.01	0.14
Mobile	0.20	0.05	0.33
TV	0.07	0.03	0.05

Table 4.28. Mean squared differences of attribute-weights using bootstrapping

4.8. Data Analysis using Hierarchical Bayesian Estimations

In the previous section, the internal consistency of the sample was examined using bootstrapping and as was found to be strong, the results are the same as that of the whole aggregate logistic regression. The researcher also decided to use another estimation method, namely the Hierarchical Bayesian (HB) technique, with specialised choice based conjoint analysis software, *Sawtooth*. The dataset was imported into the software and the HB estimation was calculated by software. The HB model is called "hierarchical" because it has two levels. At the higher level, the Sawtooth software assumes that individuals' parameters (part worth's utilities) are described by a multivariate normal distribution. Such a distribution is characterised by a vector of means and a matrix of covariances. At the lower level the software assumes that, given an individual's betas, his/her probability of achieving some outcome (choosing products, or rating brands in a certain way) is governed by a particular model, such as MNL (Orme, 2000).

Initial crude estimates of betas are estimated for each respondent to use as a starting point and new estimates are updated using an iterative process called "Gibbs Sampling". The model estimates individual betas as well as the means and covariances of the distribution of betas. During each iteration an estimate is made for each parameter, conditional on the current estimates of the others and Sawtooth does this by making a random draw from each conditional distribution. Eventually, after many iterations, this process converges to the correct estimates for each parameter. In simple term, the HB algorithm in Sawtooth produces betas that fit each individual's outcome reasonably well, but "borrows" information from other respondents to stabilise the estimates. After 20,000 iterations, convergence is assumed and the estimates of the respondent betas are saved after each or (preferably) every *n*th subsequent iteration. These saved results are called "draws" (replicates) and they reflect the uncertainty around each respondent's estimated betas. Often hundreds or even thousands of draws are saved per respondent. Point estimates of the betas are computed for each respondent by averaging the respondent's draws (Orme, 2000).

In the HB estimation algorithm used by Sawtooth, the numerical values of the feature utilities including the utility of the non-choice option were calculated rather than the attribute-weights (i.e. logistic regression in sections 4.6 and 4.7) (appendix 13). Consequently, comparing attribute-weights from logistic regressions with utilities from HB is a meaningless task; however, the change in attribute-weight to participants over time from the HB estimations can be compared with the results from the logit estimations in terms of the trends in the findings by using mean differences of utilities, mean absolute differences of utilities, and mean squared differences of utilities.

4.8.1. Mean differences of utilities using the HB estimations

The mean differences of utilities do not provide the same findings as with the logistic regression. Between R1 and R2, the laptops and TV variations are in line with the previous findings; however, mobile phones have lower variations than TVs and laptops between these two rounds, and surprisingly the fan heaters have the highest, which is addressed in the discussion section. Between R2 and R3, all the products variations are in accordance with the previous findings except for fan heaters. Between R3 and R1, all product variations are close to those of the earlier findings, except for TVs, which have a mean difference of utilities way above the rest. In addition, the negative numerical values between R1 and R3 for all four products are due to the negative results of the differences of the utilities (Table 4.29 and Figure 4.12).

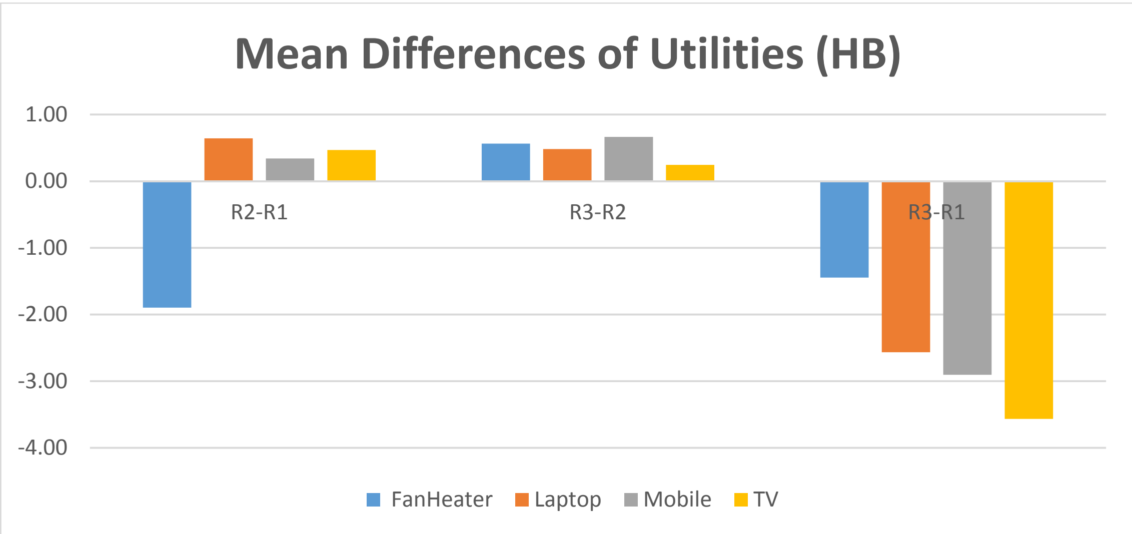


Figure 4.12. Mean differences of utilities using the Hierarchical Bayesian

Mean Difference B	R2-R1	R3-R2	R3-R1
FanHeater	-1.90	0.56	-1.45
Laptop	0.64	0.48	-2.56
Mobile	0.34	0.66	-2.90
TV	0.47	0.25	-3.57

Table 4.29. Mean differences of utilities using the Hierarchical Bayesian

4.8.2. Mean absolute differences of utilities using the HB estimations

The mean absolute difference of utilities results are the same as for the previous findings from the logit estimations, except for fan heaters' level of variations between R1 and R2 as well as between R3 and R2, which are higher. As mentioned earlier, the reasons for the significantly different results for fan heaters are explained in the discussion section (Table 4.30 and Figure 4.13).

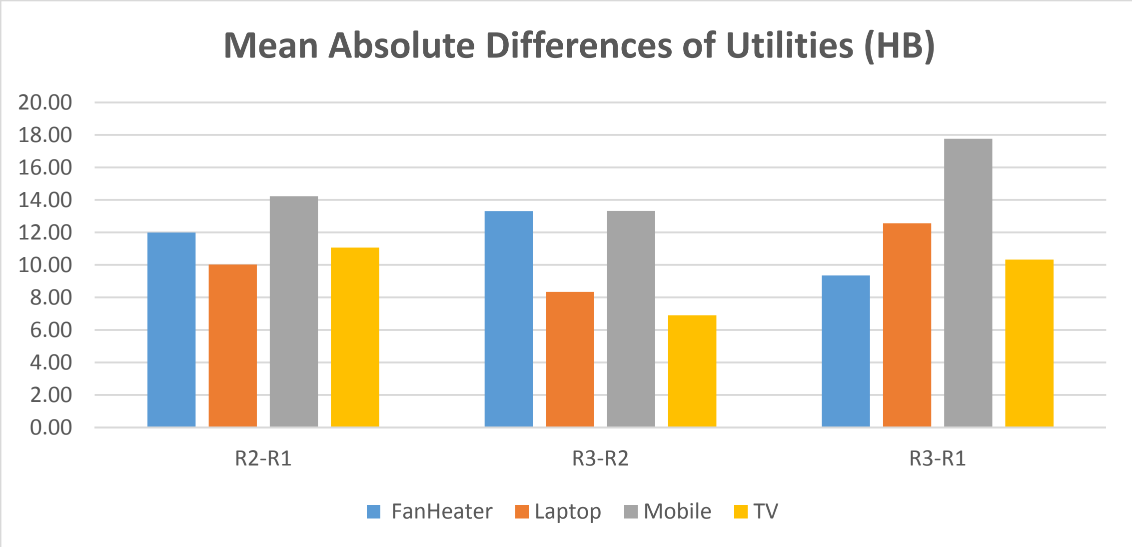


Figure 4.13. Mean absolute differences of utilities using the Hierarchical Bayesian

Mean Abs Difference B	R2-R1	R3-R2	R3-R1
FanHeater	11.99	13.32	9.35
Laptop	10.03	8.34	12.57
Mobile	14.23	13.33	17.77
TV	11.07	6.90	10.32

Table 4.30. Mean absolute differences of utilities using the Hierarchical Bayesian

4.8.3. Mean square differences of utilities using the HB estimations

The mean squared differences of utilities results were almost the same as the previous findings; except for fan heaters between R1 and R2, as well as R2 and R3. Additionally, TVs have notably higher variations than expected between R1 and R2 (Table 4.31 and Figure 4.14).

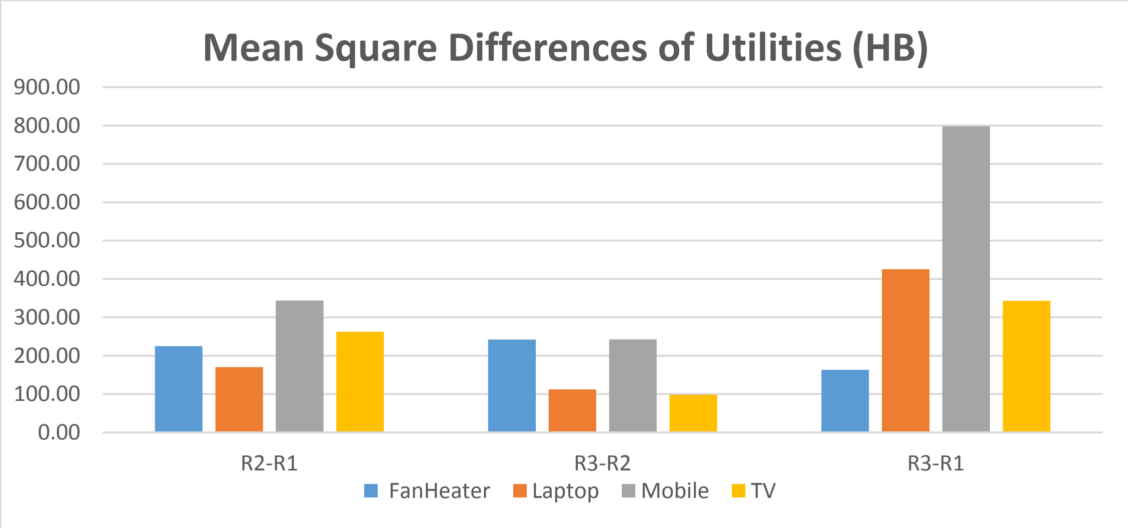


Figure 4.14. Mean squared differences of utilities using the Hierarchical Bayesian

Mean Square Difference B	R2-R1	R3-R2	R3-R1
Fan Heater	224.82	242.16	162.99
Laptop	170.41	112.07	425.42
Mobile	344.11	242.38	797.84
TV	262.52	97.87	343.11

Table 4.31. Mean squared differences of utilities using the Hierarchical Bayesian

4.8.4. Discussion: Hierarchical Bayesian Estimations

The results from HB estimation are pretty much the same as those for the logit estimations; however, there are slight differences in the former, especially for fan heaters, which could be due to the reasons below:

1. HB is a different estimation method and hence, exactly the same results as those that were obtained from logistic regression would not be expected.

2. The HB methods conducts the estimations for two levels, first, estimating the utilities of individuals using 'Gibbs sampling' and Markov Chain simulation (20,000 iterations), as each participant make several choices in each round for each product. In the second level, the aggregate utility of each feature was calculated based on the individuals' utilities. In contrast, the logit method makes the estimations only at the aggregate level without any simulations. Calculations of the results on individual levels using simulations is carried out for two main purposes: first, smoothing the inconsistencies and randomness; and second, clustering individual results using a statistical clustering methods. Therefore, some of the

inconsistencies that the researcher was expecting to observe might be eliminated through the process.

3. There is discussion in the literature regarding whether a non-choice option should be included in the equation. This researcher did not consider it as a variable in the logit estimations; however Sawtooth does do so during HB calculations.

4. The Sawtooth HB results deliver average utility for each feature, where the sum of the aggregate utility for a specific feature is equal to 0, except from a non-choice option, which has some utility value. Consequently, the difference of utilities across the different rounds leads to huge mean differences. Additionally, from the average utility data produced by Sawtooth it cannot be determined which features or levels have what importance.

5. The Sawtooth algorithm generally requires longer choice task experiments (more choice-sets) as it is more data hungry and it might require a greater amount of observations through having more profiles to choose from.
6. In R1-R2 and R2-R3, whilst fan heaters behave quite randomly, differences for laptops, mobile phones, and TVs are still obvious.
7. The unexpected results for fan heaters between R1 and R2, as well as R2 and R3 could be attributed to the comparatively low value of the average utility of the non-choice option in R2 (appendix 13) as in R1 and R3 participants chose significantly more non-choice options than in that particular round.

4.9. Conclusions

The main aim of this chapter was to address RQ1 and RQ2 as well as testing hypothesis H_1, which are:

RQ1: To what extent do the attribute-weights that consumers attach to a product change over time?

RQ2: Are the changes in attribute-weights associated with the complexity and life-cycle of products?

H_1: Attribute-weights change much quicker over time for products with more complex features and shorter life cycles when compared with less complex products with longer life cycles.

In section 4.3, the participants' choices in each round were compared with those in the other rounds to find out how many choices were different (mismatch) with the aim of testing H_1 (H_1 drawn from RQ2). Hence, the consistency of choices of products between each of the different rounds was calculated. Specifically, the number of mismatches in choice between each round for all four products (called the 'number of mismatch choice variable') was compared using a repeated measures one way ANOVA (General Linear Model) in order to investigate if there was greater change in product choice for some types of product than others. Although the results were not significant at the 5% level between R2 and R3, the results were significant in both between R1 and R2 as well as R1 and R3. Taking in account the evidence from the other measures in section 4.5 and 4.6, H_1 is accepted.

RQ1 was addressed in sections 4.5, where results on the changes in attribute-weights across different rounds for each product as well as which attributes show the most changes for a particular product reported and discussed, thereby identifying the attributes that are the major drivers of changes in consumer preferences for a specific product. It emerged from the findings that the weights that the consumer attributes to a product change over time for two reasons: randomness and systematic variations.

In section 4.6, RQ2 was responded to. First, the higher average MADs showed the greater changes in attribute-weights of mobile phones and laptops in comparison to TVs and fan heaters. Subsequently, the significance testing of the attribute-weights variations conducted in 4.6.1 confirmed the previous results. It also emerged from comparisons of the attribute-weights differences between each two rounds for each product using logit estimation in later sub-sections of 4.6, that the nature of product, in terms of complexity, technological advances and length of life cycle affect the level of changes over time. That is, if a product is more complex with a high level of technology and short life cycle, there will be more changes in attribute-weights. Subsequently, the internal consistency of the sample was examined using bootstrapping and it was found to be strong. In the last section, the Hierarchical Bayesian technique in another software package (Sawtooth) was employed as an alternative estimation method. Although the results have shown slight differences, they are generally in line with the findings from the logit estimations. In the next chapter, the effect of individual differences on participants' preferences over time is investigated.

5. Individual Consumer Characteristics and Changes in Attribute-Weights

5.1. Introduction

In the previous chapter, the data were analysed across various products over time and showed that the participants had various levels of variations in their choices across the different types of products. In this chapter, the ways in which variations in consumers' individual characteristics can influence changes in attribute-weights for a given product over time and the extent of these changes is investigated. If certain demographic, technical competency or specific consumer usage behaviour characteristics are associated with greater change in attribute-weights then, in markets where these characteristics prevail, any market share forecasts that are based on choice-based model are likely to be less reliable. The aim here is to address these issues leading to the third research question RQ3, which is:

RQ3: How do the characteristics of individual consumers relate to the stability of the attribute-weights of specific products?

First, the chapter begins with a review of previous studies on how consumers' individual characteristics can affect choice, and this is followed by consideration of how the variation of these can affect consistency of choices within a product, i.e. how demographics and technological competency can have an impact on people's consistency. In addition to the examination of demographic and perceived technology competency characteristics, the chapter also investigates the effect of other characteristics that are specific to a certain product, these being called specific consumer usage behaviour characteristics. Finally, participants' preference change over time within certain products for various characteristics is discussed.

5.2. Individual Characteristics

There are some previous studies on how individual characteristics or their usages behaviour might affect consumer behaviour or choices. As mentioned in the literature review chapter, according to Pollak (1978) preferences and tastes of individuals might change according to different demographic characteristics (e.g. socio-economic characteristics, household budgets). Moreau et al. (2001) contended that how individual consumers learn about and develop preferences for new products has not been extensively researched. These authors argued that the factors that influence consumer preferences in relation to new products from both the consumer behaviour and psychology perspectives are: knowledge of existing products, consumer perception on product advantages that could be translated into the importance of a product to the consumer and consumer comprehension regarding a product that depends on the level of technological competency of the consumer and could be measured as such.

Technological changes and advancement (Jahanbin et al., 2013) and internal desire for variety seeking (Kahn, 1995) could be the reasons for whether consumers choose to make upgrades or changes of devices. In addition to this, daily usage of technology and its influence on consumer behaviour have been studied from different perspectives in the literature, including: the effect of mobile phone daily usage on travel behaviour (Yuan et al., 2012), perceived enjoyment and perceived usefulness on internet daily usage (Teo et al., 1999), and mobile phone usage by students in college in relation to maintaining family relationships (Chen, 2009). There is also an American study that compared mobile phone usage and internet usage showing that although there are great similarities between them, there might be also some differences due to individual characteristics and demography (Rice, 2003). Ishii (2004) conducted a study on internet usage differences with PCs/laptops in comparison to mobile phones in Japan. All of these studies convinced this researcher that variation in usage of technology among individuals could provide an explanation for their differing behaviours. However, none of them has considered how these individual differences might influence the attribute-weights for a specific product over time. To address this, research question (RQ3), regarding the effect of different individual characteristics on the stability of the attribute-weights to the focal products will be examined by testing the following hypothesises:

H_2: Gender is associated with consumer choices for any of chosen products.

H_3: Age is associated with consumer choices for any of chosen products.

H_4: Education level is associated with consumer choices for any of chosen products.

H_5: Employment status is associated with consumer choices for any of chosen products.

H_6: Perceived competency level with technology affects consumer choices for any of chosen products.

H_7: The upgrade and change duration of laptops, mobile phones and TVs affect consumer choices.

H_8: The importance to consumers of the technological specifications of laptops, mobile phones and TVs affects their choices.

H_9: The daily usage by consumers of laptops, mobile phones and TVs affects their choices.

H_{10}: The importance to consumers of laptops, mobile phones and TVs affects their choices.

H_{11}: The upgrade and change duration of laptops' and mobile phones' software/application or operating system affects consumer choices.

5.3. Individual Variance's Effects on Choices with regards to a Product

Individual characteristics of the 161 participants who responded to all three rounds of the survey, i.e. gender, age, education, occupation and perceived technology competency, were included in the utility models for all the focal products, i.e. mobile phones, fan heaters, laptops and TVs. Table 5.1 show the perceived technology competency level of the participants, with 49.1% seeing themselves as technology competent and 3.1% not so.

Perceived technology competency question		Frequency	Percent
How competent are you with technology?	**Very Competent**	49	30.4
	Competent	79	49.1
	Somewhat competent	28	17.4
	Not competent	5	3.1

Table 5.1. Competency with technology

The RUM model can be written as:

$$U_{nj} = V_{nj} + \varepsilon_{nj} = \beta X_{nj} + \alpha Z_{nj} + \varepsilon_{nj}$$

Equation 5.1

$$V_{nj} = \beta X_{nj} + \alpha Z_{nj}$$

Equation 5.2

Participant n, faces J choices that obtain a certain level of utility (profit) from each alternative, which can be written as U_{nj}, j=1, 2,…., J. V_{nj} are specified to be linear as $V_{nj} = \beta X_{nj} + \alpha Z_{nj}$, where X_{nj} is the vector of the product explanatory variable and Z_{nj} is the vector of the participants' characteristic variable. When an alternative, say i, is chosen among a choice set j, the chosen alternative is assigned a value of 1 and the non-chosen, 0, which results in binary values, based on the choice of alternatives being attributed by the participant n, for the dependent variable. The explanatory variables in the equation are the alternative specifications (features and levels, as well as individual characteristics), which can be fitted to the MNL choice probability model:

$$P_{in}= \frac{e^{V_{ni}}}{\sum_j e^{V_{nj}}}$$

Equation 5.3

When random utility is assumed to follow a logistic distribution, the model is a binary logit model (Greene, 2009), which can be written as:

$$P_{in}= \frac{1}{1+e^{-(\beta X_{ni} + \alpha Z_{ni})}}$$

Equation 5.4

Once the demographic characteristics and perceived technology competency are added to the logit model as individual variables, estimation is carried out. However, none of the aforementioned demographic characteristics significantly associated or affected the choice of the participants (at 5% level of significance) for any of the products, and hence H_2, H_3, H_4, H_5 are rejected. Perceived technology competency also did not have a significant effect on the participants' choices for any of the types of products at 5% level of significance, which reject H_6. As stated in previous chapter, fan heaters and TVs do not involve such high technology and features complexity as the other two surveyed products, thus it would seem to be reasonable not to expect a significant effect of perceived technological competency when participants are choosing these products. By contrast, this researcher assumed such an effect would be found in the cases of laptops and mobile phones as both of them are higher technology products than the two aforementioned.

5.4. Effects of other Characteristics on Choosing a Specific Product

In addition to individuals' demographic characteristics and perceived level of technological competency, the participants were asked some additional questions tailored to each specific product, except for the baseline product.

5.4.1. Laptops

As shown in table 5.2, five specific questions were asked about profile of participants' usage of laptops. First, they were asked 'How often do you upgrade/change your PC/laptop?' and 55.3% of them replied that they waited for more than three years before doing so, whilst only 1.9% said they upgraded/changed it at least once a year. For the second question, the participants were asked 'How important is your PC/laptop's technical specification?', with 59.6% responding that was very important, while 11.8% replied that it was somewhat important and none reported that it was not important. In the third question, the participants were asked 'How much time do you spend in a day using your PC/laptop?' and 65.2% responded 'More than 4 hours', while 8.7% reported 'Less than an hour'. The fourth question that the participants were asked was 'How important is your PC/laptop to you?' and 76.4% responded 'Very important', while 0.6% indicated that it was 'Not important' (only a single participant). Finally, the participants were asked 'How often do you upgrade your PC/laptop's software/operating system?' and 37.3% responded 'Often', whereas 5.0% replied 'Not at all'.

Usage behaviour questions		Frequency	Percent
How often do you upgrade or change your PC/laptop?	More than 3 years	89	55.3
	2 to 3 years	54	33.5
	1 to 2 years	15	9.3
	Less than a year	3	1.9
How important is your PC/laptop's technical specification?	Very important	96	59.6
	Important	46	28.6
	Somewhat important	19	11.8
	Not important	0	0
How much time do you spend in a day using your PC/laptop?	More than 4 hours	105	65.2
	2 to 4 hours	24	14.9
	1 to 2 hours	18	11.2
	Less than an hour	14	8.7
How important is your PC/laptop to you?	Very important	123	76.4
	Important	21	13
	Somewhat important	16	9.9
	Not important	1	0.6
How often do you upgrade your PC/laptop's software or operating system?	Very often	43	26.7
	Often	60	37.3
	Not very often	50	31.1
	Not at all	8	5

Table 5.2. Participants' usage behaviour questions for PCs and laptops

5.4.2. Mobiles

For mobile phones, as with laptops, the participants were asked five specific questions about their usage of them (see table 5.3). First, they were asked ‘How often do you upgrade/change your mobile phone/s?’, and 39.1% of them reported that they did so every 2 to 3 years, while 1.2% replied at least once a year. For the second question, the participants were asked ‘How important is your mobile phone’s technical specification?’ with 49.7% responding that it was ‘Important’ for 49.7% and 5.0% believed it to be ‘not important’. In the third question, the participants were asked ‘How much time do you spend in a day using your mobile phone/s?’, and 62.2% responded either ‘more than 4 hours’ or ‘ between 2 to 4 hours’, while 14.3% replied that it was for ‘Less than an hour’. For the fourth question, they were asked ‘How important is your mobile phone to you?’ and 58.4% responded ‘Very important’, while 1.9% reported it as ‘Not important’ (only three participants). Finally, the participants were asked ‘How often do you upgrade your mobile phone's software/operating system?’ and 32.9% responded ‘Not very often’, while 8.1% replied ‘Not at all’.

Usage behaviour questions		Frequency	Percent
How often do you upgrade or change your mobile phone?	More than 3 years	37	23
	2 to 3 years	63	39.1
	1 to 2 years	59	36.6
	Less than a year	2	1.2
How important is your mobile phone’s technical specification?	Very important	44	27.3
	Important	80	49.7
	Somewhat important	29	18
	Not important	8	5
How much time do you spend in a day using your phone?	More than 4 hours	50	31.1
	2 to 4 hours	50	31.1
	1 to 2 hours	38	23.6
	Less than an hour	23	14.3
How important is your mobile phone to you?	Very important	94	58.4
	Important	44	27.3
	Somewhat important	20	12.4
	Not important	3	1.9
How often do you upgrade your mobile phone's application or operating system?	Very often	45	28
	Often	50	31.1
	Not very often	53	32.9
	Not at all	13	8.1

Table 5.3. Participants’ usage behaviour questions for mobile phones

5.4.3. TVs

For TVs, the participants were asked four specific questions about their usage of it (see table 5.4). First, they were asked 'How often do you upgrade/change your TV?' and 89.4% of them reported that they did so not less than every three years, while 1.2% took this action every 1 to 2 years. For the second question, they were asked 'How important is your TV's technical specification?', with the results showing it was 'Important' or 'Somewhat important' for the majority of participants 78.2%, and a minority of 9.9% and 11.8% believed it to be 'Very important' and 'Not important', respectively. In the third question, the participants were asked 'How much time do you spend watching TV in a typical day?' and 33.5% responded '2 to 4 hours', while 7.5% replied 'More than 4 hours'. Finally, the participants were asked 'How important is your TV to you?' and 37.3% responded 'Somewhat important', whereas 16.8% reported that it was 'Not important'.

Usage behaviour questions		**Frequency**	**Percent**
How often do you upgrade or change your TV?	**More than 3 years**	144	89.4
	2 to 3 years	11	6.8
	1 to 2 years	2	1.2
	Less than a year	4	2.5
How important is your TV's technical specification?	**Very important**	16	9.9
	Important	63	39.1
	Somewhat important	63	39.1
	Not important	19	11.8
How much time do you spend watching TV in a typical day?	**More than 4 hours**	12	7.5
	2 to 4 hours	45	28
	1 to 2 hours	54	33.5
	Less than an hour	50	31.1
How important is your TV to you?	**Very important**	28	17.4
	Important	46	28.6
	Somewhat important	60	37.3
	Not important	27	16.8

Table 5.4. Participants' usage behaviour questions for TVs

5.5. The Stability of the Attribute-Weights by Various Participants for a Specific Products

The specific questions on usage behaviour of each product in section 5.4 were added to the utility model one by one for each round. The RUM model can be written as:

$$U_{nj} = V_{nj} + \varepsilon_{nj} = \beta X_{nj} + \gamma Y_{nj} + \varepsilon_{nj}$$

Equation 5.5

$$V_{nj} = \beta X_{nj} + \gamma Y_{nj}$$

Equation 5.6

V_{nj} are specified as being linear, such that $V_{nj} = \beta X_{nj} + \gamma Y_{nj}$, where X_{nj} is the vector for the product explanatory variables and γY_{nj} is the vector of the participants' specific usage behaviour questions. The explanatory variables in the equation are the specifications, i.e. features and levels as well as individual product usage behaviour, which can be fitted to the MNL choice probability model:

$$P_{in} = \frac{e^{V_{ni}}}{\sum_j e^{V_{nj}}}$$

Equation 5.7

When random utility is assumed to follow a logistic distribution, the model is a binary logit one (Greene, 2009), which can be written as:

$$P_{in} = \frac{1}{1+e^{-(\beta X_{ni} + \gamma Y_{ni})}}$$

Equation 5.8

Once the individual product usage behaviour had been added to the logit model, the utility models were estimated. From this, it emerged that none of these behaviours significantly affected the choice participants made regarding TV and thus H_7, H_8, H_9, H_{10} and H_{11} are rejected for this appliance. On the other hand, some of these behaviours significantly affected the choices the participants made in relation to the laptops and mobile phones. Hence, only those that did have an impact were further examined to elicit whether a change in preference is associated with various participants usage behaviour towards a particular product.

5.5.1. Laptops

The only usage characteristic that exhibited having an effect at 5% level of significance by adding it to the all logit models was ‘How often do you upgrade or change your PC/laptop?’, whilst the rest only produced very small effects, which leads to the rejection of H_8, H_9, H_{10} and H_{11} for laptops, H_7 is accepted for them.

5.5.1.1. How often do you upgrade or change your PC/laptop?

Only three participants reported that they change their laptop at least once a year; so this category was combined with that for 1 to 2 years, to create a new one: ‘Less than 2 years’. Afterwards, the laptop dataset was split into three sub-datasets for participants that upgraded or changed ‘more than 3 years’, ‘2 to 3 years’, and ‘2 years or less’, for which the utility model can be written as:

$$U_{nj} = V_{nj} + \varepsilon_{nj} = \beta X_{nj} + \varepsilon_{nj}$$

Equation 5.9

$$V_{nj} = \beta X_{nj}$$

Equation 5.10

V_{nj} are specified as being linear, such that $V_{nj} = \beta X_{nj}$, where X_{nj} is the vector for the product explanatory variable. Finally, logit models were estimated for each round for each sub-data sets, whereby the binary logit model can be written as:

$$P_{in} = \frac{1}{1+e^{-(\beta X ni)}}$$

Equation 5.11

The results are presented in the following subsections.

5.5.1.1.1. More than 3 years

For participants who upgrade or change their laptop with the least frequency, there are more variations in the brand and processors weights over time in comparison to other attributes. In particular, brands have slightly higher weights in rounds 2 and 3 in comparison to other attributes, which have more steady weights over time. These results seem to suggest that participants who change their laptop less often are less sensitive to technical attributes, but more sensitive to brand perception and identity when the duration of the experiment is six months. In addition, there are also small changes in the price and hard drive weights over time (See Table 5.5 and Figure 5.1).

Laptop B	R1	R2	R3
Brand_Apple	1.73	2.47	2.04
Brand_Samsung	0.39	0.73	0.58
Brand_HP	0.37	0.99	1.01
Brand_Sony	0.40	1.05	0.85
Brand_Dell	0.47	0.99	0.89
Brand_Lenovo	-0.06	0.51	0.44
Brand_Toshiba	0.27	1.12	1.13
Price_Low	1.20	1.30	0.99
Price_Med	0.76	0.69	0.51
Price_Hi	0.51	0.57	0.44
Dis_S	-0.56	-0.47	-0.52
Dis_M	-0.12	0.07	0.22
Proc_Fas	0.72	0.38	0.37
Proc_Hi	0.77	0.19	0.34
Mem_M	0.50	0.67	0.59
Mem_H	0.82	0.72	0.73
HDD_Hi	0.40	0.53	0.16
HDD_VerHi	0.22	0.40	0.05
Weight_UltraL	0.63	0.56	0.46
Constant	-3.74	-4.36	-3.85

Table 5.5. More than 3 years before upgrading/changing laptop

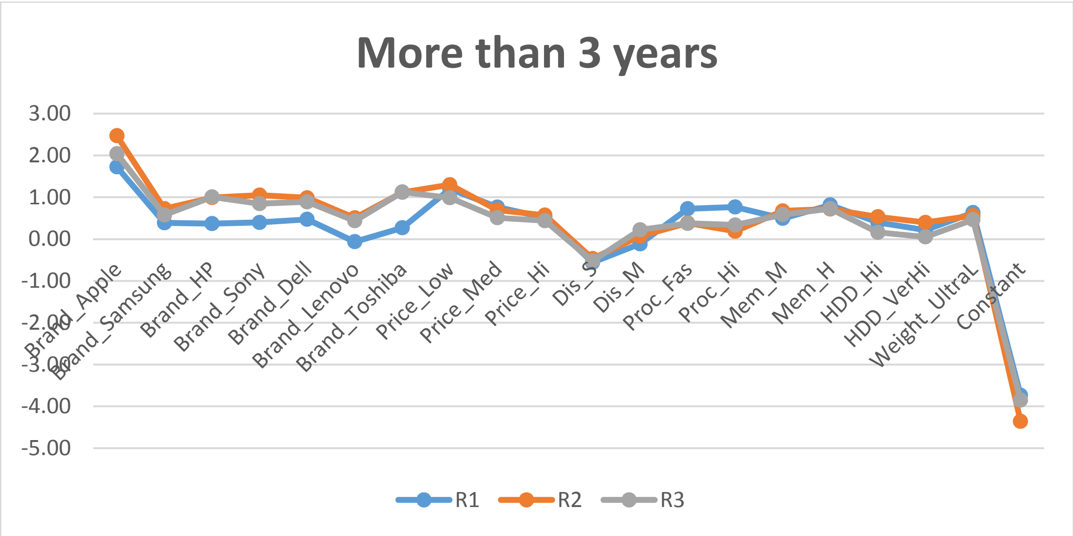


Figure 5.1. More than 3 years before upgrading/changing laptop

5.5.1.1.2. 2 to 3 years

For the participants who change or upgrade their laptops every 2 to 3 years, there are the same levels of changes within all attributes over time (See Table 5.6 and Figure 5.2). Brands weights rise over time, while the other attributes have some fluctuations.

Laptop B	R1	R2	R3
Brand_Apple	2.00	2.09	2.42
Brand_Samsung	0.19	0.71	1.08
Brand_HP	0.57	0.62	1.06
Brand_Sony	0.66	0.68	1.03
Brand_Dell	0.12	0.62	1.10
Brand_Lenovo	-0.06	0.55	1.08
Brand_Toshiba	0.40	0.73	1.11
Price_Low	0.80	0.68	0.87
Price_Med	0.57	0.34	0.48
Price_Hi	0.65	0.37	0.14
Dis_S	-0.14	-0.63	-0.53
Dis_M	0.29	0.23	-0.01
Proc_Fas	0.49	0.15	0.65
Proc_Hi	0.74	0.63	0.60
Mem_M	0.27	0.66	0.72
Mem_H	0.54	1.14	0.81
HDD_Hi	0.74	0.31	0.21
HDD_VerHi	0.33	-0.24	0.40
Weight_UltraL	0.63	0.42	0.50
Constant	-3.82	-3.47	-4.16

Table 5.6. Upgrading/changing laptop every 2 to 3 years

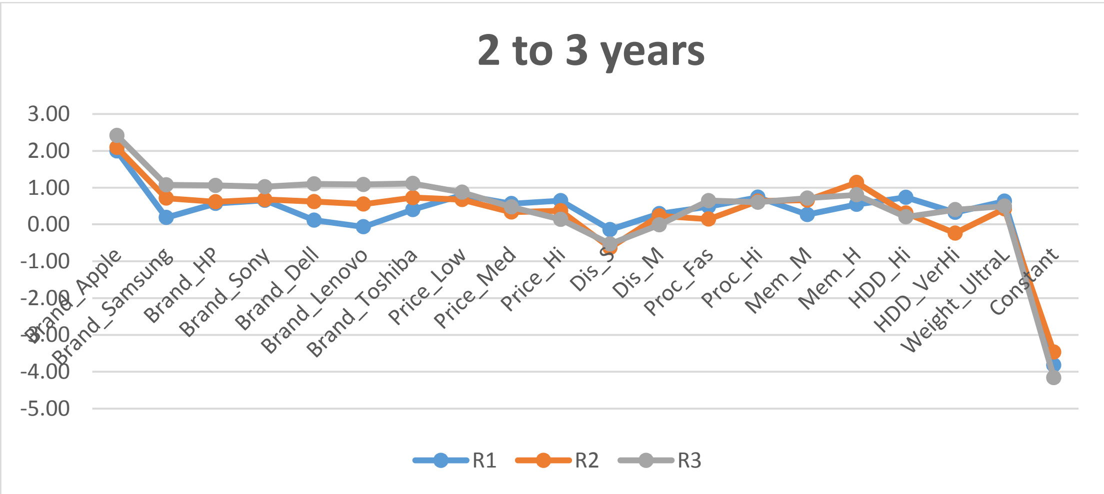


Figure 5.2. Upgrading/changing laptop every 2 to 3 years

5.5.1.1.3. Less than 2 years

Regarding the participants who change their laptops more often than others, most brand weights increase over time, while other attributes, such as memory and hard drive, exhibit slight fluctuations (See Table 5.7 and Figure 5.3). Thus, the weights of technical attributes of those participants who change their laptops most frequently would appear to vary over time owing to their sensitivity regarding these, which is not found to be the case for the others.

Laptop B	R1	R2	R3
Brand_Apple	1.68	1.96	1.48
Brand_Samsung	0.43	1.08	0.78
Brand_HP	0.52	0.98	1.27
Brand_Sony	0.17	0.97	0.59
Brand_Dell	0.64	1.19	1.45
Brand_Lenovo	0.26	0.57	0.85
Brand_Toshiba	1.00	1.76	1.25
Price_Low	1.33	0.86	0.99
Price_Med	1.02	0.79	1.16
Price_Hi	0.81	0.56	0.59
Dis_S	0.03	-0.35	-0.10
Dis_M	0.41	0.37	0.26
Proc_Fas	0.39	0.82	0.66
Proc_Hi	0.96	1.01	1.14
Mem_M	1.08	0.24	1.22
Mem_H	0.81	0.69	1.56
HDD_Hi	0.71	0.30	0.83
HDD_VerHi	-0.08	0.12	0.49
Weight_UltraL	0.71	0.29	0.13
Constant	-4.70	-4.35	-5.07

Table 5.7. Upgrading/changing laptop less than 2 years

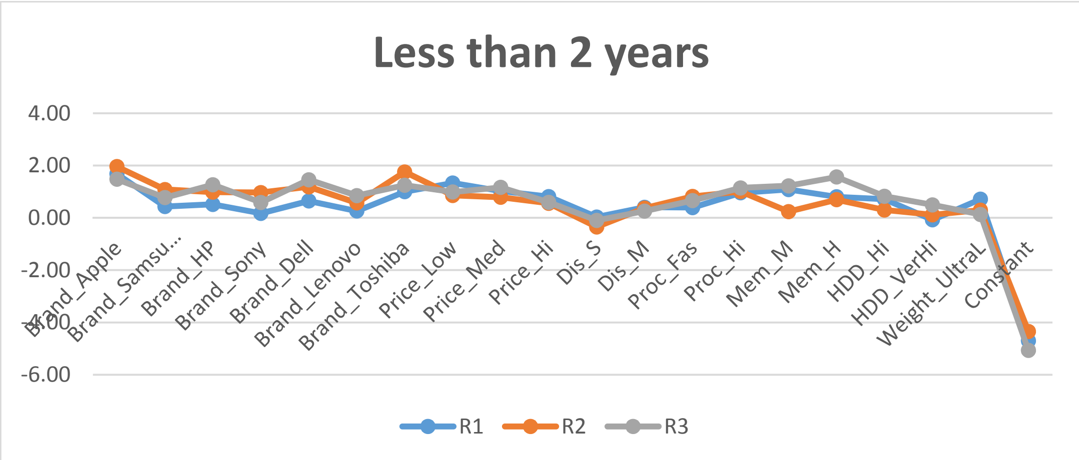


Figure 5.3. Upgrading/changing laptop less than 2 years

5.5.1.1.4. Mean absolute deviations (MADs) across all participants with different upgrade or change behaviour

In the previous section, the attribute-weights of laptops were calculated in each round for participants with differing upgrade or change behaviour across rounds. In this section, the mean absolute deviations (MADs) of the weights are calculated for each attribute in order to improve the comparison of weight fluctuations. First, each attribute's mean weight is calculated and then the absolute deviation of each attribute-weight in each round are computed. Finally, the mean of these absolute deviations of all three rounds was calculated to obtain the mean absolute deviations (MADs). The MAD formula for a given feature is as follows:

$MAD_{feature} = (|R1_{feature} - Mean_{feature}R1, R2, R3| + |R2_{feature} - Mean_{feature}R1, R2, R3| + |R3_{feature} - Mean_{feature}\ R1, R2, R3|)/3$

Equation 5.12. Mean Absolute Deviation (MAD) formula

For example, the MAD formula for Brand Apple can be written as:

$MAD_{brand\_apple(More\ than\ 3\ years)} = (|R1_{brand\_apple(More\ than\ 3\ years)} - Mean_{brand\_apple}R1, R2, R3_{(More\ than\ 3\ years)}| + |R2_{brand\_apple(More\ than\ 3\ years)} - Mean_{brand\_apple}R1, R2, R3_{(More\ than\ 3\ years)}| + |R3_{brand\_apple(More\ than\ 3\ years)} - Mean_{brand\_apple}\ R1, R2, R3_{(More\ than\ 3\ years)}|)/3$

The MAD shows how much an attribute-weight deviates from its mean over three rounds and the brand MADs are generally higher than other attributes across all three groups of participants. The MADs for hard drive are also high for all groups, especially for 2 to 3 years, and less than 2 years group with more 0.2 for almost all of them. Memory has high MADs for the 2 to 3 years category with more than 0.18, and less than 2 years category with more than 0.36. Additionally, participants who change or upgrade their laptops most often (less than 2 years) have high variation in laptop attribute-weight (Table 5.8).

Laptop B	Mean Absolute Deviations (MADs)		
	More than 3 years	2 to 3 years	Less than 2 years
Brand_Apple	0.261	0.166	0.169
Brand_Samsung	0.117	0.313	0.221
Brand_HP	0.280	0.207	0.270
Brand_Sony	0.245	0.160	0.269
Brand_Dell	0.208	0.330	0.300
Brand_Lenovo	0.237	0.392	0.200
Brand_Toshiba	0.379	0.243	0.280
Price_Low	0.115	0.072	0.183
Price_Med	0.098	0.083	0.136
Price_Hi	0.046	0.174	0.106
Dis_S	0.032	0.196	0.140
Dis_M	0.116	0.121	0.059
Proc_Fas	0.153	0.187	0.155
Proc_Hi	0.224	0.054	0.072
Mem_M	0.060	0.186	0.406
Mem_H	0.042	0.207	0.362
HDD_Hi	0.136	0.214	0.208
HDD_VerHi	0.117	0.266	0.211
Weight_UltraL	0.059	0.076	0.223
Constant	0.251	0.233	0.242

Table 5.8. MADs across all participants with different upgrade or change behaviour

Finally, the average MADs are calculated for all attributes of a given category of participants to investigate whether they are different across participants with various upgrade or change behaviour or not. The average MADs show that participants who change or upgrade their laptop most often (less than 2 years) have highest value, 0.211, while people who do so least often have the least average MADs of 0.159. The results of the MADs show that participants who change or upgrade their laptops more often have more variations in their attribute-weights in comparison to those who do so less often (Table 5.9).

Average MADs	Change or upgrade laptops		
	More than 3 years	2 to 3 years	Less than 2 years
	0.159	0.194	0.211

Table 5.9. Average MADs across all participants with different upgrade or change behaviour

5.5.1.1.5. Change of attribute-weights over time for participants with differing upgrade or change behaviour

The average MADs shows a very clear trend in that participants with higher frequency of upgrade or change have more change in attribute-weights over time. However, the changes of attribute-weights between the different rounds using the mean differences of attribute-weights among the participants who have differing behaviour in relation to changing and upgrading their laptops, does not clearly show a very noticeable pattern, except between R1-R3 (Table 5.10 and Figure 5.4). However, the mean absolute differences of attribute-weights, and mean squared differences of attribute-weights yield results that are consistent with the average MADs (See Tables 5.11, 5.12 and Figures 5.5, 5.6).

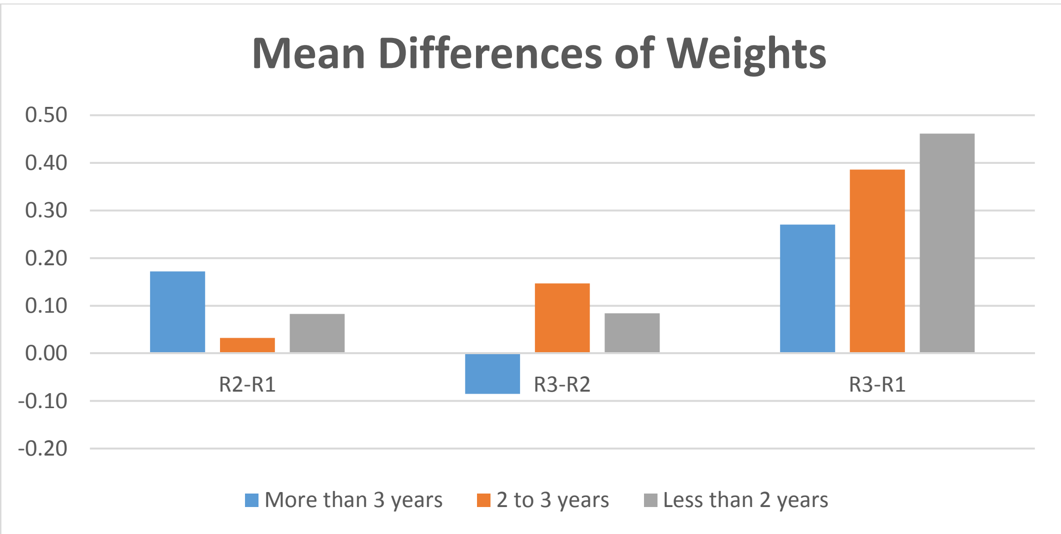


Figure 5.4. Mean differences of attribute-weights for participants with differing upgrade or change behaviour

Mean Difference B	R2-R1	R3-R2	R3-R1
More than 3 years	0.17	-0.09	0.27
2 to 3 years	0.03	0.15	0.39
Less than 2 years	0.08	0.08	0.46

Table 5.10. Mean differences of attribute-weights for participants with differing upgrade or change behaviour

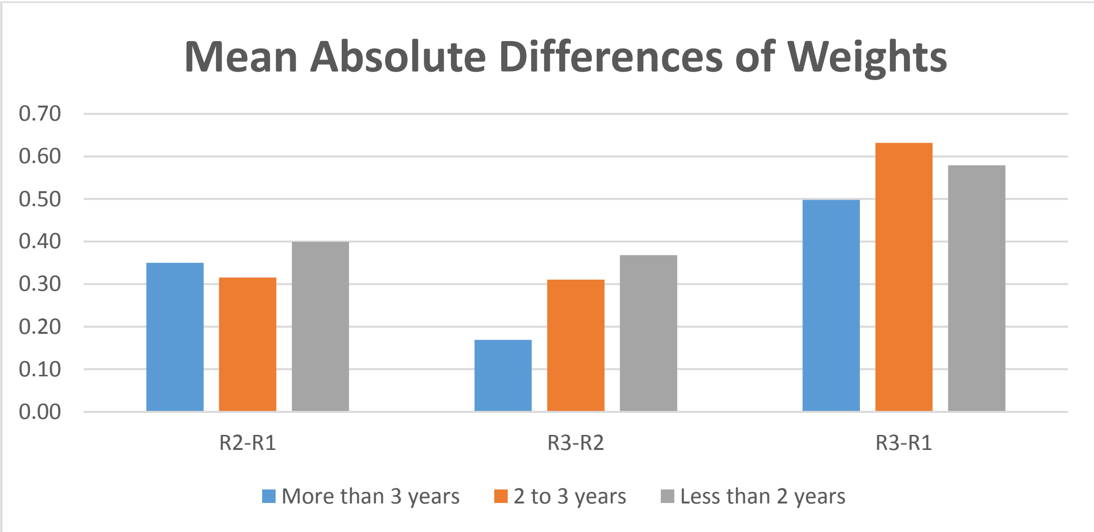


Figure 5.5. Mean absolute differences of attribute-weights for participants with differing upgrade or change behaviour

Mean Abs Difference B	R2-R1	R3-R2	R3-R1
More than 3 years	0.35	0.17	0.50
2 to 3 years	0.32	0.31	0.63
Less than 2 years	0.40	0.37	0.58

Table 5.11. Mean absolute differences of attribute-weights for participants with differing upgrade or change behaviour

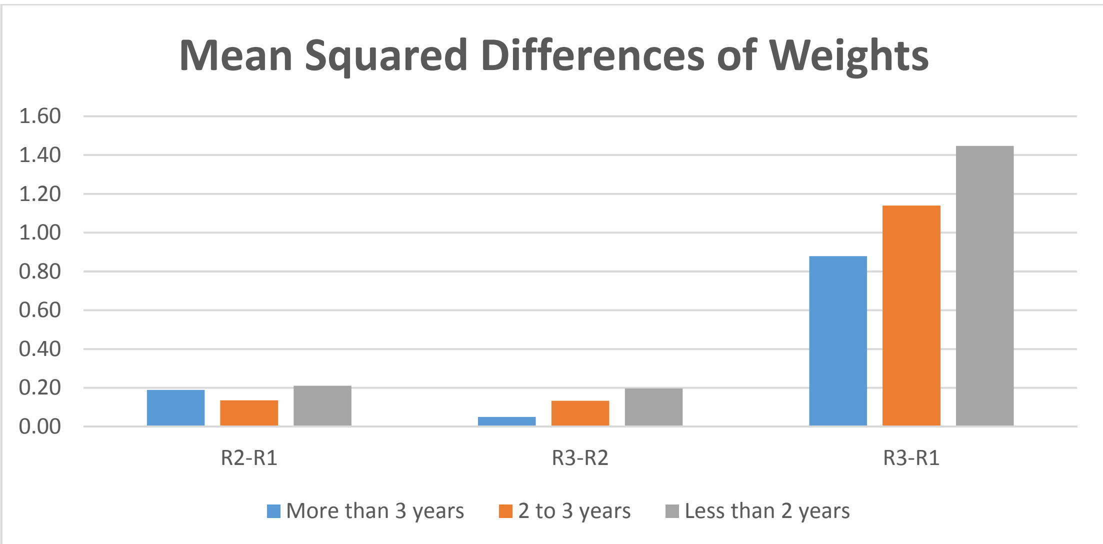


Figure 5.6. Mean squared differences of attribute-weights for participants with differing upgrade or change behaviour

Mean Square Difference B	R2-R1	R3-R2	R3-R1
More than 3 years	0.19	0.05	0.88
2 to 3 years	0.14	0.13	1.14
Less than 2 years	0.21	0.20	1.45

Table 5.12. Mean squared differences of attribute-weights for participants with differing upgrade or change behaviour

5.5.2. Mobiles

Three out of the five individual characteristics questions from section 5.4 have a noticeable effect (at the 5% significance level) when they are added to the mobile phones logit model as independent variables in the various rounds, these being: ‘How important is your mobile phone technical specification?’, ‘How much time do you spend in a day using your phone?’ and ‘How important is your mobile phone to you?’. Therefore H_8, H_9 and H_{10} are accepted, whilst the two other questions exhibits no or very small effects, which lead to the rejection of H_7 and H_{11} for mobile phones.

5.5.2.1. How important is your mobile phone technical specification?

As there were only eight participants that believed their mobile specification was not important, this category was combined with the ‘Somewhat important’ category to create a new one called ‘Not or somewhat important’. Subsequently, the mobile phones dataset was split into three sub-datasets according to the participants different views on mobile phones technical specification, namely: ‘Very important’, ‘Important’, and ‘Not or somewhat Important’. The utility model (Equations 5.9, 5.10) and binary logit model (Equation 5.11) is the same as that used for laptops in subsection 5.5.1.1. This is estimated for each round of each sub-data set and the results are presented in the next subsections.

5.5.2.1.1. Very important

Participants, for whom their mobile phone technical specification is very important, are very inconsistent in their preferred features over time (See Table 5.13 and Figure 5.7). Regarding which, brand gains more importance over time, whereas price, camera resolution, battery length and phone weight diminish in terms of salience across the three rounds.

Mobile B	R1	R2	R3
Brand_Apple	0.80	1.62	1.49
Brand_Samsung	0.03	0.93	0.83
Brand_Nokia	-0.34	0.91	0.67
Brand_HTC	-0.40	0.53	0.94
Brand_Sony	-0.52	0.47	0.91
Brand_BB	-0.94	0.46	0.54
Price_Low	1.55	0.28	0.32
Price_Med	1.15	0.46	0.24
Price_Hi	0.75	0.07	0.06
Cam_Norm	1.51	0.99	1.25
Cam_Hi	2.50	1.64	1.85
Mem_M	0.11	0.39	0.61
Mem_H	0.84	0.50	0.88
Dis_S	-0.66	-0.11	-0.24
Dis_M	0.07	0.24	0.20
Batt_M	1.08	1.09	0.02
Batt_H	1.67	1.21	0.25
Batt_VerHi	1.48	1.53	0.67
Weight_VerL	1.32	0.01	0.06
Weight_Li	1.46	-0.39	-0.17
Constant	-6.00	-4.73	-4.30

Table 5.13. Features attribute-weights for participants that technical specification is very important

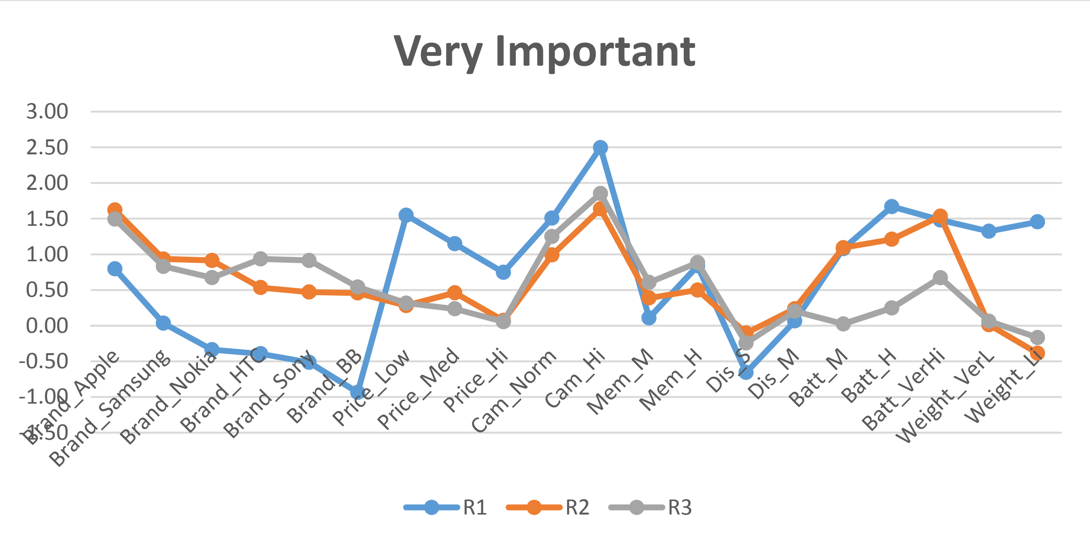


Figure 5.7. Features attribute-weights for participants that technical specification is very important

5.5.2.1.2. Important

Participants who indicate that their mobile phone technical specification is important are more consistent in their preferences for all attributes over time than those in the previous group, i.e. for whom this specification is very important (See Table 5.14 and Figure 5.8). Moreover, the results show that these participants' are more stable in relation to technical attributes over time than those for brand perception.

Mobile B	R1	R2	R3
Brand_Apple	0.86	1.46	2.05
Brand_Samsung	0.76	0.74	1.22
Brand_Nokia	0.12	0.10	0.65
Brand_HTC	0.44	0.53	1.14
Brand_Sony	-0.14	0.33	0.83
Brand_BB	-0.15	0.34	0.72
Price_Low	0.91	1.07	1.20
Price_Med	0.69	0.91	1.16
Price_Hi	0.34	0.55	0.45
Cam_Norm	1.79	1.60	1.71
Cam_Hi	2.35	2.34	2.51
Mem_M	0.45	0.77	0.57
Mem_H	0.32	0.78	0.55
Dis_S	-0.45	-0.47	-0.61
Dis_M	0.22	-0.25	-0.09
Batt_M	0.49	0.78	0.97
Batt_H	0.99	0.94	1.27
Batt_VerHi	1.19	1.37	1.38
Weight_VerL	0.22	0.41	0.64
Weight_Li	0.02	0.28	0.16
Constant	-4.73	-5.44	-6.32

Table 5.14. Features attribute-weights for participants that technical specification is important

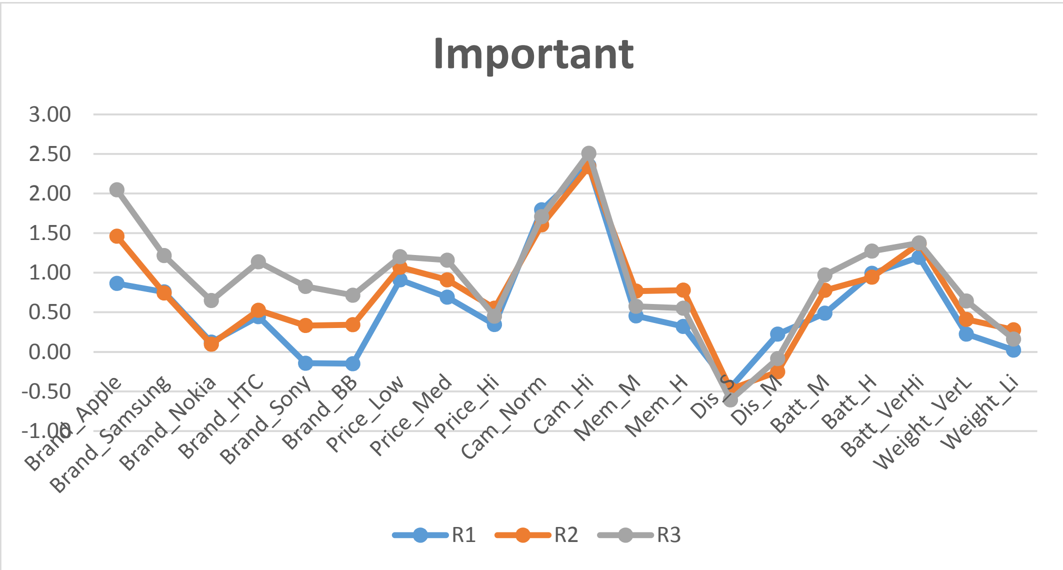


Figure 5.8. Features attribute-weights for participants that technical specification is important

5.5.2.1.3. Not or somewhat important

Participants who reported that their mobile phone technical specification is ‘Not or somewhat important’ are generally more consistent in the preferences regarding all features over time than all other participants, with the exception of brands weights. Additionally, for these participants price has the highest weight in their preferences, whereas for the other two groups the camera resolution take this position (See Table 5.15 and Figure 5.9).

Mobile B	R1	R2	R3
Brand_Apple	0.85	1.41	1.72
Brand_Samsung	0.38	1.11	1.21
Brand_Nokia	-0.14	1.09	0.58
Brand_HTC	-0.31	0.44	0.92
Brand_Sony	-0.58	0.97	1.10
Brand_BB	-0.94	0.91	1.31
Price_Low	0.77	2.39	2.20
Price_Med	0.69	1.31	1.14
Price_Hi	0.37	0.66	0.43
Cam_Norm	1.23	1.29	1.41
Cam_Hi	1.79	1.83	1.74
Mem_M	0.53	0.69	0.64
Mem_H	0.22	0.72	0.41
Dis_S	-0.23	0.27	-0.40
Dis_M	0.49	0.25	0.01
Batt_M	0.29	0.56	0.73
Batt_H	0.76	1.03	0.76
Batt_VerHi	1.01	1.27	1.23
Weight_VerL	0.21	0.17	0.34
Weight_Li	0.09	0.01	-0.08
Constant	-4.18	-6.22	-6.00

Table 5.15. Features weights for participants that technical specification is not important or somewhat

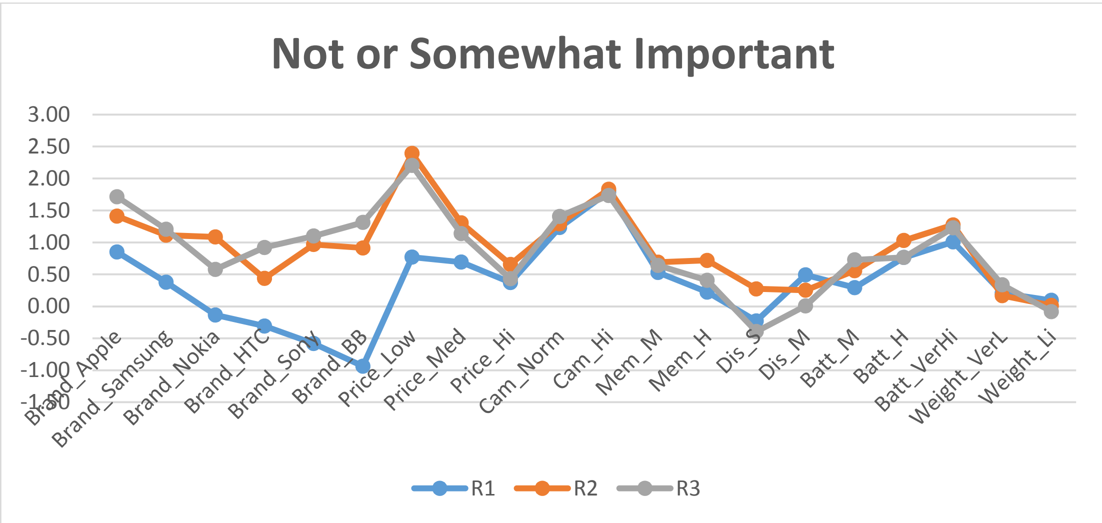


Figure 5.9. Features weights for participants that technical specification is not important or somewhat

5.5.2.1.4. Mean absolute deviations (MADs) across all participants with different technical importance attributed to their mobile phones

The features' weights were calculated for the participants for each of the features of mobile phones across the rounds with different technical specifications importance in the previous section. In this section, the mean absolute deviations (MADs) are calculated for each feature in order to improve the comparison of weight fluctuations (Equation 5.12). The MADs for brands and prices are generally higher than other features across all three groups of participants. The MADs for camera resolutions, battery life and weights are only high for those who rate the technical specifications of their mobile phones as very important (Table 5.16).

Mobile	Mean Absolute Deviations (MADs)		
	Very Important	Important	Not or Somewhat Important
Brand_Apple	0.339	0.396	0.316
Brand_Samsung	0.377	0.207	0.347
Brand_Nokia	0.502	0.239	0.430
Brand_HTC	0.502	0.290	0.438
Brand_Sony	0.537	0.325	0.718
Brand_BB	0.638	0.302	0.911
Price_Low	0.555	0.100	0.679
Price_Med	0.356	0.159	0.235
Price_Hi	0.303	0.069	0.112
Cam_Norm	0.172	0.065	0.064
Cam_Hi	0.334	0.072	0.034
Mem_M	0.172	0.112	0.060
Mem_H	0.161	0.153	0.179
Dis_S	0.214	0.065	0.260
Dis_M	0.068	0.174	0.162
Batt_M	0.472	0.172	0.155
Batt_H	0.530	0.136	0.118
Batt_VerHi	0.372	0.079	0.107
Weight_VerL	0.571	0.144	0.066
Weight_Li	0.770	0.088	0.060
Constant	0.660	0.549	0.857

Table 5.16. MADs across all participants with different technical importance attributed

The average MADs are calculated for all features of a given category of participants to investigate whether they differ according to the importance of technological specifications to participants. The average MADs do not suggest that there is any association between the overall variability of weights and the participants' rating of the importance of technical specifications (Table 5.17).

Average MADs	Technical Specifications Importance		
	Very Important	Important	Not or Somewhat Important
	0.410	0.186	0.301

Table 5.17. Average MADs across all participants with different technical importance attributed

5.5.2.1.5. Change of weights over time for participants with different technical importance attributed to their mobile phones

As with average MADs, there is no general trend in the variations of weights between the different rounds using mean differences of weights, mean absolute differences of weights, and mean squared differences of weights among the different participants when considered from the perspective of different importance being given to technical specifications (See Tables 5.18, 5.19, 5.20 and Figures 5.10, 5.11, 5.12).

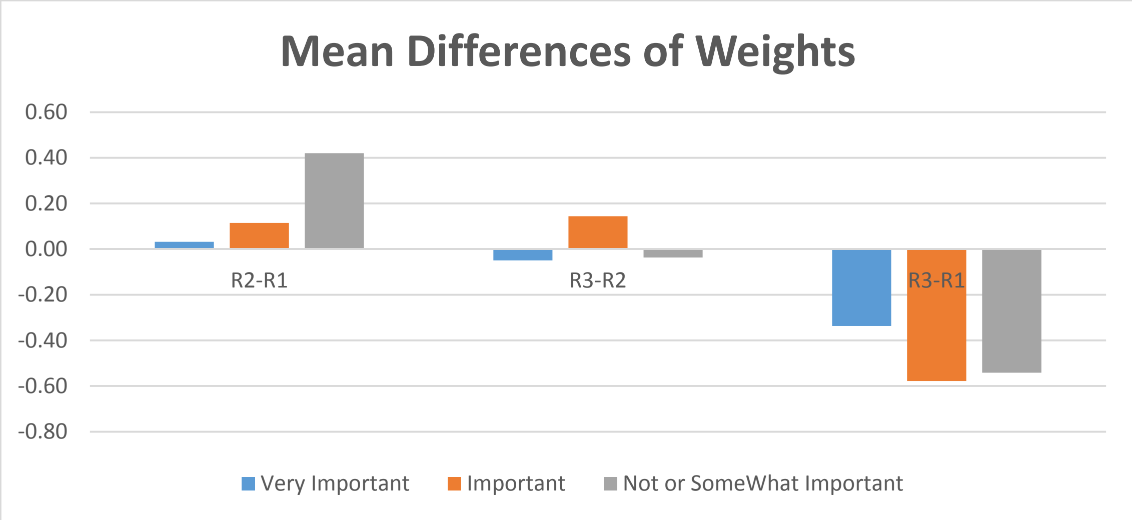


Figure 5.10. Mean differences of weights for participants with different technical importance

Mean Difference B	R2-R1	R3-R2	R3-R1
Very Important	0.03	-0.05	-0.34
Important	0.11	0.14	-0.58
Not or Somewhat Important	0.42	-0.04	-0.54

Table 5.18. Mean differences of weights for participants with different technical importance

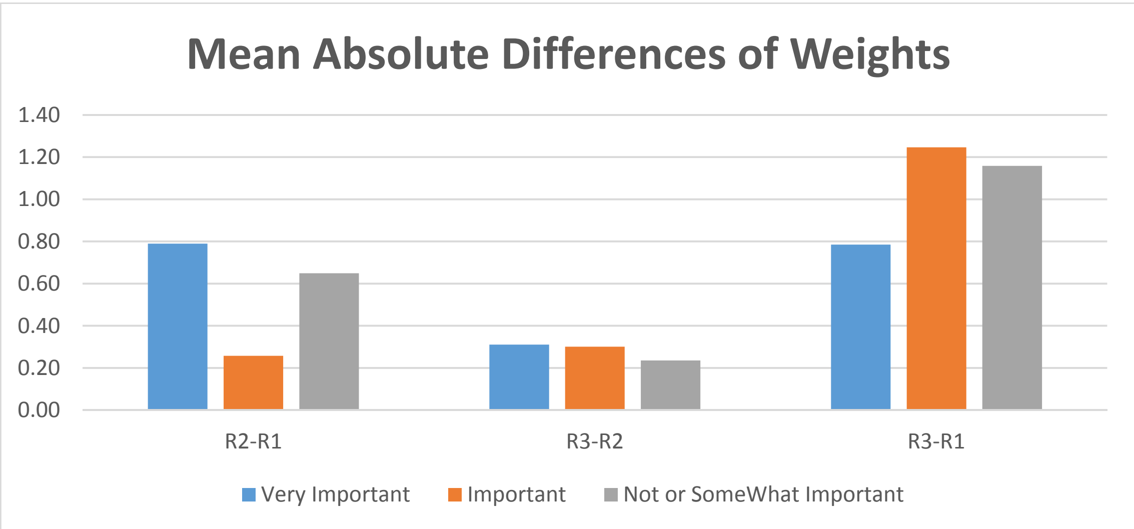


Figure 5.11. Mean absolute differences of weights for participants with different technical importance

Mean Abs Difference B	R2-R1	R3-R2	R3-R1
Very Important	0.79	0.31	0.79
Important	0.26	0.30	1.25
Not or Somewhat Important	0.65	0.24	1.16

Table 5.19. Mean absolute differences of weights for participants with different technical importance

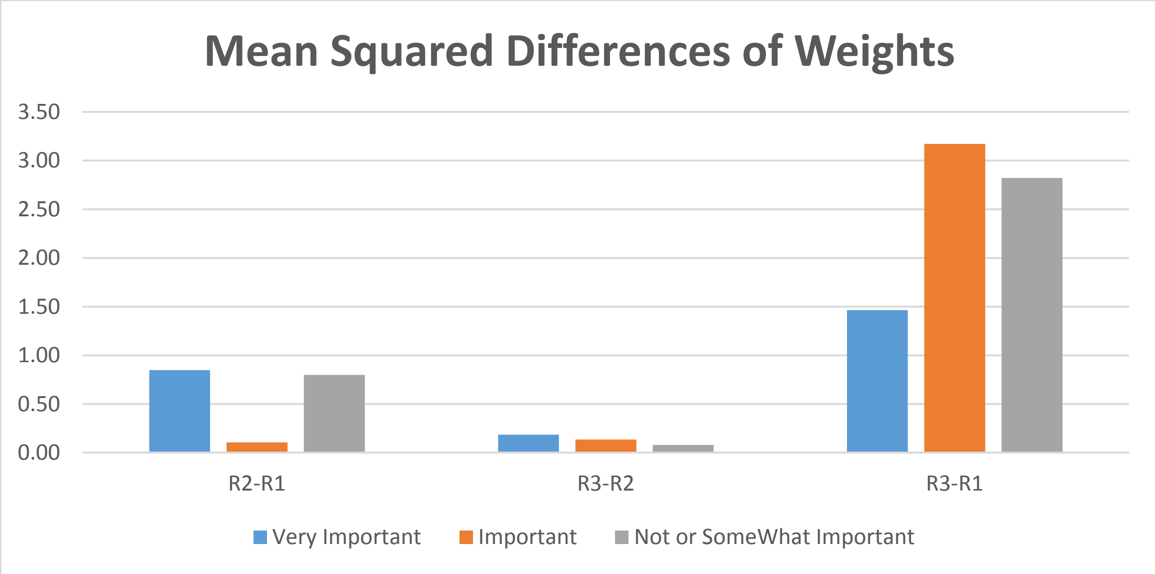


Figure 5.12. Mean squared differences of weights for participants with different technical importance

Mean Square Difference B	R2-R1	R3-R2	R3-R1
Very Important	0.85	0.18	1.46
Important	0.11	0.14	3.17
Not or Somewhat Important	0.80	0.08	2.82

Table 5.20. Mean squared differences of weights for participants with different technical importance

5.5.2.2. How much time do you spend in a day using your phone?

The mobile phones dataset was split into four sub-datasets for the participants according to their daily usage: ‘more than 4 hours’, ‘2 to 4 hours’, ‘1 to 2 hours’, and ‘Less than an hour’. Once again the utility model (Equations 5.9, 5.10) and binary logit model (Equation 5.11) is same as that used for laptops in subsection 5.5.1.1, which is estimated for each round of each sub-data set, and the results are presented in the next subsections.

5.5.2.2.1. More than 4 hours

Participants who use their mobile phones more than 4 hours a day are inconsistent in terms of all features weights over time. Interestingly, across the rounds the camera resolution becomes less important, whereas brands and display size become more (See Table 5.21 and Figure 5.13).

Mobile B	R1	R2	R3
Brand_Apple	0.78	2.33	1.58
Brand_Samsung	0.72	1.69	1.02
Brand_Nokia	-0.98	1.08	0.28
Brand_HTC	0.19	0.89	0.74
Brand_Sony	-0.59	0.71	0.44
Brand_BB	-0.64	1.37	0.59
Price_Low	0.61	0.40	0.62
Price_Med	0.52	0.58	0.40
Price_Hi	0.23	0.03	-0.02
Cam_Norm	1.87	0.77	1.16
Cam_Hi	2.66	1.86	1.93
Mem_M	0.52	0.75	0.60
Mem_H	0.54	0.73	0.77
Dis_S	-0.88	-0.17	-0.31
Dis_M	0.11	0.15	0.18
Batt_M	0.62	1.10	0.34
Batt_H	0.81	1.17	0.49
Batt_VerHi	1.18	1.64	0.89
Weight_VerL	0.68	0.09	0.06
Weight_Li	0.52	-0.19	-0.20
Constant	-4.57	-5.46	-4.33

Table 5.21. Features weights for participants with more than 4 hours daily usage

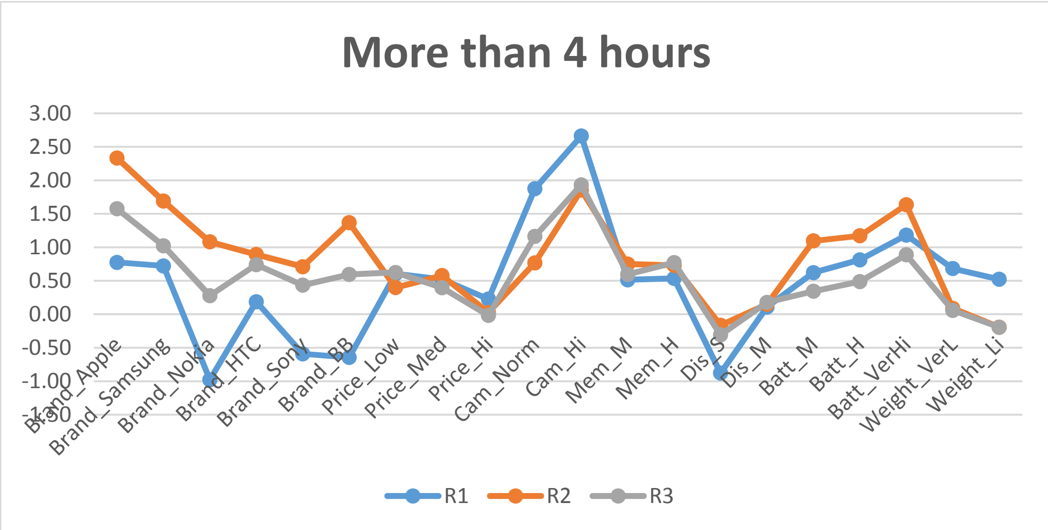


Figure 5.13. Features weights for participants with more than 4 hours daily usage

5.5.2.2.2. 2 to 4 hours

For this group of participants, there is greater inconsistency in the relative importance of brands and price in comparison to the other features over time, although there are some slight variations in the lattermost (See Table 5.22 and Figure 5.14). Moreover, the brands and camera resolution weights rise across the rounds, whereas the price weights decrease.

Mobile B	R1	R2	R3
Brand_Apple	0.76	1.15	1.90
Brand_Samsung	0.72	0.46	1.00
Brand_Nokia	-0.08	0.33	1.01
Brand_HTC	-0.13	0.29	1.21
Brand_Sony	-0.54	0.41	1.38
Brand_BB	-0.05	0.25	1.17
Price_Low	1.59	0.66	0.73
Price_Med	1.26	0.80	0.85
Price_Hi	0.57	0.36	0.41
Cam_Norm	1.04	1.51	1.52
Cam_Hi	1.70	1.93	2.06
Mem_M	0.49	0.45	0.51
Mem_H	0.50	0.39	0.54
Dis_S	-0.23	-0.39	-0.69
Dis_M	0.19	-0.34	-0.09
Batt_M	0.35	0.70	0.86
Batt_H	1.13	0.83	0.98
Batt_VerHi	1.30	1.18	1.02
Weight_VerL	0.24	0.04	0.40
Weight_Li	0.01	-0.02	0.02
Constant	-4.79	-4.37	-5.57

Table 5.22. Features weights for participants with 2 to 4 hours daily usage

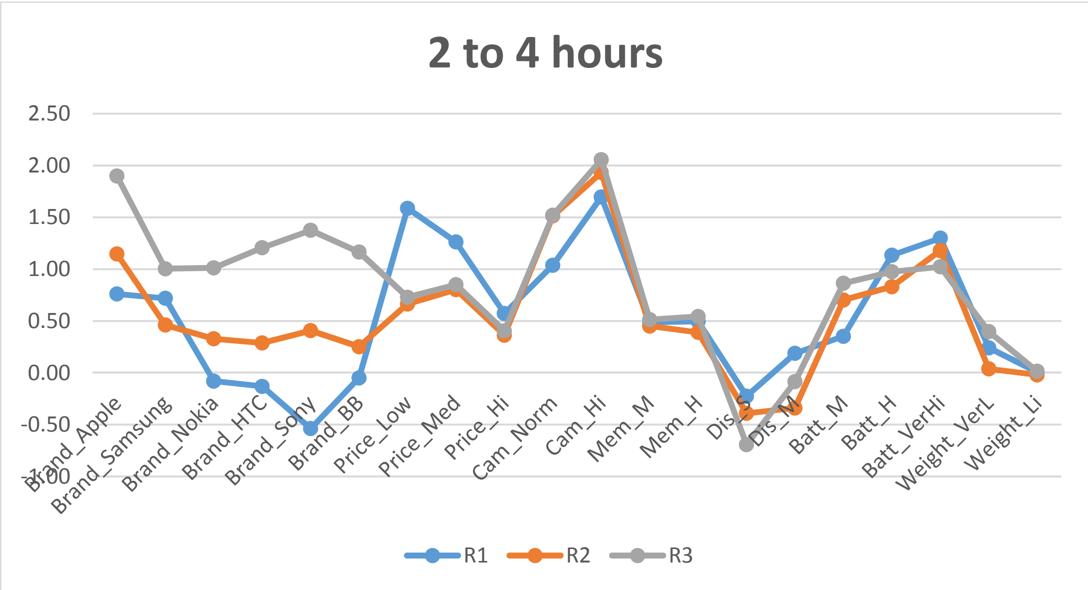


Figure 5.14. Features weights for participants with 2 to 4 hours daily usage

5.5.2.2.3. 1 to 2 hours

For participants who use their phone for 1 to 2 hours a day there are quite similar levels of inconsistency over time for all features, but camera resolution and price are generally the most important (See Table 5.23 and Figure 5.15).

Mobile B	R1	R2	R3
Brand_Apple	1.04	1.13	2.43
Brand_Samsung	0.11	0.45	1.14
Brand_Nokia	0.86	0.59	0.92
Brand_HTC	0.28	0.51	0.17
Brand_Sony	0.11	0.46	-0.11
Brand_BB	-0.77	0.00	0.56
Price_Low	1.44	2.43	2.92
Price_Med	0.92	1.68	2.42
Price_Hi	0.69	1.32	1.29
Cam_Norm	2.19	2.13	2.29
Cam_Hi	2.86	2.81	3.51
Mem_M	0.11	0.59	0.55
Mem_H	0.24	0.90	0.36
Dis_S	-0.32	-0.01	0.10
Dis_M	0.09	0.16	0.74
Batt_M	0.37	0.52	0.45
Batt_H	1.32	1.31	1.69
Batt_VerHi	0.83	1.18	1.89
Weight_VerL	0.67	0.62	1.07
Weight_Li	0.77	0.51	0.45
Constant	-5.56	-7.05	-9.08

Table 5.23. Features weights for participants with 1 to 2 hours daily usage

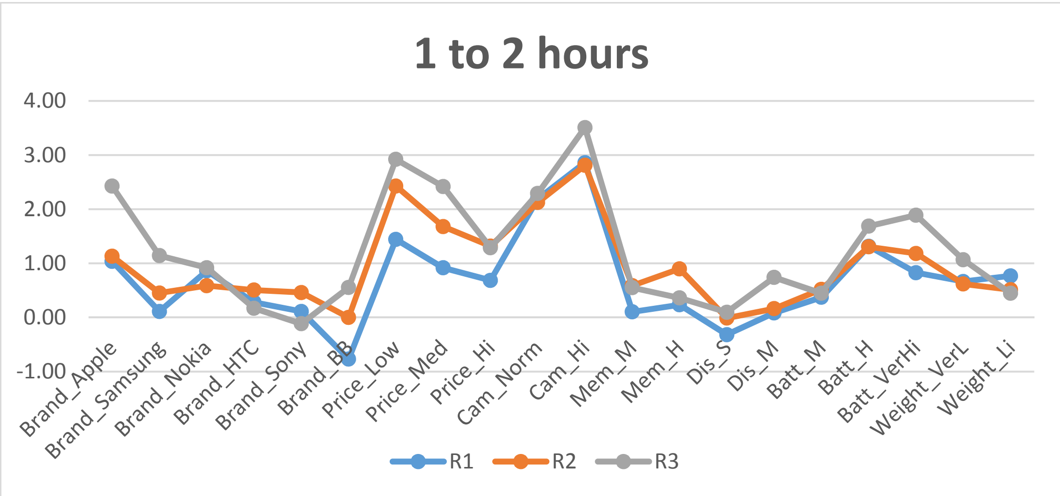


Figure 5.15. Features weights for participants with 1 to 2 hours daily usage

5.5.2.2.4. Less than an hour

Participants who use their phone the least during one day have less variation in their preferences in Round 2 and Round 3 in comparison to Round 1, which could be due to less involvement with their device (See Table 5.24 and Figure 5.16). Camera and phone memory become relatively less important over time, while brands like Blackberry and Nokia become more salient for this group of people.

Mobile B	R1	R2	R3
Brand_Apple	1.09	1.59	1.48
Brand_Samsung	-0.03	0.60	1.01
Brand_Nokia	-8.16	1.01	0.57
Brand_HTC	0.00	-0.20	1.75
Brand_Sony	-0.48	0.51	1.52
Brand_BB	-10.46	0.66	0.47
Price_Low	0.06	2.78	2.30
Price_Med	0.62	1.35	1.06
Price_Hi	0.78	0.48	0.27
Cam_Norm	5.74	0.34	1.59
Cam_Hi	6.44	1.60	1.83
Mem_M	5.02	0.97	0.30
Mem_H	4.61	1.24	0.63
Dis_S	0.31	0.11	-0.72
Dis_M	1.44	0.36	-0.60
Batt_M	-2.50	1.77	0.65
Batt_H	-2.74	1.59	0.80
Batt_VerHi	2.41	2.26	0.86
Weight_VerL	4.61	0.77	0.71
Weight_Li	-0.45	0.20	0.31
Constant	-10.50	-7.37	-6.01

Table 5.24. Features weights for participants with less than an hour daily usage

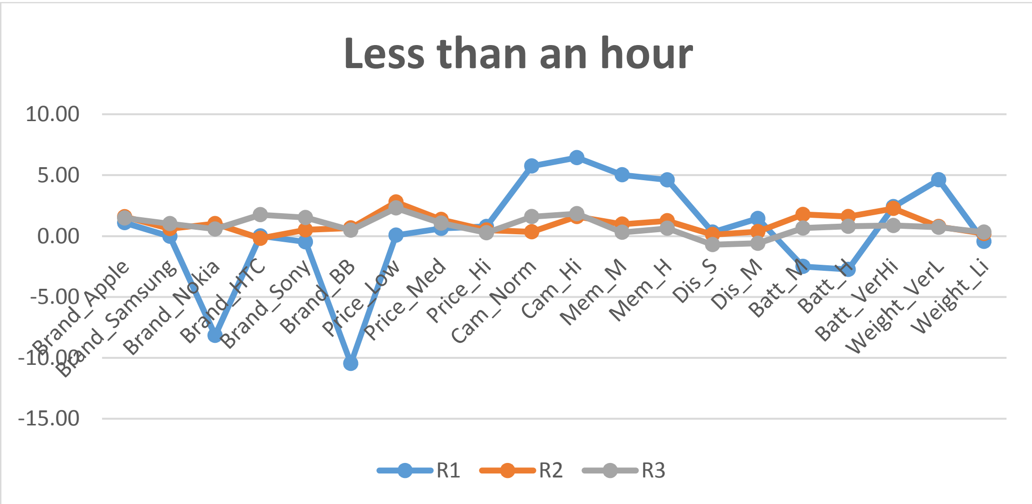


Figure 5.16. Features weights for participants with less than an hour daily usage

5.5.2.2.5. Mean Absolute Deviations (MADs) across all participants with different daily usages behaviour for mobile phones

In this sections, the mean absolute deviations (MADs) are calculated for each feature of mobile phones for participants across the rounds with different daily usage in order to improve the comparison of weight variations (Equation 5.12). Brands, camera resolutions, and mobile phones weight have the highest variations or MADs across all participants' categories. For the participants in the two groups with the least daily use i.e. 1 to 2 hours, and less than an hour, price and battery life have the highest variations or MADs (Table 5.25).

Mobile	Mean Absolute Deviations (MADs)			
	More than 4 hours	2 to 4 hours	1 to 2 hours	Less than an hour
Brand_Apple	0.524	0.420	0.597	0.198
Brand_Samsung	0.363	0.184	0.383	0.371
Brand_Nokia	0.736	0.395	0.134	3.980
Brand_HTC	0.280	0.502	0.124	0.820
Brand_Sony	0.517	0.640	0.205	0.669
Brand_BB	0.722	0.473	0.465	4.902
Price_Low	0.096	0.396	0.548	1.102
Price_Med	0.068	0.194	0.503	0.259
Price_Hi	0.099	0.084	0.275	0.179
Cam_Norm	0.404	0.213	0.059	2.124
Cam_Hi	0.342	0.132	0.299	2.100
Mem_M	0.087	0.022	0.207	1.950
Mem_H	0.096	0.058	0.267	1.632
Dis_S	0.286	0.171	0.160	0.413
Dis_M	0.024	0.178	0.274	0.692
Batt_M	0.272	0.192	0.049	1.648
Batt_H	0.232	0.103	0.168	1.750
Batt_VerHi	0.267	0.096	0.393	0.655
Weight_VerL	0.271	0.125	0.189	1.719
Weight_Li	0.318	0.014	0.128	0.315
Constant	0.451	0.440	1.233	1.694

Table 5.25. MADs across all participants with various daily usage behaviour

The average MADs were calculated for all features of a given category of participants to investigate whether they are different across those with various daily usage behaviour or not. The average MADs show that those who use their mobile phones more are more stables in their preferences over time. Participants with daily usage of more than 4 hours and between 2 and 4 hours have the lowest average MADs of 0.307 and 0.240, respectively (Table 5.26).

Average MADs	Daily usage			
	More than 4 hours	2 to 4 hours	1 to 2 hours	Less than an hour
	0.307	0.240	0.317	1.389

Table 5.26. Average MADs across all participants with various daily usage behaviour

5.5.2.2.6. Change of weights over time for participants with different daily usage of their mobile phones

In Tables 5.27, 5.28, 5.29 and Figures 5.17, 5.18, 5.19 the variations of weights between the different rounds using mean differences of weights, mean absolute differences of weights, and mean squared differences of weights across the participants in terms of differing daily usage of mobile phones habit are presented. Although there are some exceptions, the general trend is that those with more daily usage of their phones are more consistent in their choices in the different rounds in comparison to those who use it less, which confirms the results from average MADs in the previous sub-section.

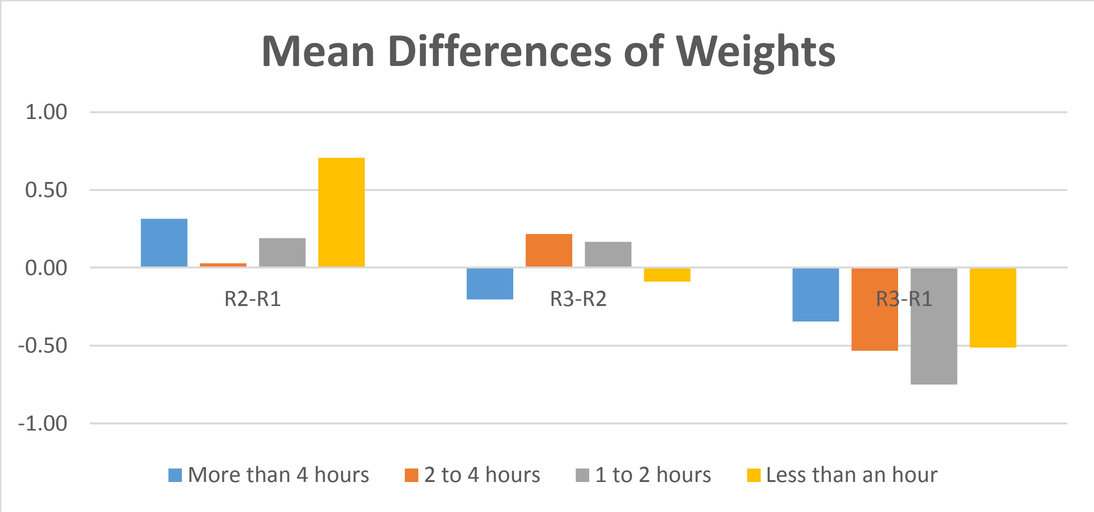


Figure 5.17. Mean differences of weights for participants with different daily usage

Mean Difference B	R2-R1	R3-R2	R3-R1
More than 4 hours	0.31	-0.20	-0.34
2 to 4 hours	0.03	0.22	-0.53
1 to 2 hours	0.19	0.17	-0.75
Less than an hour	0.71	-0.09	-0.51

Table 5.27. Mean differences of weights for participants with different daily usage

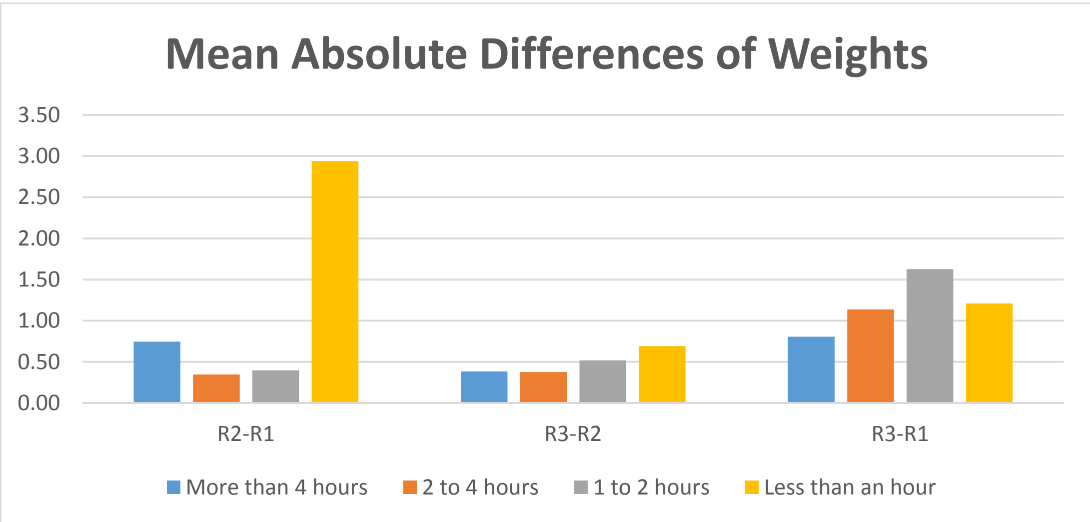


Figure 5.18. Mean absolute differences of weights for participants with different daily usage

Mean Abs Difference B	R2-R1	R3-R2	R3-R1
More than 4 hours	0.75	0.38	0.81
2 to 4 hours	0.35	0.38	1.14
1 to 2 hours	0.40	0.52	1.63
Less than an hour	2.94	0.69	1.21

Table 5.28. Mean absolute differences of weights for participants with different daily usage

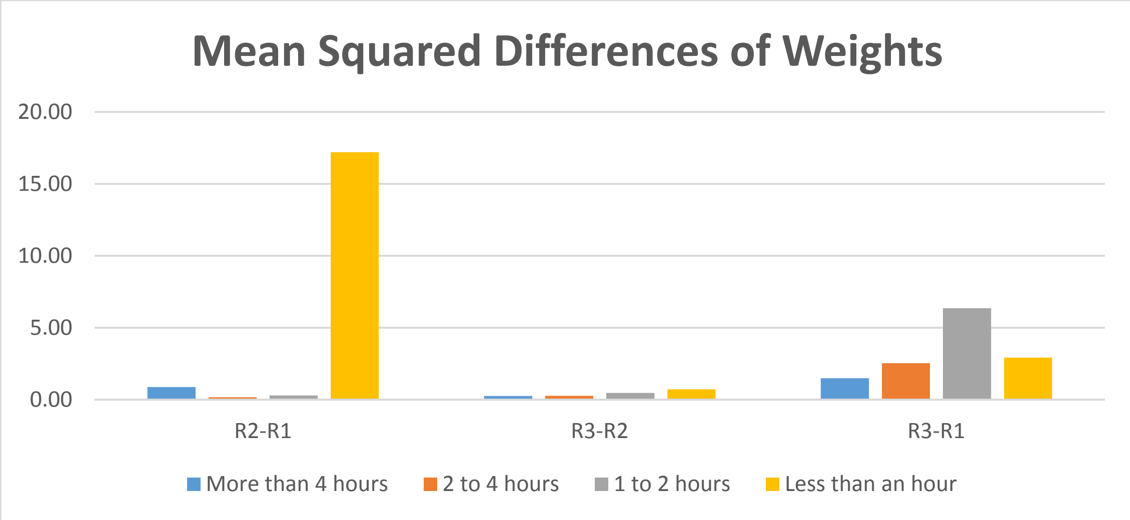


Figure 5.19. Mean squared differences of weights for participants with different daily usage

Mean Square Difference B	R2-R1	R3-R2	R3-R1
More than 4 hours	0.89	0.26	1.49
2 to 4 hours	0.18	0.28	2.54
1 to 2 hours	0.29	0.47	6.35
Less than an hour	17.20	0.73	2.92

Table 5.29. Mean squared differences of weights for participants with different daily usage

5.5.2.3. How important is your mobile phone to you?

As there were only three participants who believed their mobile phone was not important to them, this category was combined with the 'Somewhat important' category and a new one was created, called 'Not or somewhat important'. Afterwards, the mobile phones dataset was split into three sub-datasets, those participants for whom mobile phones are: 'Very important', 'Important', and 'Not or somewhat important'. The utility model (Equation 5.9, 5.10) and binary logit model (Equation 5.11) is the same as for laptops in subsection 5.5.1.1, which is estimated for each round of each sub-data set and the results are presented in the next subsections.

5.5.2.3.1. Very important

For the participants who reported that their mobile phones are very important to them the weights of various features are quite stable over time, with two exceptions to this being brand and battery length (See Table 5.30 and Figure 5.20). Brands become more important over time, while battery length and product weights become relatively less so.

Mobile B	R1	R2	R3
Brand_Apple	0.79	1.73	1.70
Brand_Samsung	0.45	0.85	0.99
Brand_Nokia	-0.05	0.73	0.55
Brand_HTC	0.10	0.75	1.05
Brand_Sony	-0.54	0.36	0.81
Brand_BB	-0.52	0.60	0.56
Price_Low	0.93	0.67	0.77
Price_Med	0.65	0.73	0.62
Price_Hi	0.15	0.34	0.29
Cam_Norm	1.48	1.12	1.39
Cam_Hi	2.20	1.92	2.07
Mem_M	0.26	0.47	0.57
Mem_H	0.51	0.55	0.63
Dis_S	-0.55	-0.25	-0.37
Dis_M	0.07	0.13	0.15
Batt_M	0.74	1.09	0.45
Batt_H	1.19	1.07	0.56
Batt_VerHi	1.29	1.48	0.93
Weight_VerL	0.50	0.20	0.21
Weight_Li	0.42	-0.12	-0.12
Constant	-4.59	-5.16	-4.93

Table 5.30. Features weights for participants that mobile phones is very important to them

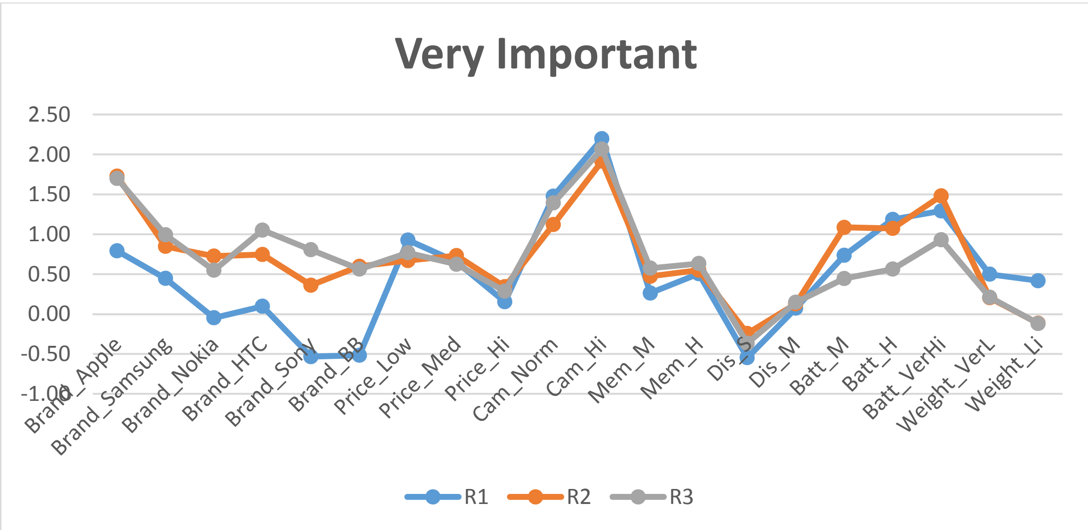


Figure 5.20. Features weights for participants that mobile phones is very important to them

5.5.2.3.2. Important

Although those participants who reported that their mobile phones are important to them exhibit slightly greater variations of weights in Round 3, the relative importance of features is generally quite consistent. Moreover, brand and battery length become more salient over time, while price becomes relatively less so (See Table 5.31 and Figure 5.21).

Mobile B	R1	R2	R3
Brand_Apple	0.92	0.86	1.71
Brand_Samsung	0.20	0.60	0.98
Brand_Nokia	0.36	0.10	0.11
Brand_HTC	0.01	-0.03	1.12
Brand_Sony	0.01	0.33	0.52
Brand_BB	-0.35	0.31	1.01
Price_Low	1.81	1.41	1.56
Price_Med	1.52	0.93	0.89
Price_Hi	1.01	0.82	0.22
Cam_Norm	1.84	1.71	2.00
Cam_Hi	2.39	2.14	2.61
Mem_M	0.44	0.86	0.68
Mem_H	0.31	0.56	0.76
Dis_S	-0.32	-0.10	-0.93
Dis_M	0.42	-0.32	-0.41
Batt_M	0.04	0.98	0.67
Batt_H	1.00	1.27	0.93
Batt_VerHi	0.78	1.58	1.13
Weight_VerL	0.38	-0.03	0.81
Weight_Li	0.30	0.18	0.35
Constant	-5.46	-5.39	-6.08

Table 5.31. Features weights for participants that mobile phones is important to them

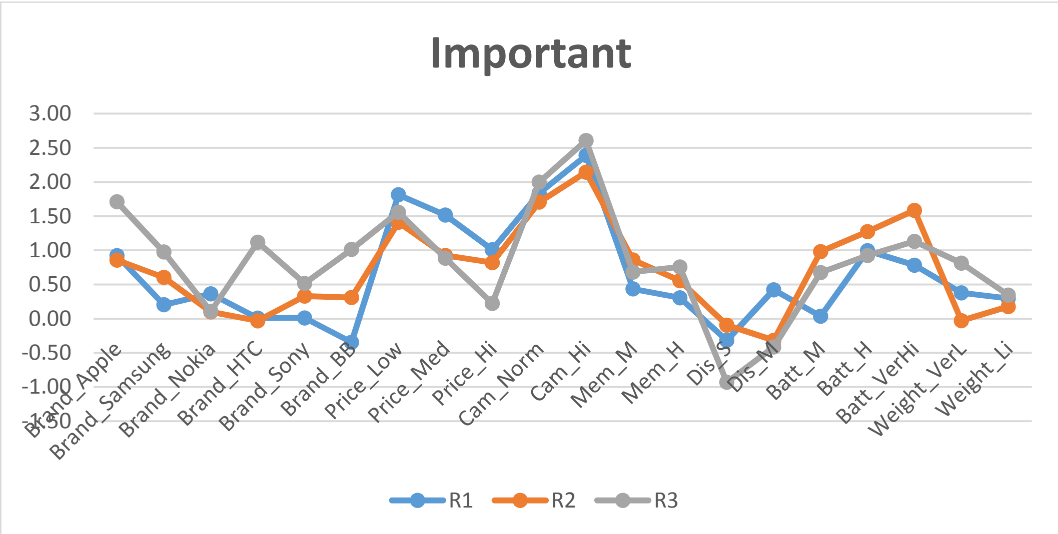


Figure 5.21. Features weights for participants that mobile phones is important to them

5.5.2.3.3. Not or somewhat important

Participants who report that phone is not important or somewhat important have the same level of variation as those using their phone for less than an hour daily. They also have less variation in their preferences in Round 2 and Round 3 in comparison to Round 1. Camera resolution and phone memory become relatively less important over time, while brands like Blackberry and Nokia become more so for this group of people (See Table 5.32 and Figure 5.22).

Mobile B	R1	R2	R3
Brand_Apple	0.62	1.68	2.35
Brand_Samsung	1.00	1.84	1.26
Brand_Nokia	-9.40	0.89	1.43
Brand_HTC	-0.45	0.24	-0.43
Brand_Sony	-0.52	1.22	0.92
Brand_BB	-9.58	0.65	0.52
Price_Low	0.26	3.40	2.84
Price_Med	0.68	2.16	2.12
Price_Hi	0.95	0.27	0.13
Cam_Norm	5.81	2.10	1.00
Cam_Hi	6.49	2.77	2.12
Mem_M	4.97	0.98	0.27
Mem_H	4.20	1.42	0.74
Dis_S	-0.13	-0.11	-0.11
Dis_M	0.53	0.13	0.67
Batt_M	-3.59	-0.95	1.57
Batt_H	-3.43	0.90	2.63
Batt_VerHi	1.34	0.57	2.69
Weight_VerL	4.47	0.65	1.16
Weight_Li	0.24	0.33	0.82
Constant	-8.88	-7.44	-8.90

Table 5.32. Features weights for participants that mobile phones is not or somewhat important to them

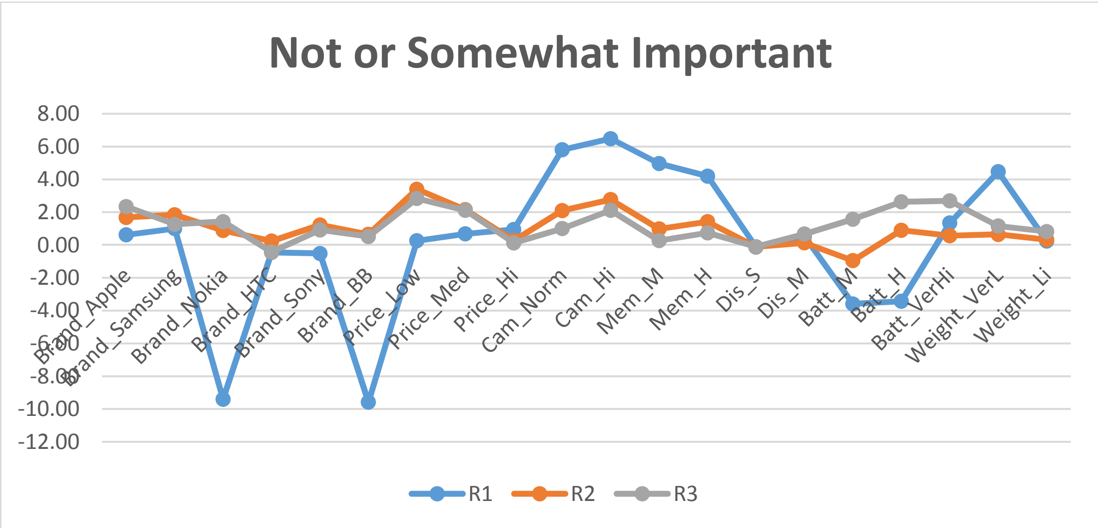


Figure 5.22. Features weights for participants that mobile phones is not or somewhat important to them

5.5.2.3.4. Mean absolute deviations (MADs) across all participants with differing levels of importance attributed to their mobile phones

The features' weights were calculated for the participants for each of the features across the rounds for participants with different level of importance for their mobile phones in the previous section. In this section, the mean absolute deviations (MADs) are calculated for each feature in order to improve the comparison of weight fluctuations (Equation 5.12). Brand and battery life have the highest variations or MADs across all participant categories (Table 5.33).

Mobile	Mean Absolute Deviations (MADs)		
	Very Important	Important	Not or Somewhat Important
Brand_Apple	0.409	0.364	0.618
Brand_Samsung	0.210	0.260	0.317
Brand_Nokia	0.304	0.116	4.693
Brand_HTC	0.356	0.503	0.302
Brand_Sony	0.497	0.183	0.705
Brand_BB	0.488	0.458	4.518
Price_Low	0.092	0.146	1.270
Price_Med	0.042	0.271	0.648
Price_Hi	0.071	0.307	0.332
Cam_Norm	0.139	0.101	1.891
Cam_Hi	0.096	0.158	1.797
Mem_M	0.116	0.149	1.930
Mem_H	0.047	0.156	1.385
Dis_S	0.108	0.322	0.008
Dis_M	0.028	0.350	0.206
Batt_M	0.220	0.352	1.735
Batt_H	0.252	0.139	2.309
Batt_VerHi	0.203	0.279	0.770
Weight_VerL	0.130	0.284	1.584
Weight_Li	0.238	0.064	0.238
Constant	0.204	0.292	0.644

Table 5.33 MADs across all participants with differing levels of importance attributed to their mobile phones

The average MADs were calculated for all features of a given category of participants to investigate whether they are different across those with differing levels of importance attributed to their mobile phones or not. The average MADs show that the participants for whom their mobile phones are more important are more stable in their preferences over time, with 0.202 and 0.250 average MADs, respectively, while those for whom mobile phones are not important or somewhat important have the highest MADs value of 1.329 (Table 5.34).

Average MADs	Mobile Phones Importance		
	Very Important	Important	Not or Somewhat Important
	0.202	0.250	1.329

Table 5.34. Average MADs across all participants with differing levels of importance

5.5.2.3.5. Change of weights over time for participants with differing levels of importance attributed to their mobile phones

Tables 5.35, 5.36, 5.37 and figures 5.23, 5.24, 5.25 show the variations of weights between the different rounds using mean differences of weights, mean absolute differences of weights, and mean squared differences of weights among the participants in relation to the different levels of importance conveyed upon their mobile phones. Those who think their phone is more important to them are clearly more consistent in their choices in the different rounds in comparison to the others.

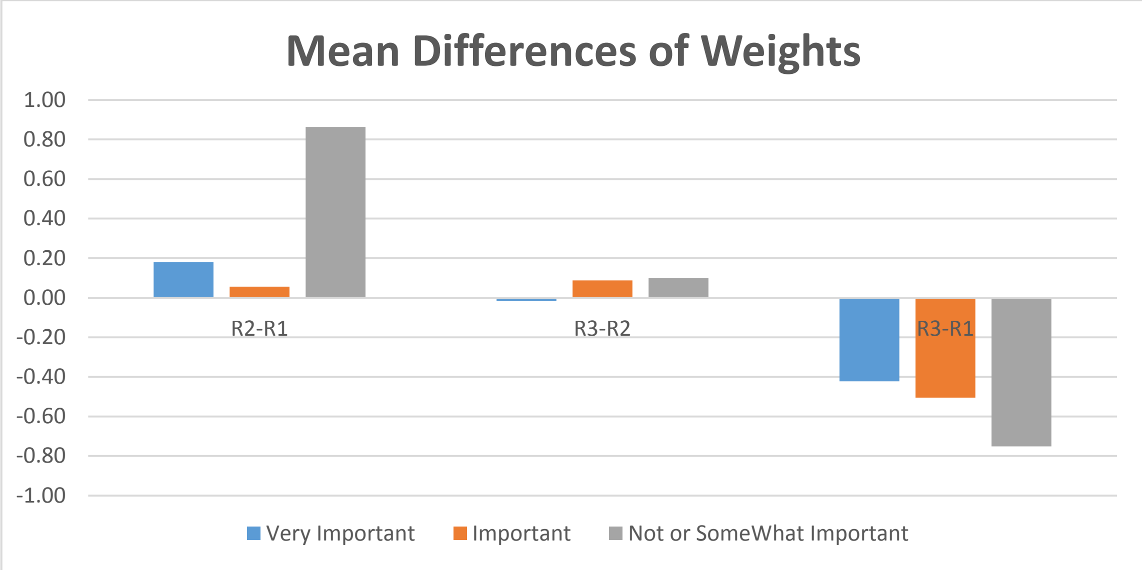


Figure 5.23. Mean differences of weights for participants with differing levels of importance

Mean Difference B	R2-R1	R3-R2	R3-R1
Very Important	0.18	-0.02	-0.42
Important	0.06	0.09	-0.51
Not or Somewhat Important	0.86	0.10	-0.75

Table 5.35. Mean differences of weights for participants with differing levels of importance

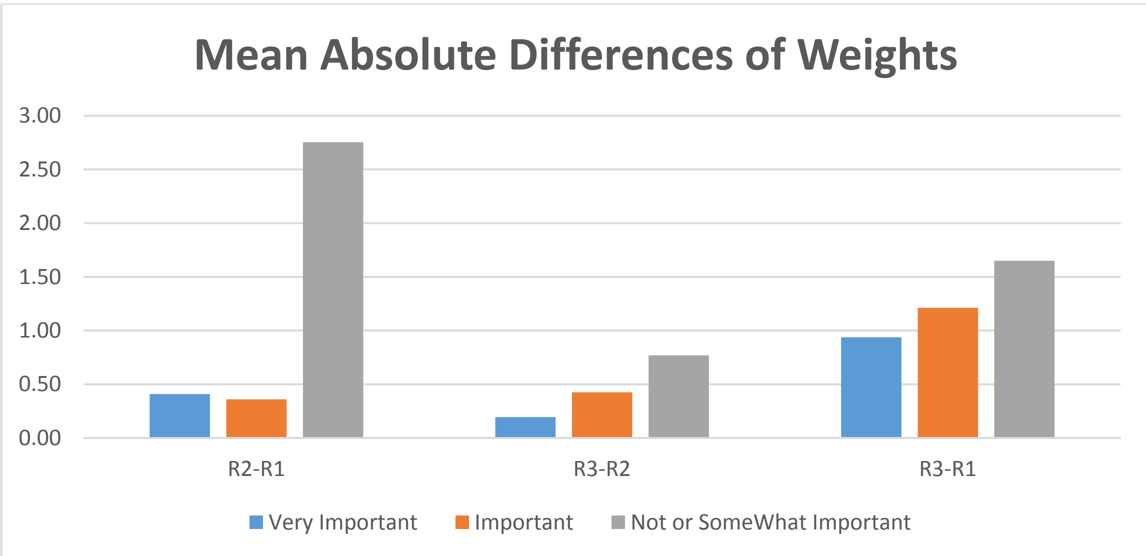


Figure 5.24. Mean absolute differences of weights for participants with differing levels of importance

Mean Abs Difference B	R2-R1	R3-R2	R3-R1
Very Important	0.41	0.19	0.94
Important	0.36	0.43	1.21
Not or Somewhat Important	2.75	0.77	1.65

Table 5.36. Mean absolute differences of weights for participants with differing levels of importance

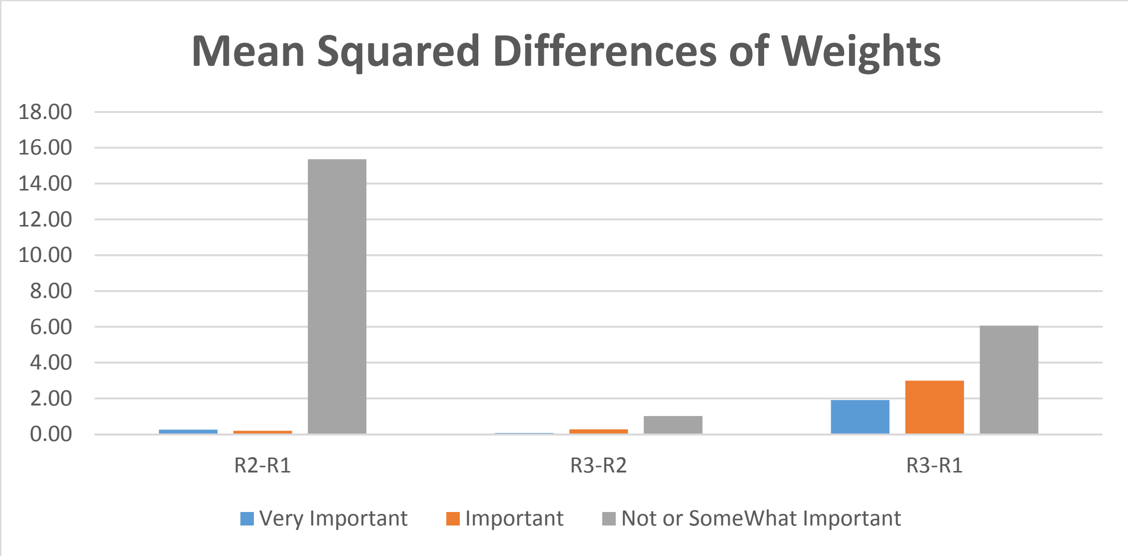


Figure 5.25. Mean squared differences of weights for participants with differing levels of importance

Mean Squared Difference B	R2-R1	R3-R2	R3-R1
Very Important	0.26	0.07	1.91
Important	0.19	0.28	2.99
Not or Somewhat Important	15.36	1.02	6.06

Table 5.37. Mean squared differences of weights for participants with differing levels of importance

5.6. Discussions and Conclusion

All of the previous studies on the subject of individual behaviour differences in technology use have suggested that consumers' individual characteristics may provide an explanation for variations in their preferences in relation to electronic goods in general. However, none of those studies considered how the individual differences might influence the consistency of their preferences for a specific product over time.

Several studies have been conducted to compare male and female consumer behaviour and preferences. These have been in relation to the clothing brand loyalty formation process in South Korea (Jin and Koh, 1999), self-concept and self-image (Oumlil and Erdem, 1997), perception of product warnings (Larue et al., 1987), and the effectiveness of celebrity endorsers (Premeaux, 2006). This suggested that it is worthwhile, to investigate the potential effects of gender on changes in attribute-weights over time. However, gender did not significantly affect participants' choices in the current study at the 5% level, which leads to H_2 being rejected. This could be due to increasing gender equality and consequent convergence in the behaviour of males and females in terms of change in attribute-weights over time in the UK as a developed country.

The demographic factors, i.e. age, education, and occupation did not significantly affect change in the attribute-weights of the participants over time at the 5% level, hence H_3, H_4 and H_5 are rejected. Perceived technology competency also did not have a significant effect on the participants' choices for any of the types of products at the 5% level of significance, which means H_6 is rejected. As stated in previous chapters, fan heaters and TVs do not involve such high technology and complexity of features as the other two surveyed products, thus it would seem reasonable not to expect a significant effect of perceived technological competency when consumers are choosing these products. By contrast, this researcher assumed such an effect would be found in the cases of laptops and mobile phones as both of them are higher technology products than the two aforementioned. Another explanation for perceived technology competency not being significant could be that these products and their technology have become inseparable parts of the general population's daily life in the UK, in which case higher technological competency will not necessarily affect people's choice.

The effects of individual usage behaviour for TVs, laptops and mobile phones were also examined by asking participants specifically designed questions about each product. None of those behaviours tested exhibited any effect on the participants' choices and preferences regarding TV, which results in H_7, H_8, H_9, H_{10} and H_{11} being rejected for this product. However, one of those tested behaviour had a significant effect on laptops and hence the H_7 is accepted for them, whereas three of those behaviours affect mobile phones and so H_8, H_9 and H_{10} are accepted for this good.

There is clear evidence that the choice and preferences of the participants' were affected by the length of time that elapsed before they changed or upgraded their laptops. The more often participants changed or upgraded their laptops, the more unstable their choices were over time. This could be interpreted as being due to variety seeking behaviour (Kahn, 1995) by these participants that led them to change or upgrade their laptop more often and also led to more inconsistency in their preferences. Variety seeking could be due to internal desires or personal motivations, which are related to the concept of satiation and stimulation. For example, once a consumer has reached an optimal level for an attribute provided by a brand, he or she feels satiated and hence, might choose to consume a different attribute provided by another brand next time a choice needs to be made. This could be the reason for more variations in the weights being attached to brands compared to the other features. Variety seeking could also be due to changes in consumers' external situation, such as being subject to changes in prices, short-term advertising promotions, changes in external factors that influence brand perceptions, or changes in one's economic situation (Kahn, 1995). Additionally, it does seem to be the case that regardless of the length of the interval prior to the changing/upgrading of laptops, brand weights increase over time, whilst others features' weights have slight fluctuations.

As for mobile phones, the three individual characteristics that would appear to influence participants' choices or preferences (at the 5% level of significant), are: importance of technical specifications, daily usage, and importance they attribute to their mobile phones. Regarding the foremost, although it influenced the participants' choice, the participants did not reveal any specific trend on how technical specifications affect the stability of the attribute weights for mobile phones. For all the participants, brands gain more weight over time, while the other features fluctuate. More variations in the brands weights of all participants could be due to external reasons (Kahn, 1995), such as variety seeking by the participants as well as the subjectivity and superficiality of brand perception (Fader and Lattin, 1993).

Interestingly, the participants with greater daily usages of their mobile phones as well as those who placed high importance on their mobile phones, turned out to be more stable in terms of their mobile phone choices over time. One of the reasons for these participants being more consistent in this respect could be due to their greater familiarity and prior of knowledge of mobile phones, because they place more importance on their device or use it for longer hours daily (Coupey et al., 1998; Moreau et al., 2001). These factors could have led to have more stable preferences and choices. Regarding the RQ3:

How are the characteristics of individual consumers related to the stability of the implied attribute weights for specific products?

It can be concluded that the level of importance of mobile phones to the participant and daily usage as well as length of time before changing or upgrading laptops clearly affected the stability of the attribute weights of the participants. Although there is some evidence that other individual characteristic have some effect, the findings were not strong enough to draw clear conclusions about how those characteristics influence individual choices.

6. New Product Sales Forecasting using CBC

6.1. Introduction

In this chapter, whether and if so to what extent, changes in attribute-weights affect forecasting accuracy is investigated using CBC. First, there is consideration of the challenges of sales forecasting for products with short life cycles. This is followed by a review of new product forecasting methods and dimensions as well as discussion on the pros and cons of these. Subsequently, the likely reliability of new product sales forecasting using CBC is examined by generating forecasts for various points in time for mobile phones, fan heaters, TVs and laptops using data from surveys. This allows for RQ4 to be addressed, which is:

RQ4: When using choice-based conjoint models, are forecasts for some types of new products likely to be more accurate over longer lead times than others?

Finally, the results are discussed and conclusions drawn.

6.2. Challenges of Sales Forecasting for Products with Short Life Cycles

The fast pace of new product introduction has led to shortened life cycles in many industries, especially those in the high-tech sector. According to Decker and Gnibba-Yukawa (2010), the term high-tech market refers to newly established rapidly growing markets, which are mainly driven by technological innovations. Traditional demand forecasting methods are not oriented towards the forecasting of short life cycle products. Retailers or providers who market products with a short selling season and/or a short life cycle, find the task of forecasting sales challenging because of the high levels of uncertainty in the demand for these products, especially in the absence of a long term sales history (Subrahmanyan, 2000). For short-life cycle products, the compression of the life cycle means that features normally considered to belong to the long term, such as changing trends, can appear in the short-term. Conversely, many features associated with long–term forecasting, such as the long term economic cycle, will not have a chance to manifest themselves fully during the product's short life cycle. Additionally, there are some technical challenges associated with sales forecasting for products with short life cycles in relation to using some of the traditional forecasting methods, as set out below.

Decomposition Methods and Box-Jenkins models: These have been designed to identify and separate the time series into its various components. However, they require many data points for proper identification and parameter estimation. A sufficiently long time series is not available for short life cycle products. Indeed if the product has not yet been launched, then no time series data will be available. Applying the method to series for analogous products that have already been launched may also be infeasible as, will be at the end of their cycles when the data becomes available (Kurawarwala and Matsuo, 1998).

Smoothing Methods: Methods such as moving averages, simple exponential smoothing and extensions of exponential smoothing such as the theta method (Assimakopoulos and Nikolopoulos, 2000), also perform best when sufficient past demand history is available (Petropoulos et al., 2014). Although the simpler techniques can be often applied to shorter data series they assume the absence of a systematic trend in the series. More complex methods that allow for the presence of non-linear trends and seasonality require longer series than may be available for short life-cycle products in order for their parameters to be estimated reliably. Hence, rapid changes in sales of products with short lives and/or seasonal variations, makes simple smoothing methods of sales forecasting inappropriate for such products (Kurawarwala and Matsuo, 1998). Moreover, for products that have to be launched the use of analogous products will face the same problems as those referred to above.

Multiple Linear Regression Methods: These involve fitting a linear model between dependent and independent variables and this is one of the long standing traditional forecasting methods. The application of multiple linear regression usually requires a number of assumptions to be satisfied, which could be challenging for both short and long cycle products, including: normally distributed residuals, homoscedacity, and an absence of interdependency (inter-correlation) among the independent variables. However, usually applications of the method are robust to violation of some of the assumptions as long as they are not extreme (Ord and Fildes, 2013). Nevertheless, in a study which involved forecasting the size of audiences for TV programmes in Greece, Nikolopoulos et al. (2007) found that the method performed relatively poorly because of its tendency over fit in-sample data and its inability to handle complex non-linearities in the data.

In sum, these traditional forecasting methods are not designed for application in new product forecasting (except when the analogy method is feasible), especially for those products with short life cycles. In the next section, the specific methods that have been designed for new product sales forecasting are discussed.

6.3. New Product Forecasting Methods and Dimensions

Wind (1981) refers to two general types of sales forecasting methods that may be useful in new product forecasting, these being:

- *Diffusion models*, which are usually based on time series data from previously launched similar products and assume a sigmoid-shaped curve representing product penetration over time (Bass, 1969; Mahajan, et al., 2000; Mead and Islam, 2006).

- *Choice models*, which are based on individual customer level data for investigating preferences for different characteristics of products and how these will affect their choice of which product to purchase (Greene, 2009).

In the absence of a sales history, forecasters who want to apply the above models either use a similar product sales history for diffusion models (analogy method) or employ conjoint analysis based on hypothetical scenarios so as to collect individuals' potential behaviours and preferences towards the new product before applying a choice model (Green et al, 2001; Gustafsson et al., 2007). Some recent studies have involved combining diffusion and choice models to forecast new product demand (Jun and Park, 1999; Kumar et al., 2002; Jun et al., 2002; Lee et al., 2006; Lee et al., 2008; Eager and Eager, 2011).

Apart from the aforementioned models, there are other methods that have been frequently used by forecasters in order to forecast new product sales, including:

- *Individual management judgment*, which is the most common method in new product sales forecasting, especially in the high-tech industry due to the high level of uncertainty (Lynn et al., 1999; Kahn, 2002);

- *Judgments by group of managers* can be also used to obtain different opinions and perspectives with the aim of having more accurate forecasting (Goodwin et al., 2014). Methods such as the Delphi method, prediction markets and preference markets can offer a structured process of eliciting judgments from groups of managers;

- *Customer intention surveys method*, which involves asking potential customers about their likelihood of purchasing the new product (Bass et al., 2001);
- *Market testing* and *agent-based modelling*. In the former, a firm assesses the acceptance level and success of a new product in a sub-set market before launching into the complete market. Regarding the latter approach, computer software models simulate the action and intention of customers by taking into account pre-defined behavioural rules (Jahanbin et al., 2013).

The relative effectiveness of these methods is likely to depend on the nature of the forecasting task. Jahanbin et al., (2013) have defined seven dimensions to this, of which six are applicable to the consumer electronics industry, as set out below.

1. *The product's 'newness'*. This has been defined differently by scholars. One definition relates to the 'radicalness' of an innovation, which can be divided into three categories: A. incremental: products whose innovations make a marginal improvement over existing technology, such as improvements in the camera, display resolution, and the processor in the iphone 5 compared with the iphone 4 (apple UK website, 2014); B. semi-radical: those products whose innovation represents a significant improvement over existing technology, such as a cordless phone; and C. radical: those product innovations that represent a major or revolutionary technological advance, such as the concept of the smartphone by Ericsson, produced for the first time in 2000 (Teardown Report, 2001). Regarding the lattermost, the Ericsson R380 smartphone combined the functions of a mobile phone and a personal digital assistant (PDA). The newness of the product could also influence consumer behaviour, whereby it is contended that: A. continuous innovations will not disrupt behavioural patterns, (e.g. an improved version of iphone); B. dynamically continuous innovation will lead to small changes in behaviour, (e.g. a camera phone); and C. discontinuous innovation will lead to significant changes in consumer behaviour and substantial learning will be required on the part of consumers, such as the launching of the ipad as a new generation of PDAs that created new demands on the consumers to use tablets, thereby representing a significant amount of radical innovation.

2. *The intrinsic nature of the product* determines the frequency and amount of time spent purchasing it, its essentiality and the perceived associated risk of impulse purchasing. For instance, the product might be a consumer durable (e.g. smartphone), a consumer packaged good (e.g. a new chocolate bar) or a service (e.g. internet mobile subscription).

3. *The type of purchasers*. Different purchasers exhibit various buying behaviours for the same product. For instance, there are special subscriptions for business customers in terms of tariff and usage when comparing business to business selling strategies in the mobile phone industry with those of business to consumers.

4. *Product life cycle* varies for different products, which affects sales forecasting for a new product. As discussed earlier, mobile phones and laptops, two of the focal products in this thesis, have a short life cycle. Rapid growth and decline as well as the short maturity of mobile phones due to the speed of innovation in this industry, makes the forecasting task much more complicated than were it otherwise.

5. *Whether the aim of the forecast is to predict the size of the total market or the market share of a product*. Forecasts of market share require estimates of the probability of consumers choosing a particular product or brand (e.g. the probability of a consumer choosing an Apple iphone over the Samsung Galaxy). However, sometimes the total size of a market for a specific product over a certain period of time is the goal of the forecast (e.g. total size of smart phone market in the UK in summer 2012).

6. *The extent to which forecasting accuracy is essential* for a company may vary for different industries. It is crucial to keep the right balance between the level of complexity of the forecasting method and the accuracy required when deciding to adopt one.

Next, the likely pros and cons of the methods outlined above when they are applied to new product sales forecasting in the mobile phone industry are considered.

6.3.1. Management judgments

Graefe and Armstrong (2011) suggest that human judgment can be used in new product sales forecasting where a lack of appropriate available information precludes the use of quantitative methods. Human judgment or management judgement can be divided into two categories: individual manager judgment and judgment by groups of managers. In a survey by Kahn (2002), judgment by individual managers was found to be the most common method used to forecast new product sales, especially for forecasting sales of high-tech products.

A number of drawbacks are associated with the application of management judgment as a single method of forecasting. The main concern is that managers have difficulties in accurately extrapolating simple linear patterns and consequently, the more complex non-linear patterns associated with new product life cycles are much less amenable to this method of forecasting. That is, this method is likely to be less reliable as result of inconsistency and cognitive limitations (Goodwin et al., 2014).

In addition, there are other elements that may influence individual manager judgments, such as unrealistic views about the prospects for a specific product by those who are involved in developing the product. Another element that influences such judgments can be resources competition among managers to support the development and commercialisation of a new product. Additionally, peer pressure may influence human judgments. Moreover, sometimes motivational biases from independent bodies, such as forecasters outside the company, deliberately give the managers an overestimated forecast as they perceive this is what they wish to hear to keep them satisfied. Finally, sometimes wrong indicators from the market may mislead management (Goodwin et al., 2014). While the use of judgment on its own may be problematical, it can be a valuable method in combination with other methods of forecasting (e.g. diffusion model or statistical models). For example, it can be used to estimate initial sales or to select appropriate analogies when applying diffusion models. Also, judgmental adjustments of statistical forecasts can improve accuracy when a manager has market information that is not covered by the statistical methods.

Judgment by groups of managers instead of individuals' can be a way to decrease biases and improve the accuracy of the judgment. Common approaches in this regards are: unstructured face to face meetings, nominal groups, the Delphi method and prediction and preference markets. The unstructured face to face meeting is the most common form of group decision making in organisations. However, while the approach may give participants the enjoyment and satisfaction of direct human interaction from working together, it also may be subject to several biases and drawbacks. For instance, a group requires time and effort to be maintained, and also peer pressure may influence members' decisions. In addition, the presence of people from different hierarchical levels within an organisation may mean that, not all members are willing to express their own ideas or decisions openly (Armstrong, 2006).

Van den Van and Delbecq (1974) tried to improve traditional unstructured face to face meeting drawbacks by giving such interactions structure through a method called the nominal group technique. This technique consists of three steps: first, group members work independently and produce their own decisions based on their individual estimations; second, the group enters an unstructured face to face meeting to discuss the issue with the aim of finding a solution; and finally, they work independently again to prepare their final individual decision. The group result is the aggregated outcome of these final individual estimates. The face to face interaction in the second phase of the nominal group technique helps group members to justify and clarify their point of view so as achieve more informed decisions. On the other hand, the final phase of decision making, which prevents direct interaction between group members, decreases the drawbacks associated with traditional face to face meetings.

The Delphi method was developed in the 1950s by RAND corporation workers while they were involved in a US Air force sponsored project and involves an anonymous multiple-round survey about a problem. After each round, summaries of the individual estimates are reported to all participants and then, taking into account this information, participants start their new round of estimation. The result is the aggregate estimate of the final round outcome of all individuals. Clearly, this method avoids the drawbacks and biases that are associated with direct interaction. “Delphi is not a procedure intended to challenge statistical or model-based procedures, against which human judgment is generally shown to be inferior: it is intended for use in judgment and forecasting situations in which pure model-based statistical methods are not practical or possible because of the lack of appropriate historical /economic/ technical data, and thus where some form of human judgmental input is necessary” (Rowe and Wright, 1999).

Prediction markets and preference markets can also be categorised as a group judgment approach (Graefe and Armstrong, 2011); however, they will be discussed in the next section as they are based on a significantly different approach, which has received much attention in recent years.

6.3.2. Prediction and preference markets

Graefe and Armstrong (2011) found that prediction markets are gaining attention in various fields of forecasting. The approach involves setting up a contract, the payoff of which depends on the result of an uncertain future situation and the participants of prediction markets can trade this contract, which can be interpreted as a bet on the outcome of the underlying future event. Participants are paid off in exchange for contracts they hold as soon as the outcome is revealed and they can win money based on their individual performance in the same way as on the stock market. Ivanov (2009) believes that the prediction market is a useful tool of forecasting as it can harness collective wisdom. Unlike Delphi, it offers incentives for accurate forecasting and can instantly respond to new information. However, there are several serious challenges associated with the method. First, user friendly software has to be adopted and developed to support it. Second, according to Graefe and Armstrong (2011), participants find it hard to understand and implement prediction markets, even after a proper training session. Third, prediction markets also suffer from long periods between the forecast and potential payoff, although this is less of a problem in the mobile phone and laptop industry given its short product life cycles. Nevertheless, despite these concerns prediction markets offer an alternative method that addresses this issue called the 'preference market', which involves replacing the occurrence of the event as the basis for the payoff with the group's mutual expectation.

6.3.3. Intentions surveys

Asking potential customers about their likelihood of purchasing a new product in a questionnaire is called an "intentions survey". Clearly, by eliciting judgments directly from potential customers important information about the potential market can be obtained. The elicited likelihoods can be measured on different scales (e.g. binary or seven point scales), which can also include the time horizon of the purchase. Intentions surveys can be used in producing time series forecasts, if a researcher assumes the adoption is probably linear over time, or asks about the likelihood of purchase at different points of time in the future, such as one month, three months, six months or one year (Van Ittersum and Feinberg, 2010). Goodwin et al. (2014) believe that in addition to the usual errors associated with surveys, such as sampling error and non-response biases, there are a number of other kinds of potential errors associated with sales forecasts based on intentions surveys.

First, the unfamiliarity of participants with a product reduces the accuracy of their judgments about their probability of purchasing it. Clearly, most users will be familiar with mobile phones; however, the speed of innovation in this industry and the newness of products may still have a negative impact on accuracy. Nevertheless, the method is known to be more reliable for durable products, like mobile phones rather than non-durables, such as packets of crisps. This is because buying decisions for durable products are less likely to be based on impulse and are more likely to be the results of thoughtful and planned buying. Second, the timing of intention surveys influences the accuracy of the responses; the closer the time of product launching, the more accurate the customer responses would be to the surveys. Third, one of the significant issues that is associated with this method in the mobile phone industry research context, is "the act of eliciting intentions can itself change purchaser's behaviour when respondents have predicted their own behaviour they are more likely to act in a way that is consistent with this; hence those who participate in an intention survey may behave differently from other members of the target population" (Goodwin et al., 2014). Finally, previous research has shown that intentions surveys are more reliable when they are related to a specific brand rather than the entire product category (Morwitz, 2001).

6.3.4. Market testing

Market testing is more common for forecasting sales of non-durable goods, such as consumer packaged goods and grocery products, than for durables. However, a few researchers have been able to generate accurate sales forecasting for one or two years periods ahead by testing the market at approximately six month intervals (Fourt and Woodlock, 1960 and Baum and Dennis, 1961 cited by Fader, 2003). Nevertheless, market testing is costly and it causes some delays in the launching of the product to the main market, with the associated risk that competitors will imitate it, especially in the mobile phone industry where novelty and innovation are likely to be key competitive advantages. Finally, as the life cycles of some of the consumer electronic goods are really short, there is often insufficient time for conducting such tests.

6.3.5. Agent-based modelling

In agent-based modelling, computer software models simulate the action and intentions of customers in accordance with pre-defined behavioural rules. This allows for a rich mixture of factors to be taken into account, such as consumer traits (e.g. social connectedness and imitativeness) and environmental characteristics (e.g. geographical variables and shopping location). Problems such as achieving a good balance between the realistic behaviour of consumers and the need for model simplicity, absence of historical data, the likely sensitivity of the models to initial conditions as well as their calibration and validation, still need to be resolved. However, if these problems can be addressed in the future, this method has the potential to become a strong tool for new product sales forecasting (Jahanbin et al., 2013).

6.3.6. Diffusion models

Diffusion models have been developed since the 1960s to model and forecast the diffusion of innovations (Mead and Islam, 2006), with three well-known such models being: the Gompertz, logistic and Bass models. Wind et al. (1981) believe that diffusion models can be adapted to model new product forecasting in the early stages. Diffusion models are one of the most extensively researched types in the literature. In the table below, there is a list of some of the studies in the high tech and electronic sectors from 1999 that have applied some sort of diffusion model.

Author(s)	Year	Country	Industry	Model
Jun & Park	1999	Worldwide	DRAM	Combined CBC and diffusion model
Jun et al.	2002	Korea	Telecom services	Combined CBC and diffusion model
Masini	2004	UK and Italy	Mobile phones	Logistic and Gompertz
Roberts et al.	2005	Australia	Telephone calls	Diffusion and choice model
Chen & Wantanbe	2006	Japan	Mobile phones	Simple logistic growth, bi(double)-logistic and choice based diffusion
Lee et al.	2006	Korea	Flat screen TVs	Combined CA and diffusion model
Robertson et al.	2007	UK	Broadband	Gompertz
Lee et al	2008	Korea	Home networking	Combined diffusion with conjoint analysis
Michalakelis et al.	2008	Greece	Mobile	Bass, Gompertz, Fisher-Pry model
Trappey & Wu	2008	Taiwan	22 Electronics Short PLC	Simple logistic, Gompertz, and time-varying extended logistic model
Chu et al.	2009	Taiwan	Mobile phones	Logistic and Gompertz
Decker & Yukawa	2010	Germany	LCD/DVD/CD	Diffusion and utility based approach
Wu & Chu	2010	Taiwan	Mobile phones	Bass, Gompertz, Logistic, ARIMA
Orbach & Fruchter	2011	US	Hybrid/Electric cars	Diffusion model
Eager & Eager	2011	Germany	Hybrid/Electric cars	Combined CBC and diffusion model
Gupta & Jain	2012	India	Mobile phones	Bass, Gompertz, Logistic
Turk & Trkman	2012	Slovakia	Broadband	Bass model

As discussed earlier, new product sales forecasting is often necessary prior to launch and the unavailability of past data is, therefore, one of the main challenges regarding the application of diffusion models in this context. One solution is “to fit the model to the sales time series of similar products that have been launched in an earlier time period and to assume that the parameter values identified for the analogy are applicable to the new product" (Goodwin et al., 2012). However, this process called "forecasting by analogy", has a number of limitations (Goodwin et al., 2014). First, there is the problem of identifying suitable analogies that have a high probability of yielding a similar sales pattern to that of the new product, which is particularly challenging with high tech sector products that have a rapid speed of innovation. Second, using a single analogy run the risk that unusual circumstances may result in huge differences in the parameters between the old product and those that would have been appropriate for the new one. Although using multiple analogies decreases the risk of the forecasts being affected by these unusual circumstances, it causes less general similarity in the estimated parameters due to averaging. Third, selection of analogies may be subject to some judgmental biases, if this is based on manager judgments. Finally, the choice of which diffusion model to represent best the analogy is another challenge.

Another issue that is specific to diffusion models is the complexity of adoption curves for high tech products. That is, sometimes after a surge at the beginning the adoption the curve falls for a while on account of competition (Lee et al, 2006), expectation of higher technology or anticipation of an upgrade in the near future (Kim and Srinivasan, 2009). Alternatively, slow growth of sales at the beginning of the product launch can turn into a boost in sales a few weeks later. This can be the result of a wrong initial marketing strategy or an ethical scandal relating to a major competitor, such as when one for Apple in China resulted in increased sales of the Samsung Galaxy (Routers, 2012).

Gupta et al (1999) contend that adoption of a product depends on a large variety of factors, which directly or indirectly affect its diffusion patterns. For instance, an increase in the number of smartphone users directly influences the number of subscriptions to the mobile internet of a service provider in the UK. However, an increase in the number of smart phone application users *indirectly* affects the number of mobile internet subscribers.

The majority of studies in forecasting so far that have used diffusion models to forecast, measured the aggregate adoption of a technology (e.g. a new type of a product, such as a smartphone or 4G connection) in a market rather than forecasting the sales of an individual model of a brand (e.g. Samsung, Galaxy S4 or iphone 4s). In particular, diffusion models forecast aggregate adoption of a new type of technology (i.e. first time buying) rather than sales of a specific product, for they cannot capture multiple purchases of a specific technology or type of product. All in all, the main concerns about the accuracy of sales forecasts based on diffusion curves by using analogy in the mobile phone industry, are the high speed of technological development and the large annual number of radical innovations in this sector, which may reduce the similarity between the analogy and the new product and hence, the similarity of the sales patterns.

6.4. New Product Sales Forecasting using CBC

As stated in the literature review chapter, CBC has advantages over other new product forecasting methods in that it addresses three key questions: Do consumers prefer one attribute of a product over other? What attributes are they looking for? How do they make trade-offs between these attributes? (Raghavarao et al., 2011). Understanding how changes in the characteristics of alternatives affect the preferences of consumers can be used to forecast market share. However, as discussed earlier, none of the new product sales forecasting methods covered so far were specifically designed to forecast market share of a specific product (except for CBC), i.e. diffusion models forecast the total market size of a new technology, such as that of the smart phone in the UK or smart watches. As explained in the literature chapter, one of the major concerns with CBC studies is that they only give a researcher a snapshot of the current situation, i.e. they are static models for simulating the current attitudes of consumers. The results of the experiments and responses to RQ1 and RQ2 show that the attribute-weights for the participants changed more over time for the complex products with short life cycles and high level technology in the consumer electronic goods industry. Consequently, this researcher decided to investigate how and to what extent these changes influence forecasting through applying CBC for different products at different time points, thus providing a response to RQ4:

RQ4: When using choice-based conjoint models, are forecasts for some types of new products likely to be more accurate over longer lead times than others?

Based on RQ4, the H_{12} are developed as:

H_{12}: New product sales forecasts, based on choice-based conjoint analysis are likely to be less accurate at a given lead time for products with more complex features and shorter life cycles.

Regarding which, the decision was taken to calculate the forecasts for a number of mobile phones and laptops, as they exhibited the most variations over time in the chapter four findings.

6.4.1. Mobile phones market share forecast

The specifications for six mobile phones were picked from the UK market in January 2015 from a major retailer website (three website, 2015), as follows:

Name	iphone 6 plus	Galaxy S4 mini	Curve 9320	Acer Liquid E3	Desire 610	Z2 Xperia
Brand	Apple	Samsung	BlackBerry	Generic Brand	HTC	Sony
Price (£)	699.99	199.99	109.99	134.99	164.99	509.99
Camera Resolution (Mpix)	8	8	3.2	13	8	20.7
Memory Size (GB)	64	8	0.5	4	8	16
Display Size (inch)	5.5	4.3	2.44	4.7	4.7	5.2
Battery Life (Talking hours)	14	10.75	7	5	15.8	15
Weight (g)	172	107	103	135	143.5	158

Table 6.1. The chosen mobile phones specification

As stated in section 4.4, the logit estimation model to calculate the probability that a product with a given set of feature and level specifications would be chosen by a consumer was based on the following equation:

$$P_{in} = \frac{e^{\beta X ni}}{\sum_j e^{\beta X nj}}$$

Equation 6.1

where, X is an attribute of a product and β is the coefficient. For example, to calculate the probability of apple iphone 6 plus in Round 1 of the experiment, the equation for the explanatory variables is:

Brand_Apple (0.76*1) + Brand_Samsung (0) + Brand_Nokia (0) + Brand_HTC (0) + Brand_Sony (0) + Brand_BB (0) + Price_Low (0) + Price_Med (0) + Price_Hi (0) + Cam_Norm (0) + Cam_Hi (1*2.20) + Mem_M (0) + Mem_H (1*0.41) + Dis_S (0) + Dis_M (0) + Batt_M (0) + Batt_H (1*1.06) + Batt_VerHi (0) + Weight_VerL (0) +Weight_Li (0) +Constant (1*-4.70)= Weighted sum of attribute values $_{\text{apple phone 6 plus}}$ =-**0.27**

The same formula was also used to calculate the weighted sum of the other designated mobile phones. Once the weighted sum was calculated for the all six mobile phones, then it was replaced in the formula to estimate the apple iphone 6 plus market share (the assumption is that there are only the six laptops in table 6.1 available to customers in the whole UK market) using data from experiment R1, as follows:

$$P_{\text{apple iphone 6 plus}} = \frac{e^{\text{weighted sum for iphone 6 plus}}}{\sum_6 e^{\text{Weighted sum for each of six phones}}}$$

Equation 6.2

The probabilities of choice (purchase) for each product were calculated using the data from all three rounds. Afterwards, the probabilities were obtained by averaging weights from R1 and R2, R1 and R3, R2 and R3, as well as R1, R2, and R3 (Table 6.2 and Figure 6.1) to see how sensitive market share forecasts are to changes in consumers' weights over time. It was assumed that a manufacturer or retailer wants to forecast the market share in January 2015. Seven different scenarios were examined as follows:

The first scenario is to use one data point nine months prior to the launch of the product on the UK market, i.e. only the weights from R1;
The second scenario is to use one point data six months prior to launch, i.e. only the weights from R2;
The third scenario is to use data three months prior to launch, i.e. only the weights from R3;
The fourth scenario is to use two point data nine months and six months prior to launch, i.e. averaging the weights from R1 and R2;
The fifth scenario is to use two point data six months and three months prior to launch, i.e. averaging the weights from R2 and R3;
The sixth scenario is to use two point data nine months and three months prior to launch, i.e. averaging the weights from R1 and R3;
The final scenario is to use three point data, nine months, six months, and three months prior to launch, i.e. averaging the weights from R1, R2, and R3.

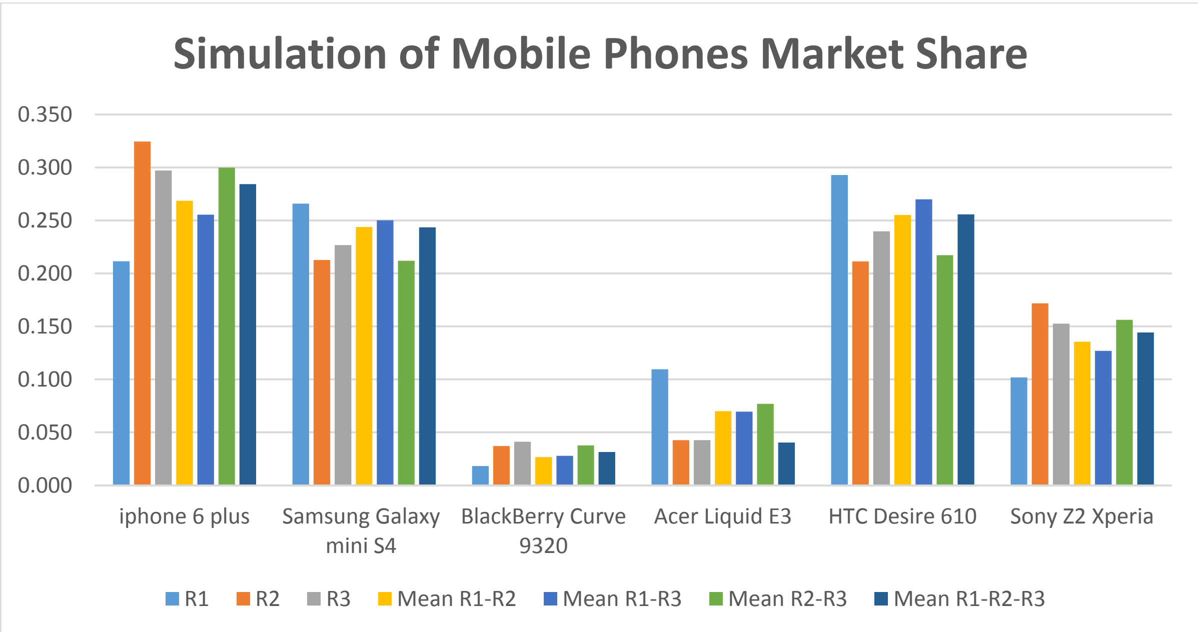


Figure 6.1. Market share forecast using chosen mobile phones specifications

Market Share Forecast	R1	R2	R3	Mean (R1, R2)	Mean (R1, R3)	Mean (R2, R3)	Mean (R1, R2, R3)
iphone 6 plus	0.212	0.325	0.297	0.269	0.255	0.300	0.284
Samsung Galaxy mini S4	0.266	0.213	0.227	0.244	0.250	0.212	0.244
BlackBerry Curve 9320	0.018	0.037	0.041	0.027	0.028	0.038	0.032
Acer Liquid E3	0.110	0.043	0.043	0.070	0.070	0.077	0.040
HTC Desire 610	0.293	0.211	0.240	0.255	0.270	0.217	0.256
Sony Z2 Xperia	0.102	0.172	0.153	0.136	0.127	0.156	0.144

Table 6.2. Market share forecast using chosen mobile phones specifications

Although the researcher approached many service providers and retailers in the UK, such as O2, Orange, T-mobile and Apple in order to access sales data, they did not agree to provide the sales or market share data. As there are also no real market share data for January 2015, it is not possible to measure the accuracy of the forecast for each mobile phone for the different rounds or combinations of them. Although, as a consequence, it cannot be concluded with certainty which method forecasts more accurately most of the time, a key finding is how sensitive the forecasts are to the different weights. If the forecasts change a lot when the weights change this suggests that the earlier forecasts are unreliable. For example, the Round 1 forecast for all mobile phones is very different than those of Rounds 2 and 3. Therefore, if a retailer based the forecasts for these products just on the Round 1 survey, the forecast would be very different than if it was based on just a Round 2 survey. Given the lack of real data as well as there being no opportunity to test this technique against another new product forecasting method, constitutes a limitation of this research.

6.4.2. Laptops market share forecast

Specifications for six laptops were selected from the UK market in January 2015 from major manufacturer websites in the UK, as follows.

Name	MacBook Pro	Inspiron 5000	Acer Aspire-V3	Samsung	Yoga 2 Pro	HP 15j-143
Brand	Apple	Dell	Generic Brand	Samsung	Lenovo	HP
Price (£)	1199	329	499.99	217.99	1049	799
Display Size (inch)	13	17	15.6	10.1	13.3	15.6
Processor	Fast	Normal	High Performance	Normal	High Performance	High Performance
Memory Size (GB)	8	4	8	2	4	12
Hard Drive (GB)	256	500	1000	256	500	1000
Weight (g)	1570	3000	2550	1400	1390	2560

Table 6.3. The chosen laptops specifications

As stated in the previous subsection, the estimation model is a logit model. This was used to calculate the probability that a customer would purchase a brand given its features and level specifications. The model has the following equation:

$$P_{in} = \frac{e^{\beta X_{ni}}}{\sum_j e^{\beta X_{nj}}}$$

Equation 6.3

where, X is an attribute of a product and β is the coefficient. For example, to calculate the probability of purchasing for the Dell Inspiron 5000 in Round 2 of the experiment, the equation for the explanatory variables is:

Brand_Apple (0) + Brand_Samsung (0) + Brand_HP (0) + Brand_Sony (0) + Brand_Dell (1*0.89) + Brand_Lenovo (0) + Brand_Toshiba (0) + Price_Low (1*1.02) + Price_Med (0) + Price_Hi (0) + Dis_S (0) + Dis_M (0) + Proc_Fas (0) + Proc_Hi (0) + Mem_M (0) + Mem_H (0) + HDD_Hi (1*0.41) + HDD_VerHi (0) + Weight_UltraL (0) + Constant (1*-4.01)= Weighted sum of attribute values $_{\text{Dell Inspiron 5000}}$ =**-1.41**

The same formula was also used to calculate the weighted sum of attribute values of the other designated laptops. Once the weighted sum was calculated for the all six laptops, then it was replaced in the formula to estimate the Dell Inspiron 5000 market share (the assumption is that there are only six designated laptops in Table 6.4 available to customers in the whole UK market) using data from experiment R2, as follows:

$$P_{\text{apple iphone 6 plus}} = \frac{e^{\text{Weighted sum of attribute values for Dell Inspiron 5000}}}{\sum_6 e^{\text{Weighted sum for each of six laptops}}}$$

Equation 6.4

As with mobile phones, the probability for each product was calculated using data from all three rounds. Afterwards, the probabilities were calculated by averaging the weights from R1 and R2, R1 and R3, R2 and R2, as well as R1, R2, and R3 (Table 6.4 and Figure 6.2) to see how the market share changes, if a manufacturer or retailer wanted to forecast this share in January 2015. Seven different scenarios were examined as follows:

First scenario is to use one data point nine months prior to launching the product on the UK market, i.e. only the weights from R1;
Second scenario is to use one point data six months prior to launch, i.e. only the weights from R2;
Third scenario is to use data three months prior to launch, i.e. only the weights from R3;
Fourth scenario is to use two point data nine months and six months prior to launch, i.e. averaging the weights from R1 and R2;

Fifth scenario is to use two point data six months and three months prior to launch, i.e. averaging the weights from R2 and R3;

Sixth scenario is to use two point data nine months and three months prior to launch, i.e. averaging the weights from R1 and R3;

Final scenario is to use three point data, nine months, six months, and three months prior to launch, i.e. averaging the weights from R1, R2, and R3.

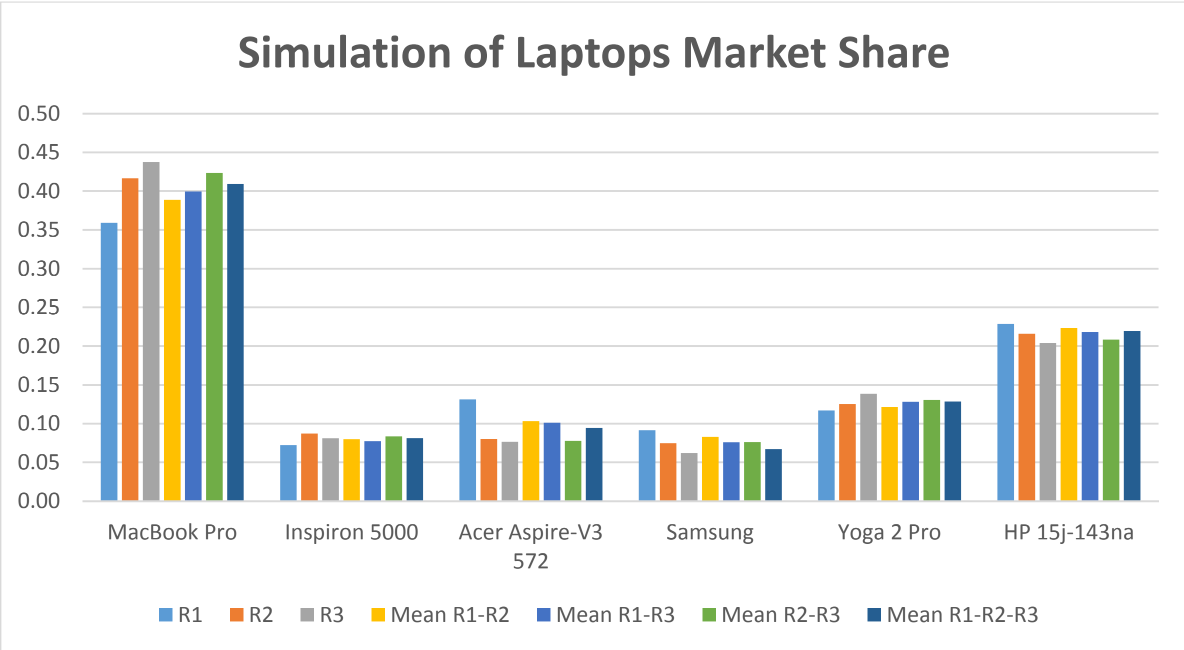


Figure 6.2. Market share forecast using the chosen laptops specifications

Market Share Forecast	R1	R2	R3	Mean (R1, R2)	Mean (R1, R3)	Mean (R2, R3)	Mean (R1, R2, R3)
MacBook Pro	0.359	0.416	0.437	0.389	0.399	0.423	0.409
Inspiron 5000	0.072	0.087	0.081	0.080	0.077	0.083	0.081
Acer Aspire-V3 572	0.131	0.080	0.077	0.103	0.101	0.078	0.095
Samsung	0.091	0.075	0.062	0.083	0.076	0.076	0.067
Yoga 2 Pro	0.117	0.125	0.139	0.122	0.128	0.131	0.129
HP 15j-143na	0.229	0.216	0.204	0.224	0.218	0.208	0.219

Table 6.4. Market share forecast using chosen laptop specifications

As with mobile phones, no market share data was available for January 2015, so as before, the sensitivity of the forecasts to the weights generated in the different rounds was used to assess their reliability.

6.5. Forecasting Accuracy for Various Products

As stated earlier, there were no actual market share data for any products available to the researcher to measure the accuracy of the forecasts. However, the researcher tried to address the question of whether the forecast accuracy for high-tech products with short life cycle is likely to be less than for 'more stable' consumer products. Hence, the comparison is between the types of products and not between different forecasting methods. Consequently, this examination does not require a benchmark forecasting model. In addition, standard benchmarks, such as naive forecasts, would not be available here as there is no past data for new products. Therefore, the Round 3 results from survey were used as proxy for the actual market share. Prior to that, the market share forecasts for products regarding which the participants had more stable preferences were calculated, i.e. fan heaters and TVs.

6.5.1. Fan heaters

The specifications of six fan heaters from one of the major retailers (Argos website, 2015) were taken, as shown in Table 6.5.

Name	Challenge	De Longhi	Dyson	Stanely	Dimplex	De Longhi
Brand	Challenge	De Longhi	Dyson	Generic Brand	Dimplex	Challenge
Price (£)	19.99	29.99	369.99	27.99	35.99	44.99
Power (KW)	2.4	2.5	2.8	1.8	1.8	2.5
Type	Flat	Upright	Upright	Upright	Upright	Upright
Oscillating	Yes	No	Yes	Yes	No	No

Table 6.5. The chosen fan heaters specification

Subsequently, the features and level specifications were fitted in the estimation model (Equation 6.1), in order to calculate the probability of purchasing each fan heater based on the R1, R2 and R3 weights (Table 6.6 and Figure 6.3).

Fan Heaters Market Share Forecast	R1	R2	R3
Challenge	0.153	0.134	0.154
De Longhi	0.221	0.224	0.199
Dyson	0.106	0.121	0.138
Generic Brand	0.192	0.202	0.209
Dimplex	0.107	0.094	0.101
De Longhi	0.221	0.224	0.199

Table 6.6. Simulated fan heaters market share forecast evaluations

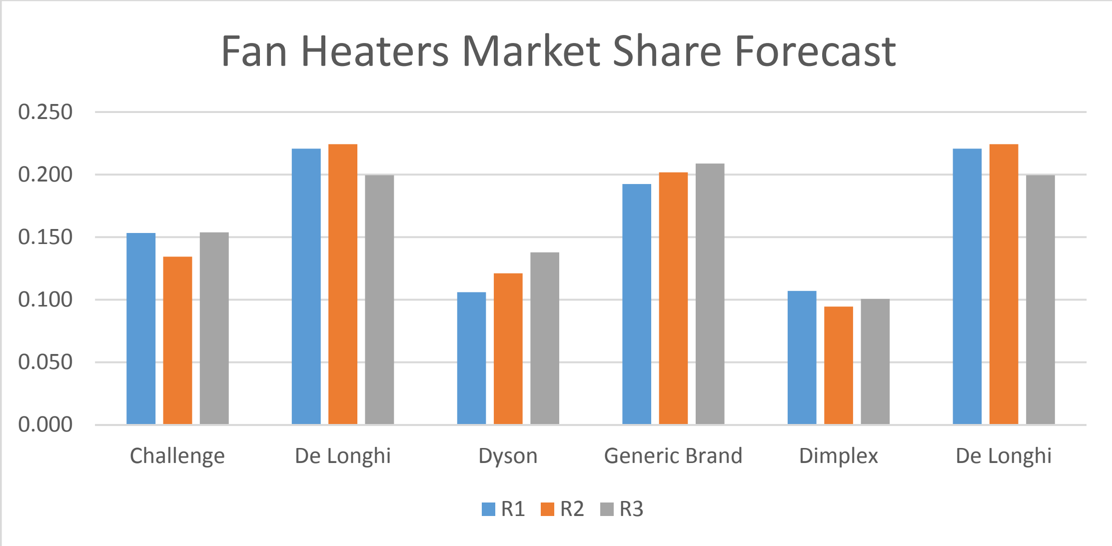


Figure 6.3. Simulated fan heaters market share forecast evaluations

6.5.2. TVs

The specifications of six TVs from one of the major retailers (Currys website, 2015) were taken as shown in Table 6.7.

Name	Toshiba	Samsung	LG	Sony	Panasonic	JVC
Brand	Toshiba	Samsung	LG	Sony	Panasonic	JVC
Price (£)	189	129	629	499	599	280
Screen Size (inch)	32	22	47	42	45	32
Smart	No	No	Yes	Yes	Yes	No
3D	No	No	No	Active	Active	No
Freeview	No	Yes	Yes	Yes	Yes	Yes

Table 6.7. The chosen TVs specification

As before, the features and level specifications were fitted in the estimation model (Equation 6.1), in order to calculate the probability of purchasing each simulated TV based on the R1, R2 and R3 weights (Table 6.8 and Figure 6.4).

TVs Market Share Forecast	R1	R2	R3
Toshiba	0.072	0.102	0.095
Samsung	0.054	0.056	0.080
LG	0.127	0.113	0.100
Sony	0.586	0.586	0.558
Panasonic	0.077	0.061	0.080
JVC	0.084	0.082	0.088

Table 6.8. Simulated TVs market share forecast evaluations

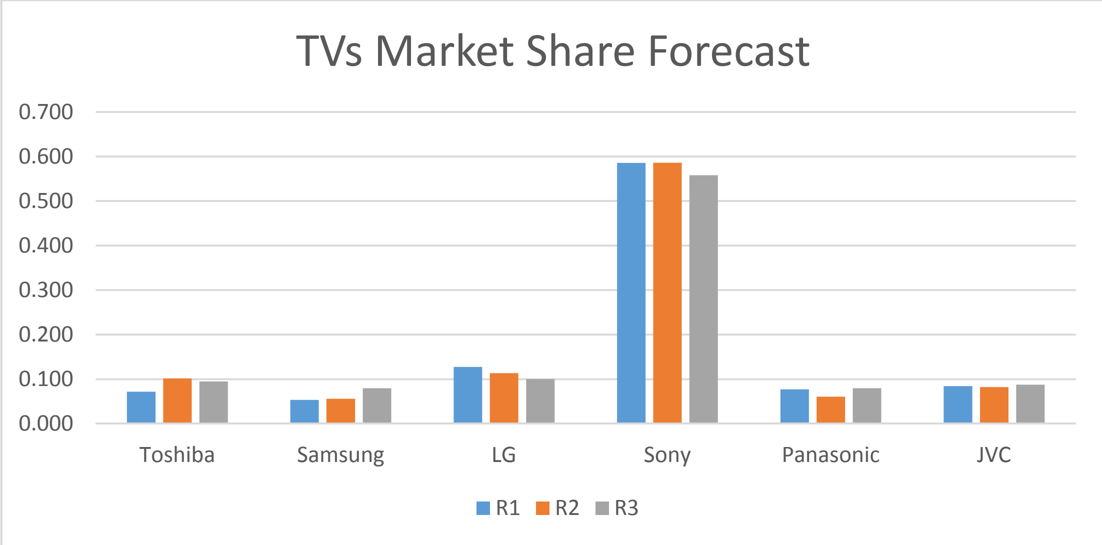


Figure 6.4. Simulated TVs Market Share Forecast evaluations

6.5.3. Forecasting accuracy analysis

After calculating the market share forecast for six examples of Mobile phone, Laptops, TVs and fan heaters, the Round 3 results from the survey were used as proxies for the actual market share across all the focal products in order to estimate the accuracy of forecasting using CBC for various products. For both R1 and R2 forecast the mean absolute error (MAE) were calculated separately for each product by averaging the absolute error across all brands in Tables 6.2, 6.4, 6.6, and 6.8.

Mean Absolute Error	R1	R2
Fan heaters	0.016	0.017
TVs	0.018	0.016
Laptops	0.036	0.011
Mobile phones	0.053	0.015

Table 6.9. Mean absolute error (MAE) based on R3 data as proxy for actual market data

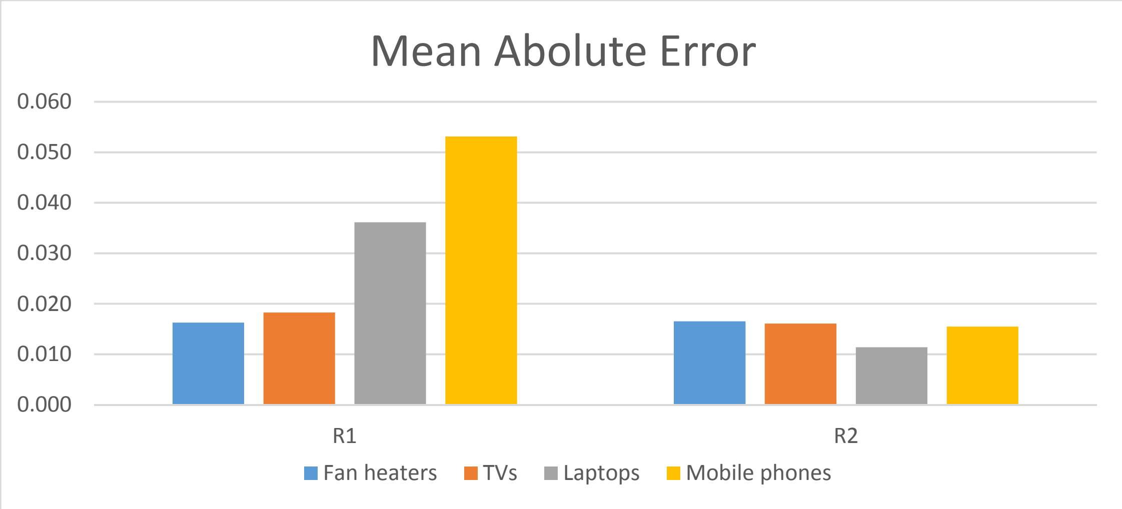


Figure 6.5. Mean absolute error (MAE) based on R3 data as proxy for actual market data

The findings show that market share forecasting for short life cycle, high tech products seems to be less reliable because of changing consumer preferences. Therefore, it can be concluded that forecasting for 'stable' products can be relatively reliable and can probably be performed by carrying out just one survey, which can be undertaken well in advance of product launch. In contrast, for short life cycle high tech products forecasts based on surveys that take place well in advance of a product's launch can lead to highly inaccurate forecasts of market share and therefore, H_{12} is accepted.

Also, the results in Table 6.9 and Figure 6.5 are in line with the findings in chapter 4. Eventually, despite these findings being based on proxies (Round 3), the mean absolute errors from Round 1 are much larger than those for Round 2, suggesting that the greater the time interval between the survey and the product's launch, the greater the error in forecasting the product's market share.

6.6. Further Analysis

As stated earlier, the researcher did not have access to actual market share data and therefore, it was decided to generalise the results in a different way. That is, the chosen products for this research were treated as a sample of consumer electronic products and statistical inference techniques were used to generalise the results from this sample (inference means drawing conclusions about a population from a sample). These four products are not a random sample of all consumer electronic products.

One way ANOVA were applied to the absolute errors (AE), with the results showing that the means of these absolute errors for the four products (i.e. MAEs) are significantly different between R1 and R3 (F-test = 4.91 and P-value = 0.010). However, those between R2 and R3 are not significantly different (F-test = 0.73 and P-value = 0.54), which is in line with the findings in the previous section.

ANOVA: Single Factor (R1 and R3)

Groups	*Count*	*Sum*	*Average*	*Variance*
Fan Heaters	6	0.1	0.0167	0.00013
Mobile Phones	6	0.318	0.0530	0.00046
Laptops	6	0.207	0.0345	0.00071
TV	6	0.106	0.0177	0.00013

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F-critical*
Between Groups	0.005	3	0.002	4.909	**0.010**	3.098
Within Groups	0.007	20	0.000			
Total	0.012	23				

Table 6.10. Single factor ANOVA of absolute error between R1 and R3

ANOVA: Single Factor (R2 and R3)

Groups	*Count*	*Sum*	*Average*	*Variance*
Fan Heaters	6	0.101	0.0168	0.00007
Mobile Phones	6	0.094	0.0157	0.00015
Laptops	6	0.059	0.0098	0.00005
TV	6	0.097	0.0162	0.00008

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F-critical*
Between Groups	0.000	3	0.0001	0.735	0.543	3.098
Within Groups	0.002	20	0.0001			
Total	0.002	23				

Table 6.11. Single factor ANOVA of absolute error between R1 and R3

Also, the following analysis displays the confidence intervals for the MAEs. It can be seen that the interval for the MAE of phones is much higher than for TVs and fan heaters.

```
                                Individual 95% CIs For Mean Based on
                                Pooled StDev
Level   N     Mean    StDev    +---------+---------+---------+---------
Fan     6  0.01667  0.01141    (-------*-------)
Phone   6  0.05300  0.02154                     (--------*-------)
Laptop  6  0.03450  0.02664              (-------*-------)
TV      6  0.01767  0.01127     (-------*-------)
                               +---------+---------+---------+---------
                             0.000     0.020     0.040     0.060

Pooled StDev = 0.01892
```

Subsequently, a Kruskal-Wallis test was conducted on the median of absolute errors between R1 and R3, the results of which shows significant differences between the medians of the AEs based on the different types of products (p = 0.024) and this confirms the previous results.

Kruskal-Wallis Test: C2 versus C1

```
Kruskal-Wallis Test on C2

C1        N   Median  Ave Rank      Z
1         6  0.01950       8.0  -1.80
2         6  0.05200      19.1   2.63
3         6  0.02700      14.0   0.60
4         6  0.02200       8.9  -1.43
Overall  24               12.5

H = 9.44  DF = 3  P = 0.024
H = 9.45  DF = 3  P = 0.024  (adjusted for ties)
```

Table 6.12. Kruskal-Wallis test for absolute errors of various products

6.7. Discussion and Conclusion

Based on the findings in chapter 4 on changes in attribute-weights over time, mobile phones and laptops were selected to investigate their market share forecast in terms of the best available combinations over time; however there were no real data for measuring the forecast accuracy available to researcher. According to the findings, the weights of attributes to consumers changes more often for mobile phones than for laptops. Consequently, forecasting for mobile phones using CBC is more changes over time in comparison to laptops. Finally, after calculating the market share forecast for six examples of TVs and Fan heaters, the Round 3 results from the survey were used as a proxy for the actual market share across all products to estimate the accuracy of forecasting using CBC for various products and hence, H_{12} is accepted. The findings are line with those in chapter 4 and show that market share forecasting for short life cycle high tech products could be less reliable because of changing in attribute-weights. Therefore, it can be concluded that forecasting for 'stable' products can be relatively reliable and, forecasts can probably be made by carrying out just one survey, which can be undertaken well advance of the product launch. In contrast, for short life cycle high tech products forecasts based on surveys that take place well in advance of a product's launch can lead to highly inaccurate forecasts of market share.

7. Conclusions

7.1. Introduction

This chapter provides a summary of the research work that has been covered in this thesis and highlights the key results as well as the research contributions. In the 'Summary of the Research Proposition' section, an overview of the chapters of this thesis is provided. This is followed by consideration of the contribution of the research to the current literature along with the managerial and practical implications of the key findings. Subsequently, the limitations of the current research are discussed and some suggestions for possible future research avenues put forward.

7.2. Summary of the Research Proposition

Key concerns for companies that produce consumer electronics goods are changes in the attribute-weights over time and the fact that procurement decisions need to be made well in advance of a new product's introduction stage, both of which are becoming more salient in today's market. Hence, accurate forecasting in this sector is becoming an increasingly challenging task. Knowledge of attribute weights and accurate forecasts of the likely demand for new products can give companies better insights during the product development stages, inform go-no-go decisions on whether to launch a developed product and also support decisions on whether a recently launched product should be withdrawn or not due to poor early stage sales. One of the methods that is very popular among both market researchers and forecasters, which can provide insights into consumer preferences at any stage as well as providing new product sales forecasting, is choice based conjoint analysis (CBC). In addition to simulating how consumers might react to changes in current products or to the introduction of new ones, as well as forecasting, this method has much wider applications in a range of different fields, as stated in the literature chapter. However, the weights of attributes to consumers are not stable over time, as demonstrated in all previous chapters, but CBC only takes a snapshot of preferences at a particular moment, which means that it might not be able to capture the reality of the changing market. Hence, if the speed of change in attribute-weights is as rapid as that observed with some products in the consumer electronics industry, then the validity and reliability of results obtained by this method come into question.

7.3. Contributions of the Research and Managerial Implications

In this section, the findings regarding each research question and their contributions to the literature are discussed along with their managerial implications.

RQ1: To what extent do the attribute-weights that consumers attach to a product change over time?

The evidence from the research suggests that attribute-weights change over relatively short periods of time. In terms of the most important attribute, camera resolution was found to have the highest weight for mobile phones, while for laptops, brand took this place. However, for TVs it emerged that no feature significantly exhibits greater weight than any other. With fan heaters, which are simple low technology products with the longest life cycle of all those tested, price have highest weight.

For mobile phones, laptops and TVs, although brand was not the most important feature for all of these products, it did turn out to have the most fluctuations in the attribute-weights for all of them over time. More changes with regards to brand over time in comparison to other features could be attributed to its subjectivity and superficiality. That is, this feature is driven by people's perceptions that are shaped by marketers' adeptness at using advertisements, brand perception, brand identity, news, and lifestyle to promote their brand. In addition to brands, there are other features that have slight changes in weights over time both for mobile phones and laptops, i.e. memory and physical weight of the product. Hence, the first contribution of the research is:

The thesis provides an assessment of the extent to which the weights of attributes of choice-based conjoint models change over a six months period for consumer electronic products.

RQ2: Are the changes in attribute-weights associated with the complexity and life-cycle of products?

It was found that weight attributes change with varying rates for different types of products and mobile phones exhibited the highest variations across the different rounds. By contrast, fan heaters had the lowest variations of attribute-weights in the different rounds, thus indicating greater consistency over time in respect of consumer preferences. This suggests that the greater a product's technological advancement and complexity in terms of its features, the greater will be the changes in attribute-weights over time. In addition, the life cycle length has a reverse relationship with changes in attribute-weights over time, i.e. the shorter the life cycle, the more changes in attribute-weights over time. Some of the identified changes in attribute-weights for complex and high tech products with short life cycles in comparison with simple ones with a long life cycle could be due to cognitive factors, such as bounded rationality, the construction of choice during the experiment process or it could be due to external factors such as brand perception, technological developments, mass customisation and/or complexity of products. As a result, when using CBC research to investigate attribute-weights for such products, the models become out of date much quicker than for other products. Hence, the second contribution of the research is:

The research results demonstrate that the change in weights is greater for products that have high technological complexity and shorter life-cycles. Prior to this research, models in the literature had assumed that the weights do not change over time – even when the nature of the attributes was assumed to change.

Market researchers and practitioners need to take the above finding into account when using CBC for high tech products with short life cycles, as their models will become out-of-date very quickly. They either need to conduct their survey very close to their required date or they can conduct multiple round surveys and extrapolate the attribute weights.

RQ3: How do the characteristics of individual consumers relate to the stability of the attribute-weights of specific products?

All of the previous studies in the area of individual behaviour differences in technology use suggest that individual consumer characteristics might provide an explanation for changes in attribute-weights of consumer electronic goods. However, none of these studies considered how individual differences might influence the changes in attribute-weights for a specific product over time. This is potentially important when products are targeted at particular demographic groups of consumers or particular sectors of the market as preferences may be more variable for one sector than another with different implications for the accuracy of demand forecasts in each sector. The experimental results showed that gender did not significantly affect participants' choices in this study at the 5% level of significant. This could be due to greater gender equality in the UK as a developed country, which has resulted in convergence of the behaviour of males and females in terms of changes in preferences over time. The results from this chapter also show that other demographic factors, i.e. age, education, and occupation did not significantly affect change in preferences of the participants over time at the 5% level. Moreover, perceived technology competency did not have a significant effect on the participants' choices for any of the types of products at the 5% level. As pointed out in previous chapters, fan heaters and TVs do not involve such high technology and complexity of features as the other two surveyed products, thus it would seem to be reasonable not to expect a significant effect of perceived technological competency when participants are choosing these products. By contrast, this researcher assumed such an effect would be found in the cases of laptops and mobile phones as both of them are much higher level technology products than the two aforementioned. Another explanation for perceived technology competency not being found to be significant could be that these products and their technology have become inseparable parts of the general population's daily life in the UK, in which case higher competency in this regard will not necessarily affect people's choices.

Subsequently, the effects of individual usage behaviour for TVs, laptops and mobile phones were also examined by asking the participants specifically designed questions about each product. None of the behaviours tested exhibited any effect on the participants' choices and preferences regarding TV, whereas one had a significant effect on laptops and three on mobile phones. Regarding the former effect, there is evidence from findings that the choice and preferences of participants' were affected by the length of time that elapsed before they changed or upgraded their laptops. Specifically, the more often participants changed or upgraded their laptops, the more unstable their choices over time. This could be interpreted as being due to variety seeking behaviour by these participants that led them to change or upgrade their laptop more often and also led to more inconsistency in their preferences. Variety seeking could be due to internal desires or personal motivations, which are related to the concept of satiation and stimulation.

As for mobile phones, the three individual characteristics that were found to influence participants' choice or preferences (at the 5% level of significant) are: importance of technological specifications, daily usage, and importance of their mobile phones to them. Regarding the foremost, although it influenced the participants' choice, the participants did not reveal any specific trend in relation to how technological specifications affect the stability of the attribute weights for mobile phones. Interestingly, the participants with the greater daily usage of their mobile phones as well as those who placed higher importance on them, turned out to be more stable in terms of their choices for this product over time. That is, greater familiarity and prior knowledge of mobile phones would appear to result in more consistent behaviour regarding preference for this product type. Additionally, over time people build more solid preferences based on the perceived advantages of a particular product as well as knowledge of other existing products; a process that is likely to be speeded up through greater usage of the product and greater salience of it in their lives. In sum, these factors would appear to lead to more stable preferences and choices. Hence, the third contribution of the research is:

The changeability of attribute-weights does not have any association with and individual's gender, age, education, and occupation as well as their perceived technology competency for any of the focal products. However, some individual usage behaviours can influence attribute-weights over time for products that have high technological complexity and shorter life-cycles, i.e. laptops and mobile phones.

RQ4: When using choice-based conjoint models, are forecasts for some types of new products likely to be more accurate over longer lead times than others?

No out-of-sample data was available for measuring the accuracy of market share forecasts produced by the different CBC models, which constitutes a limitation of this research. However, the third round data was used as a proxy for the actual market share to assess the likely accuracy of forecasts based on CBC. While this proxy outcome was clearly not independent of the forecasts, the simulated forecast error did give an idea of the consistency of the forecasts over time. After calculating the market share forecast for six examples of Mobile phone, Laptops, TVs and fan heaters, the Round 3 results from the survey were used as proxies for the actual market share across all the focal products in order to estimate the accuracy of forecasting using CBC for various products. The findings show that market share forecasting for short life cycle high tech products seems to be less reliable because of changing consumer preferences. Therefore, it can be concluded that forecasting for products where consumer preferences are relatively stable can be relatively reliable and can probably be performed by carrying out just one survey, which can be undertaken well in advance of a product's launch. In contrast, for short life cycle high tech products forecasts based on surveys that take place well in advance of a product's launch can lead to highly inaccurate forecasts of market share. The fourth contribution of the research is:

The result demonstrates that the assumption of constant weights can potentially lead to inaccurate market share forecasts for high-tech, short life-cycle products that are launched several months after the choice-based modelling has been conducted.

Finally, the managerial implication of this research relating to forecasting is that when market share forecasts for high-tech, short life-cycle products are based on choice-based conjoint models these should, ideally, be based on data that are collected as close as possible to the launch date of these products, otherwise the attribute weights inherent in these models will be out-of-date. This is particularly the case where the potential consumers being surveyed demonstrate high levels of usage of products in the relevant category. Where surveying close to the launch date is not possible forecasts need to be based on methods that can estimate and extrapolate changes in weights over time. For low tech consumer durables, where the weight are unlikely to change significantly over time, surveys conducted six months ahead of the launch should produce reliable forecasts.

7.4. Limitations and Directions for Future Research

This study only involved examining three consumer electronics products, due to limited resources and time constraints. Future work could examine other consumer electronics products with different specifications as well as products from different categories or in different countries covering a range of cultural backgrounds or socioeconomic factors.

A large number of choices were made by examining products displayed on a computer screen. Hence, unlike many real choices people were unable to physically see or handle the products or read reviews of them. In addition the choices were simulated, rather than real as well as possible fatigue resulting from the number of choices required may have itself induced inconsistency. Nevertheless, many of these limitations are inherent in applications of CBC whatever the purpose it is being used for. If ways could be developed to overcome these problems (e.g. virtual reality) or more efficient designs restricting the number of choices required, this could reduce inconsistency and thus lead to CBC being a more reliable forecasting tool.

In this study, because of limited resources and time constraints convenience sampling was used, which was based on volunteers who might have different characteristics than people who chose not to volunteer. Additionally, the research lost some of the participants each time a new survey was conducted, which was inevitable. It is therefore not possible to ascertain with certainty whether those who left the process were more or less inconsistent than those who stayed. Even though there was a danger of self-selecting bias in this study, e.g. participants who are less consistent in their choices may have had a greater propensity to volunteer and complete all three surveys, there are many studies that rely on convenience samples in psychology and marketing. In spite of convenience sampling being subject to some potential biases, the aim of the study was to uncover variation in preferences over time for the same cohort of participants over three rounds. That is, the research was less about drawing general inferences about a population, but rather, about exploring the extent to which a given group of potential consumers could manifest instability in their preferences for different consumer electronic products over time. Nevertheless, it would have been better if the participants had been chosen using quota sampling, as this would have allowed for generalisation of the findings to a wider population. From a statistical perspective the use of a probability sample, such as a stratified sample, would have been ideal, but this would have been impractical given the unavailability of a sampling frame and the costs involved in accessing a large geographically disparate population

This study involved examining the influence of some of the demographic characteristics of participants and their perceptions of technology as well as their specific consumer usage behaviour. Future research could focus on socio-economic factors, such as income or monthly disposable money as well as other individual characteristics in order to identify influences on consumer preference changes that were not discovered in the current research. Further, the lack of availability of real market share data to examine the accuracy of the market share forecasts obtained is a clear limitation of this study, although much can be inferred from the observed variations in weights over time. If such data for consumer electronic products were available, future work could test the validity of the outcomes from this research in real-time forecasting. Also, if surveys were carried out on a greater number of points in time, then time series analysis could be applied to the attribute weights in order to forecast their future values. For example, weights could be exponentially smoothed over time, allowing more recent weights to have a greater influence on the subsequent market share forecasts. Finally, forecasts based on CBC could be combined with those obtained from other forecasting methods (such as forecasting-by-analogy) to see if this improves accuracy.

8. References

Accenture, 2014. It's Anyone's Game in the Consumer Electronics Playing Field: The 2013 Accenture Consumer Electronics Products and Services Usage Report, available from: http://www.accenture.com/SiteCollectionDocuments/PDF/2013-Accenture-Consumer-Electronics-Products-and-Services-Usage-Report.pdf [12 March 2015].

Amir, O. and Levav, J., 2008. Choice construction versus preference construction: The instability of preferences learned in context. *Journal of Marketing Research*, 45(2), pp.145-158.

Anderson, A.R., 1984. Life status change and changes in consumer preferences and satisfaction. *Journal of consumer research*, 11(3), pp.784-794.

Angelus, A. and Porteus, E.L., 2002. Simultaneous capacity and production management of short life cycle, product to stock goods under stochastic demand. *Management Science*, 48(3), pp.399-413.

Apple UK Website, 2014. Available from: http://www.apple.com/uk/iphone/compare-iphones/ [Last access 3 May, 2014].

Argos website, 2015. Available from: http://www.argos.co.uk/static/Home.htm?sRefURL=https%3A//www.google.co.uk/ [Last access 3 March 2015].

Arguea, N. M., Hsiao, C. and Taylor, G. A., 1994. Estimating consumer preferences using market data-an application to us automobile demand. *Journal of applied economic*, 9, pp.1-18.

Armstrong, J.S., 2006. How to make better forecasts and decisions: Avoid face-to-face meetings. *Foresight -The International Journal of Applied Forecasting*, 5, pp.3-8.

Assimakopoulos, V., and Nikolopoulos, K., 2000. The theta model: a decomposition approach to forecasting. *International Journal of Forecasting*, 16(4), pp. 521-530.

Baltas, G. and Doyle, P., 2001. Random utility models in marketing research: a survey. *Journal of Business Research*, 51, pp.115-125.

Bairdtelevision website, 2015. Available from: http://www.bairdtelevision.com/1932.html [Last accessed 12 March 2015].

Basmann, R.L., 1956. A theory of demand with variable consumer preferences. *Econometricia*, 24(1), pp.47-58.

Bass, F.M., 1969. A New Product Growth Model for Consumer Durables. *Management Science,* 15, pp. 215-227.

Bass, F.M., Gordon, K., Ferguson, T.L. and Githens, M.L., (2001). DIRECTV: Forecasting diffusion of a new technology prior to product launch. Interfaces, 31, S82–S93.

Baum, J. and Dennis, K., 1961. The estimation of the expected brand share of a new product. VIIth ESOMAR/WAPOR Congress.

Bettman, J.R., 1979. An Information Processing Theory of Consumer Research. Reading, MA: Addison-Wesley.

Bettman, J.R., Luce, M.F. and Payne, J.W., 1998. Constructive Consumer Choice Processes. *Journal of Consumer Research*, 25, pp.187–217.

Bijmolt, T. and Wedel, M., 1995. The effects of alternative methods of collecting similarity data for multidimensional scaling Internet, *Journal of Research in Marketing*, 12, pp.363-371.

Bilir, L.K., 2014. Patent laws, product life-cycle lengths, and multinational activity. *The American Economic Review*, 104(7), pp.1979-2013.

Briley, D.A., Morris, M.W. and Simonson, I., 2000. Reasons as carriers of culture: Dynamic versus dispositional models of cultural influence on decision making, *Journal of consumer research,* 27(2), pp.157-178.

Bryman, A., 2008. Social Research Methods, 3rd Edition. Oxford, England: Oxford University Press, pp.604-606.

Bryman, A., 2011. Social Research Methods, 4th Edition. Oxford, England: Oxford University Press, pp.15-630.

Bryman, A. and Bell, E., 2011. Business Research Methods, 3rd Edition. Oxford, England: Oxford University Press, pp.4-30.

Calfee, J., Winston, C. and Stempski, R., 2001. Econometric issues in estimating consumer preferences from stated preference data: a case study of the value of automobile travel time. *Review of Economics and Statistics*, 83(4), pp.699-707.

Chen, Y.C., Duann, L.S. and Hu, W.P., 2005. The estimation of discrete choice models with large choice set. *Journal of the Eastern Asia Society for Transportation Studies*, 6, pp.1724-1739.

Chen, C. and Watanabe, C., 2006. Diffusion, substitution and competition dynamism inside the ICT market: The case of Japan. *Technological Forecasting and Social Change,* 73, pp. 731-759.

Chen, Y.F. and Katz, J.E., 2009. Extending family to school life: College students' use of the mobile phone. *International Journal of Human-Computer Studies*, 67(2), pp.179-191.

Chintagunta, P.D., Jain, D.C. and Vilcassim, N.J. 1991. Investigating Heterogeneity in Brand Preferences in logit models for panel data. *Journal of Marketing Research,* pp.417-428.

Chiu, H.C., Hsieh, Y.C., Lic, Y.C. and Lee, M., 2005. Relationship marketing and consumer switching behaviour. *Journal of Business Research*, 58, pp.1681– 1689.

Churchman, C.W., 1961. Prediction and optimal decisions: philosophical issues in a science of values. Englewood Cliffs, NJ: Prentice-Hall.

Chu, W.L., Wu, F.S., Kao, K.S. and Yen, D.C., 2009. Diffusion of mobile telephony: An empirical study in Taiwan. *Telecommunication Policy,* 33, pp. 509-520.

Coupey, E., Irwin, J.R. and Payne, J.W., 1998. Product category familiarity and preference construction. *Journal of Consumer Research*, 24.

Costley, C.L. and Brucks, M., 1992. Selective Recall and Information Use in Consumer Preferences. *Journal of Consumer Research*, 18(4), pp.464-474.

Crosbie, T., 2008. Household Energy consumption and consumer electronics: the case of television. *Energy Policy*, 36, pp. 2119-2199.

Cox, W.E., 1967. Product Life Cycles as Marketing Models. *The Journal of Business,* 40(4), pp.375-384.

Cox, W.M. and ALM, R., 1998. The right stuff; America's move to mass customization. Federal Reserve Bank of Dallas, Annual Report, pp.3–26.

Curwin, J. and Slater, R., 2007. Quantitative Methods for Business Decisions, Sixth edition. South Western.

Currys website, 2015. Available from: http://www.currys.co.uk/gbuk/index.html [Last access 3 March, 2015].

Davis, S., 1989. From future perfect: Mass customizing, Planning Review. 17(2), pp.16-21.

Day, G.S., 1981. The Product Life Cycle: Analysis and Applications Issues. *Journal of Marketing*, 45(4), pp. 60-66.

Decker, R. and Gnibba-Yakawa, K., 2010. Sales Forecasting in High-Technology Markets: A Utility-Based Approach. *Journal of Product Innovation Management*, 27, pp.115-29.

Dhar, R., 1997. Consumer preference for a no-choice option. *Journal of Consumer Research*, pp. 215-231.

Eager, F. and Eager, F., 2011. Where have all the flowers gone? Forecasting green trends in the automobile industry with a choice-based conjoint adoption model. *Technological Forecasting and Social Change*, 78, pp. 51–62.

Elrod, T., 1988. Inferring a product market map from panel data. *Marketing Science*, 7(1), pp.21-40.

Erdem, T., 1996. A dynamics analysis of market structure based on panel data. *Marketing Science*, 15(4), pp.359-378.

Erdem, T. and Keane, M.P., 1996. Decision making under uncertainty: Capturing dynamic brand choice process in turbulent consumer goods market. *Marketing Science*, 15(1), pp.1-20.

Euro Monitor, 2014. Available from: http://www.euromonitor.com/computers-and-peripherals [Last accessed 12 March 2015].

Everret, R., 1962. The diffusion of innovations. The Free Press, New York.

Fader, P.S. and Lattin, J.M., 1993. Accounting for heterogeneity and non-stationary in a cross-sectional model of consumer purchase behaviour. *Marketing Science,* 12(3), pp.304-317.

Fader, P.S., Hardie, B.G.S. and Zeithammer, R., 2003. Forecasting New Product Trial in a Controlled Test Market Environment. *Journal of Forecasting,* 22, pp. 391–410.

Feilzer, M.Y., 2010. Doing mixed methods research pragmatically: Implications for the rediscovery of pragmatism as a research paradigm. *Journal of Mixed Methods Research*, 4(1), pp.6-16.

Field, A., 2013. Discovering Statistics Using IBM SPSS Statistics, 4th Edition. London, UK: SAGE publication Ltd.

Forbes, A., 2013. Mobile Telephony, first the revolution, now the evolution. CMI annual dinner and joint meeting with the IET presentation, Bath Spa Hotel, 17th January 2013.

Fourt, L.A and Woodlock, J.W., 1960. Early prediction of market success for new grocery products. *Journal of Marketing*, 25, pp. 31–38.

Friedman, J., Gerlowski, D. and Silberman, J., 1992. What attracts foreign multinational corporations? Evidence from branch plant location in the United States. *Journal of Regional Science*, 32, pp.403-418.

Gallo, A., 1992. Record number of new products in 1991. *Food Review*, July-September, pp.19.

Gardner, D., 1987. The product life cycle: a critical look at the literature. *Review of Marketing*, pp.162-94.

Gartner website, 2014. Available from: http://www.gartner.com/newsroom/id/2647517 [Last accessed 18 October 2014].

Goodwin, P., Dyussekeneva, K. and Meeran, S., 2013. The use of analogies in forecasting the annual sales of new electronics products. *IMA Journal of Management Mathematics*, 24 (4), pp.407-422.

Goodwin, P., Dyussekeneva, K. and Meeran, S., 2014. The challenges of pre-launch forecasting of adoption time series for new durable products. *International Journal of Forecasting,* 30(4), pp.1082-1097.

Golder, P.N. and Tellis, G.J., 2004. Growing, Growing, Gone: Cascades, Diffusion, and Turning Points in the Product Life Cycle. *Marketing Science,* 23 (2), pp.207-218.

Gowrisankaran, G. and Rysman, M., 2012. Dynamics of consumer demand for new durable goods. *National Bureau of Economic Research*, Working Paper No. 14737.

Graefe, A. and Armstrong, S.J., 2011. Comparing Face-to-Face Meetings, Nominal Groups, Delphi and Prediction Markets on an Estimation Task. *International Journal of Forecasting*, 27(1), pp. 183-195.

Green, P.E., Krieger, A.M. and Wind Y.J., 2001. Thirty Years of Conjoint Analysis: Reflections and Prospects, *Interfaces*, 31(3), pp.S56-S73.

Greene, W.H., 2009. Discrete choice modelling; Mills T. and Patterson K. (eds), *Palgrave Handbook of Econometrics*: Volume 2: *Applied Econometrics.* London: Palgrave.

Grigolon, B.A., Borgers, A.W.J., Kemperman, A.D.A.M. and Timmermans, H.J.P., 2014. Vacation length choice: A dynamic mixed multinomial logit model. *Tourism Management*, 41, pp. 158-167.

Guadagni, P.M. and Little J.D.C., 1983. A logit model of brand choice calibrated on scanner data. *Marketing science,* 2(3), pp.203-238.

Gupta, S., Jain, C. D. and Sawhney, M. S. 1999, “Modeling The`Evolution of Markets with Indirect Network Externalities: An Application to Digital Television”, *Marketing Science*, 18, pp.396-416.

Gupta, S. and Jain, K., 2012. Diffusion of mobile telephony in India: An empirical study, *Technological Forecasting and Social Change*, 79, pp. 709-715.

Gustafsson, A., Herrmann, A. and Huber, F., 2007. *Conjoint Measurement: methods and applications*. 4th ed. Berlin: Springer.

Halme, M. and Kallio, M., 2011. Estimation methods for choice-based conjoint analysis of consumer preferences. *European Journal of Operational Research*, 214, pp. 160–167.

Hansen, E., 1987. Industrial location choice in Sao Paulo, Brazil: a nested logit model. *Regional Science and Urban Economics*, 17, pp.89-108.

Hauser, J.R. and Rao, V.R., 2004. Conjoint Analysis, Related Modelling, and Applications cited by Qian, L. 2012. Essays on Forecasting Demand and Preferences for Cars in emerging Markets: The Case of china. Thesis (PhD), Lancaster University.

History learning website, 2014. Available from: http://www.historylearningsite.co.uk/personal_computer.htm [Last accessed 21 October 2014].

Hledik, E., 2012. Product attributes and preferences: A study of product attribute preferences of consumers and preference stability. Doctoral theses: University of Szeged Faculty of Economics and Business Administration.

Hoch, S.J. and Loewenstein, G.F., 1991. Time-inconsistent preferences and consumer self-control. *Journal of Consumer Research*, 17(4), pp. 492-507.

Hoeffler, S. and Ariely, D., 1999. Constructing stable preferences: a look into dimensions of experience and their impact on preference stability. *Journal of Consumer Psychology*, 8(2), pp.113-139.

Hoffman, P.J., 1960. The paramoraphic representation of clinical judgments. Psychological Bulletin, 47, pp.167-231.

Hoffman, P.J., 1968. Cue-consistancy and configurality in human judgment, Informal representation of human judgment, pp53-90, New York: Wiley.

Hofmann, P., and Reiner, G., 2006. Drivers for improving supply chain performance – an empirical study. *International Journal of Integrated Supply Management*, 2(3), pp.214–230.

Holbrook, M.B., 1993. Nostalgia and consumption preferences: Emerging patterns of consumer tastes. *Journal of consumer research*, 20(2), pp. 245-256.

Hu, W., Veeman, M.M. and Adamowicz, W.L., 2005. Labelling Genetically Modified Food: Heterogeneous Consumer Preferences and Value of Information. *Canadian Journal of Agricultural Economics*, 53, pp. 83-102.

Hyndman, R.J. and Athanasopoulos, G., 2014. Forecasting: principle and practice, print edition. Published by Otexts.com.

Ishii, K., Internet use via mobile phone in Japan. *Telecommunications Policy*,28(1), pp.43-58.

Ivanov, A., 2009. Using Prediction Markets to Harness Collective Wisdom for Forecasting. *Journal of Business Forecasting*, Fall, pp. 9-14.

Jahanbin, S., Goodwin, P. and Meeran, S., 2013. New Product Sales Forecasting in the Mobile Phone Industry: an evaluation of current methods. *Proceeding 33rd International Symposium of Forecasting*, 23-26 June Seoul, Korea.

Jain, D.C., Vilcassim, N.J. and Chintagunta, P.K., 1994. A random coefficients logit brand choice model applied to panel data. *Journal of Business and Economic Statistic*, 12(3), pp.317-328.

James, S. and Burton, M., 2003. Consumer preferences for GM food and other attributes of the food system. *The Australian Journal of Agricultural and Resource Economics*, 47(4), pp.501-518.

Jensen, W., 1982. Grocery product exhibit different life cycle curve. *Marketing News*, 6 August, pp.6.

Jin, A. and Koh, A., 1999. Differences between South Korean male and female consumers in the clothing brand loyalty formation process: model testing. *Clothing and Textiles Research Journal*, 17(3), pp.117-127.

Johnson, R.B., Onwuegbuzie, A.J., Turner, L.A., 2007. Towards a definition of mixed methods research. *Journal of Mixed Methods Research*, 1(2), pp.112-133.

Jun, D.B. and Park, Y.S., 1999. A choice based diffusion model for multiple generations of products. *Technological Forecasting and Social Change*, 61, pp. 45– 58.

Jun, D.B., Kim, S.K., Park, Y.S., Park, M.H. and Wilson, A.R. 2002. Forecasting telecommunication service subscribers in substitutive and competitive environments. *International Journal of Forecasting*, 18, pp.561–581.

Kahn, B.E., 1995. Consumer variety-seeking among goods and services. *Journal of Retailing and Consumer Services*, 2(3), pp.139-148.

Kahn, K.B., 2002. An Explanatory Investigation of New Product Forecasting Practices. *Journal of Product Innovation Management*, 19, pp. 133-143.

Kahn, K.B., 2006. *New Product Forecasting: An Applied Approach*. Armonk, NY: ME Sharpe.

Kamakura, W.A., Kim, B.D. and Lee, J., 1996. Modelling preferences and structural heterogeneity in consumer choice. *Marketing Science*, 15(2), pp.152-172.

Keane, M.P., 1997. Modelling Heterogeneity and State Dependence in Consumer Choice Behaviour. *Journal of Business & Economic Statistics*, 15(3), pp.310-327.

Keane, M.P. and Wolpin, K.I., 2009. Empirical applications of discrete choice dynamic programming models. *Review of Economic Dynamics*, 12, pp.1–22.

Kim, S.H., and V. Srinivasan. 2009. A Conjoint-Hazard Model of the Timing of Buyers' Upgrading to Improved Versions of High-Technology Products. *Journal of Product Innovation Management*, 26, pp. 278-290.

Kotler, P., Wong, V., Saunders, J. and Armstrong, G. 2005. Principles of Marketing, 4th Edition. Harlow, England: Pearson Education Limited.

Kontzalis, P., 1992. Identification of Key Attributes, Gap Analysis and Simulation Techniques in Forecasting Market Potential of Ethical Pharmaceutical Products. *International Journal of Forecasting*, 8, pp.243-249.

Kuhfeld, W.F., 2010. Marketing Research Methods in SAS: Experimental Design, Choice, Conjoint, and Graphical Techniques. SAS Institute Inc.

Kumar, V. and Krishnan, T.V., 2002. Multinational diffusion models: An alternative framework. *Marketing Science*, 21, pp. 318– 330.

Kurawarwala, A.A. and Matsuo, H., 1996. Forecasting and Inventory Management of Short Life-Cycle Products. *Operation Research*, 44(1), pp.131–150.

Kurawarwala, A.A. and Matsuo, H., 1998. Product Growth Models for Medium-Term Forecasting of Short Life Cycle Products. *Technological Forecasting and Social Change*, 57, pp.169–196.

Kwak, Y.S. and Yoo, S.H., 2012. Ex-ante evaluation of the consumers' preference for the 4th generation mobile communications service. *Technological Forecasting and Social Change*, 79, pp. 1312–1318.

Lancaster, K.J., 1966. A new approach to consumer theory. *The Journal of Political Economy*, 74, pp.132-157.

Lapparent, D.M. and Cernicchiaro, G., 2012. How long to own and how much to use a car? A dynamic discrete choice model to explain holding duration and driven mileage. *Economic Modelling*, 29, pp. 1737–1744.

Larue, C. and Cohen, H.H., 1987. Factors Affecting Consumers' Perceptions of Product Warnings: An Examination of the Differences between Male and Female Consumers. Proceedings of the Human Factors and Ergonomics Society Annual Meeting September, 31, pp.610-614.

Lee, J., Cho, Y., Lee, J.D. and Lee, C.Y., 2006. Forecasting future demand for large-screen television sets using conjoint analysis with diffusion model. *Technological Forecasting and Social Change*, 73, pp. 362–376.

Lee, C.Y., Lee, J.D. and Kim, Y.B., 2008. Demand forecasting for new technology with a short history in a competitive environment: the case of the home networking market in South Korea. *Technological Forecasting and Social Change*, 75(1), pp.91-106.

Lee, J. and Cho, Y., 2009. Demand forecasting of diesel passenger car considering consumer preference and government regulation in South Korea. *Transportation Research Part A-Policy and Practice*, 43(4), pp.420-429.

Li, S., Madhok, A., Plaschka, G. and Verma, R., 2006. Supplier-Switching Inertia and Competitive Asymmetry: A Demand-Side Perspective. *Decision Sciences*, 37(4), pp. 547-576.

Liechty, J.C., Fong, D.K.H. and DeSarbo, W.S., 2005. Dynamic model incorporating individual heterogeneity: Utility evolution in conjoint analysis. *Marketing Science*, 24(2), pp. 285-293.

Louviere, J.J. and Woodworth, G., 1983. Design and Analysis of Simulated Consumer Choice or Allocation Experiments: An Approach Based on Aggregate Data. *Journal of Marketing Research*, 20(4), pp. 350-367.

Lynn, G.S., Schnaars, S.P. and Skov, R.B., 1999. Survey of new product forecasting practices in industrial high technology and low technology businesses. *Industrial Marketing Management*, 28, pp.565–571.

Mahajan, V., Muller, E., and Wind, Y. 2000, New product diffusion models; London. Kluwer Academic Publishers.

Malhotra, N.K. and Birks, D.F., 2007. Marketing Research: An Applied Approach, 3rd Edition. Prentice-Hall, London, England.

Manrai, A.K., 1995. Mathematical models of brand choice behaviour. European Journal of Operational Research, 82(1), pp.1–17.

March, J.G., 1978. Bounded Rationality, Ambiguity, and the Engineering of Choice. *The Bell Journal of Economics*, 9(2), pp. 587-608.

Maringe, F., 2006. University and course choice. *International Journal of Educational Management*, 20(6), pp.466 – 479.

Marketwatch Report, 2014. Global Consumer Electronics Market, available from: https://www.reportbuyer.com/product/2060275/global-consumer-electronics-market-2014-2018.html [Last accessed 12 March 2015].

Masini, S., 2004. The diffusion of mobile telephony in Italy and the UK: an empirical investigation. *Economics of Innovation and New Technology,* 13(3), April, pp.251-277.

McDade, S.R., Terence, A.O. and Pirsch, J.A., 2002. The organizational adoption of high technology products "for use": effects of size, preferences, and radicalness of impact. *Industrial Marketing Management*, 31, pp.441-456.

McDade, S.R., Terence, A.O. and Thomas, E., 2010. Forecasting organizational adoption of high-technology product innovations separated by impact: are traditional macro-level diffusion models appropriate? *Industrial Marketing Management*, 39, pp. 298-307.

McFadden, D., 1974. Conditional logit analysis of qualitative choice behaviour, cited by Zarembka, P. Edition, Frontiers in Econometrics, Academic Press, New York, pp.105–142.

McFadden, D., 1978. Modelling the choice of residential location. Cowels Foundation Discussion, No.477.

McFadden, D. and Train, K., 2000. Mixed MNL models of discrete response. *Journal of Applied Econometrics,*15, pp.447–470.

Meade, N. and Islam, T., 1995. Growth curve forecasting: An empirical comparison. *International Journal of Forecasting*, 11(2), pp.199– 215.

Meade, N. and Islam, T., 2006. Modelling and forecasting the diffusion of innovation – A 25-year review. *International Journal of Forecasting*, 22(3), pp.519–545.

Mela, C.F., Gupta, S. and Lehmann, D.R., 1997. The long-term impact of promotion and advertising on consumer brand choice. *Journal of Marketing research*, 34, pp.248-261.

Mellers, B.A., Weber, E.U., Ordonez, L.D. and Cooke, A.D.J., 1995. Utility invariance despite labile preferences in Decision making from perspective psychology, ed. Busemeyer J. R. et al. Psychology of learning and motivation series, 32, San Diego, CA: Academic Press.

Michalakelis, C., Varoutas, D. and Sphicopoulos, T., 2008. Diffusion models of mobile telephony in Greece. *Telecommunication Policy*, 32, pp.234-245.

Mobile Phone History, 2012, Available from: http://www.mobilephonehistory.co.uk/history/mobile_phone_history.php [Last accessed 1 Sep 2012].

Molina-Azorin, J.F., 2011. The Use and Added Value of Mixed Methods in Management Research. *Journal of Mixed Methods Research*, 5(1), pp.7–24.

Moreau, C.P., Lehman, D.R. and Markman, A.B., 2001. Entrenched Knowledge Structures and Consumer Responses to New Products. *Journal of Marketing Research*, 38(1), pp.14-29.

Morwitz, V. G., 2001. Methods for forecasting from intentions data, pp. 33-56 in: Principles of Forecasting: A Handbook for Researchers and Practitioners. Edited by Armstrong, J.S., Boston: Kluwer, pp.33-56.

Nagy, T.F., 2011. Essential Ethics for Psychologist. Washangton DC, United State: American Psychological Association.

Netzer, O. and Srinivasan, V., 2011. Adaptive Self-Explication of Multiattribute Preferences. *Journal of Marketing Research,* 48(1), pp.140-156.

Nikolopoulos, K., Goodwin, P., Patelis, A. and Assimakopoulos, V., (2007). Forecasting with cue information: A comparison of multiple regression with alternative forecasting approaches. *European Journal of Operational Research*, 180(1), pp. 354-368.

Orbach, Y. and Fruchter, G.E., 2011. Forecasting sales and product evolution: The case of the hybrid/electric car. *Technological Forecasting and Social Change,* 78, pp.1210-1226.

Ord, K. and Fildes, R., 2013. Principles of Business Forecasting, International Edition. South Western: Cengage Learning.

Orme, B., 2000. Hierarchical Bayes: why all the attention? Sawtooth Sofware Inc.

Orme, B., 2002. Formulating Attributes and Levels in Conjoint Analysis. Sawtooth Sofware Inc.

Orme, B., 2010. Getting Started with Conjoint Analysis: Strategies for Product Design and Pricing Research, 2nd Edition. Madison, Wis: Research Publisher.

Oumlil, A.B. and Erdem, O., 1997. Self-concept by gender: A focus on male-female consumers. *Journal of Marketing Theory and Practice,* 5(1), pp.7-14.

Ozan, E., Sireli, Y. and Kauffmann, P., 2007. A New Market Adoption Model for the Information Systems Industry. *Engineering Management Journal,* 19, pp.13-21.

Parker, P.M., 1994. Aggregate Diffusion Forecasting Models in Marketing: A Critical Review. *International Journal of Forecasting*, 10, pp.353-380.

Payne, J., Bettman, J. and Johnson, E., 1992. Behavioral decision research: A constructive processing perspective. *Annual Review Psychology*, 43, pp.87-131.

Pollak, R.A., 1978. Endogenous Taste in Demand and Welfare Analysis. *The American Economic Review*, 68(2), pp.374-379.

Petropoulos, F., Makridakis, S., Assimakopoulos, V., and Nikolopoulos, K., 2014. 'Horses for Courses' in demand forecasting. *European Journal of Operational Research*, 237(1), pp.152-163.

Premeaux, S.R., 2006. The attitudes of middle class male and female consumers regarding the effectiveness of celebrity endorsers. *Journal of Promotion Management*, 11(4), pp.33-48.

PWC, 2014. Technology Sector Scorecard Q2 2014, available from: http://www.pwc.com/en_GX/gx/technology/scorecard/assets/pwc-tech-scorecard-2014-q2.pdf [Last accessed 13 March 2014].

Qian, L., 2012. Essays on forecasting demand and preferences for cars in emerging markets: the case of china. Thesis (PhD), Lancaster University.

Rabiee, F., 2004. Focus-group interview and data analysis, *Proceedings of the Nutrition Society*, 63, pp.655-660.

Raghavarao, D., Willey, J.B. and Chitturi, P., 2011. Choice-based conjoint analysis; models and designs. Florida, United State: Chapman and Hall, Taylor and Francis Groups.

Reiner, G., Natter, M. and Drechsler, W., 2009. Life cycle profit – reducing supply risks by integrated demand management. *Technology Analysis & Strategic Management*, 21(5), pp. 653–664.

Rice, R.E. and Katz, J.E., 2003. Comparing internet and mobile phone usage: digital divides of usage, adoption, and dropouts. *Telecommunications Policy,* 27(8-9), pp.597–623.

Rink, D. and Swan, J., 1979. Product life cycle research: a literature review. Journal of Business Research, 7(3), pp.219-44.

Roberts, J.H., Nelson, C.J. and Morrison, P.D., 2005. A prelaunch diffusion model for evaluating market defence strategies. *Marketing Science*, 24(1), pp.150-164.

Robertson, A., Soopramanien, D. and Fildes, R., 2007. Segmental new-product diffusion of residential broadband services. *Telecommunications Policy,* 31(5), pp.265-275.

Routers, 2012, available from: http://www.reuters.com/article/2012/03/15/corporate-ethics-idUSL2E8ED84M20120315 [Last accessed 3 May 2012].

Rowe, G. and Wright, G., 1999. The Delphi technique as a forecasting tool: Issues and analysis. *International Journal of Forecasting*, 15, pp.353-375.

Saunders, M., Lewis, P. and Thornhill, A., 2007. Research Methods for Business Students, 4th Edition. Harlow, Pearson Education Ltd.

Sawtooth Software, 2013. The CBC System for Choice-Based Conjoint Analysis. Technical Paper Series, Sawtooth Software Inc.

Scholz, S.W., Meissner, M. and Decker, R., 2010. Measuring Consumer Preferences for Complex Products: A Compositional Approach Based on Paired Comparisons. *Journal of Marketing Research*, pp.685–698.

Sekaran, U., 2003. Research Methods for Business: A skill Building Approach, 4th Edition. New York, NY: John Wiley and Sons, Inc.

Severin, V., Louviere, J.J. and Finn, A., 2001. The stability of retail shopping choices over time and across countries. Journal of Retailing, 77(2), pp.185–202.

Simon, H., 1955. A behavioural model of rational choice. Quarterly Journal of Economics, 69 (February), pp.99–118.

Simon, H.A., 1957. Models of man: social and rational, Mathematical Essays on rational human behaviour in a social setting. New York: Wiley.

Slovic, P., 1995. The construction of preference. *American Psychology*, 50, pp.364-371.

Sodhi, M.S. and Lee, S., 2007. An analysis of sources of risk in consumer electronics industry. *Journal of Operational Research Society*, 58, pp.1430-1439.

Srinivasan, V. and Mason, C.H., 1986. Technical Note: Nonlinear Least squares Estimation of New Product Diffusion Models. *Marketing Science,* 5, pp.169-178.

Subrahmanyan, S., 2000. Using quantitative models for setting retail prices, *Journal of Product and Brand Management*, 9(5), pp. 304-315.

Sultan, S. and Henrichs, R.B., 2000. Consumer preferences for Internet services over time: initial explorations. *Journal of Consumer Marketing*, 17(5), pp.386 – 402.

The Communication Market, 2015. The Communication Market: Digital Progress Report-Digital TV, available from: http://stakeholders.ofcom.org.uk/binaries/research/tv-research/q22009.pdf [Last accessed 12 March 2015].

Thurstone, L. 1927, "A law of comparative judgement", *Psychological Review*, 34, pp 273–286.

Three website, 2013, access from: http://store.three.co.uk/Mobile_Phones [Last accessed 5 March 2015].

Teardown Report (2001), access from: http://www.teardown.com/allreports/Ericsson_R380_SmartPhone_Teardown_Analysis [Last accessed 3 May 2012].

Telecom Market Research Website, 2011, Available from: http://www.telecomsmarketresearch.com/resources/UK_Mobile_Operator_Subscriber_Statistics_2.shtml#Mobile_Operator_Market_Share_1Q10 [Last accessed 9 January 2011].

Teo, T.S.H., Lim, V.K.G. and Lai, R.Y.C., 1999. Intrinsic and extrinsic motivation in Internet usage. *Omega,* 27(1), pp.25-37.

Tibben-Lembke, R.S., 2002. Life after death: reverse logistic and product life cycle. *International Journal of Physical Distribution and Logistics Managements*, 32(3), pp.233-44.

Train, K.E., 2009. *Discrete Choice Methods with Simulation*. 2nd Edition, New York: Cambridge University Press.

Trappey, C.V. and Wu, H.Y., 2008. An evaluation of the time-varying extended logistic, simple logistic, and Gompertz models for forecasting short product lifecycles. *Advanced Engineering Informatics,* 22(4), pp.421-430.

Turk, T. and Trkman, P., 2012. Bass model estimates for broadband diffusion in European countries. *Technological Forecasting and Social Change,* 79, pp. 85-96.

Tversky, A. and Kahneman, D., 1981. The framing of decisions and the psychology of choice. *Science Magazine*, 211(4481), pp.453-458.

Van Ittersum, K. and Feinberg, F.M., 2010. Cumulative timed intent: a new predictive tool for technology adoption. *Journal of Marketing Research*, 47, pp.808–822.

Van de Ven, A.H. and Delbecq, A.L., 1974. The effectiveness of nominal, Delphi, and interacting group decision making processes. *Academy of Management Journal*, 17, pp. 605-621.

Veg, A. 2007. Simulating changing consumer preferences: A dynamic conjoint model. *Journal of Business Research*, 60, pp.904-911.

Victorino, L., Verma, R., Plaschka, G. and Dev, C., 2005. Service innovation and customer choices in the hospitality industry. *Managing Service Quality*, 15 (6), pp. 555-576.

Vinety, R., Lancaster, E. and Louviere, J., 2002. Discrete choice experiments to measure consumer preferences for health and healthcare. *Expert Review: Pharmacoeconomics Outcomes Research*, 2(4), pp.89-96.

Wind, Y., Mahajan, V. and Cardozo, R.N., 1981. *New Product Forecasting***.** Lexington, Mass.: Lexington Books.

Woodward, D., 1992. Location determinants of Japanese manufacturing start-ups in the United States. *Southern Economic Journal*, 58, pp.690-708.

Wu F. S. and Chu W. L. 2010, "Diffusion models of mobile telephony", *Journal of Business Research*, 63, pp.497-501.

Yang, S. and Allenby, G.M., 2003. Interdependent Consumer Preferences. *Journal of Marketing Research*, 40(3), pp. 282-294.

Yu, J. and Cooper, H. 1983. A Quantitative Review of Research Design Effects on Response Rates to Questionnaires. *Journal of Marketing Research*, 20(1), pp.36-44.

Yuan, Y., Raubal, M. and Liu, Y., 2012. Correlating mobile phone usage and travel behaviour– A case study of Harbin, China. Computers, Environment and Urban Systems, 36(2), pp.118-130.

9. Appendices

9.1. Appendix 1 (Trial study 1)

9.1.1. Features and Levels

The potential features and levels of a mobile phone were taken from the desktop research of a service provider website (3 website, 2012). Some of the most influential features were identified by the researcher, based on his judgment for achieving a good balance between the need to avoid an overly complex model and accurate modelling of consumer attitudes.

Price (High, Medium, Low)

Internet (Yes, No)

Battery Length (Long, Medium, Short)

Keyboard (Finger touch, Complete keypad, Numerical keypad, Combination F&K)

Camera Resolution (High, Medium, Low)

Brand (Apple, Samsung, HTC, LG, Nokia, BB, Sony, others)

Application (Apple store, Android store, other store, no app store)

9.1.2. RUM

Having acquired the features and levels, the below RUM equation can be written:

RUM=Price *(High, Medium, Low)* + ***Internet*** *(Yes, No)* + ***Battery Length*** *(Long, Medium, Short)* + ***Keyboard*** *(Finger touch, Complete keypad, Numerical Keypad, Combination F&K)* + ***Camera Resolution*** *(High, Medium, Low)* + ***Brand*** *(Apple, Samsung, HTC, LG, Nokia, BB, Sony, others)* + ***Application Store*** *(Apple store, Android store, other store, no app store)*

9.1.3. Orthogonal Design

As pointed out in section 6.4 part C, the number of possible representative alternatives for the mentioned features and levels is 3*2*3*4*3*8*4=6972, which is way too many alternatives for designing an experiment and hence fractional factorial design (orthogonal design) was used.

It is a feasible solution to select a subset of the complete design based on different sampling methods. IBM SPSS 20 was employed to generate the fractional factorial design (orthogonal design), which resulted in 32 alternatives profile (see Appendix 4).

9.1.4. Creating Dummy Variables

Based on the RUM equation, dummy variables were created for various products and features. The regression model below was written based on the created dummy variables for conduct the Rating CA.

Rating = B_0 + B_1price_high + B_2price_med + B_3internet_yes + B_4 battery_long+ B_5 + B_6battery_med + B_7key_ft + B_8key_kc + B_9cam_high + B_{10}cam_med + B_{11}apple + B_{12}samsung + B_{13}LG + B_{14}Sony + B_{15}HTC + B_{16}BB + B_{17}Nokia+ B_{18}App_apple + B_{19} App_and + B_{20} App_no

9.1.5. Data Collection and Regression Analysis

The alternatives (profiles) were shown on a printed paper based survey and the participant rated/scored each of them out of 100 (see Appendix 5). Once the data collection was completed, they were entered into SPSS and subsequently, the linear regression was run to find the coefficients of each dummy variable. The table below presents the coefficients for each part-worth.

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	32.548	7.186		4.529	.001
	Price_high	6.496	3.264	.195	1.990	.072
	Price_Medium	3.098	4.201	.077	.737	.476
	Internet_yes	22.871	2.752	.686	8.311	.000
	Batttery_long	6.054	3.601	.182	1.681	.121
	Battery_medium	-2.233	4.132	-.060	-.540	.600
	Key_FT	14.622	4.170	.380	3.506	.005
	Key_kc	4.697	4.002	.131	1.174	.265
	Key_nk	-2.405	4.346	-.060	-.553	.591
	Cam_high	3.866	3.419	.116	1.131	.282
	Cam_med	-.641	3.877	-.017	-.165	.872
	Apple	-1.250	5.392	-.025	-.232	.821
	Samsung	-22.424	5.484	-.445	-4.089	.002
	LG	-14.435	5.630	-.287	-2.564	.026
	Sony	-21.942	5.490	-.436	-3.996	.002
	HTC	-14.226	5.494	-.282	-2.589	.025

BB	-5.160	5.517	-.102	-.935	.370
Nokia	-16.250	5.392	-.323	-3.014	.012
App_apple	1.110	3.743	.029	.297	.772
App_and	3.627	3.816	.094	.950	.362
App_no	4.361	4.659	.102	.936	.369

a. Dependent Variable: Rating

9.1.5.1. Part-worth

The underlined levels of utilities are the highest utility possible and therefore the RUM can be written as follows.

Price: High= 6.49, Medium=3.1, Low=0

Internet: Yes=22.87, No=0

Battery Length: Long=8.28, Medium=0, Short=2.23

Keyboard: Finger touch=16.6 , Complete keypad=7.1, Numerical keypad=0, Combination F&K=2.4

Camera Resolution: High=4.5, Medium=0, Low=0.64

Brand: Apple=21.17, Samsung=0, HTC=8.19, LG=7.99, Nokia=6.17, BB=17.26, Sony=0.48, others=22.42

Application: App_apple=1.11, App_android=3.63, No App=4.361, Other Application=0

Total weight=6.5+22.9+8.3+16.6+4.5+22.4+4.4=85.6

9.1.5.2. Scaling of All Parts-worth

By multiplying each part worth by 1.17, the scaled part-worth out of 100 is obtained, as follows:

Price: High= 7.6, Medium=3.6, Low=0

Internet: Yes=26.8, No=0

Battery Length: Long=9.7, Medium=0, Short=2.6

Keyboard: Finger touch=19.4 , Complete keypad=8.3, Numerical keypad=0, Combination F&K=2.8

Camera Resolution: High=5.3, Medium=0, Low=0.7

Brand: Apple=24.8, Samsung=0, HTC=9.6, LG=9.4, Nokia=7.2, BB=20.2, Sony=0.6, others=26.2

Application: App_apple=1.3, App_android=4.2, No App=5.1, Other Application=0

Having the above parts-worth, now we can write any new possible utilities. For example:

I. $\mathbf{RUM}_{\textbf{apple iphone 4}}$ =Price(high)+Internet(yes)+Battery length(short)+Keyboard(finger touch)+Camera resolution(high)+Brand(apple)+Application(apple store)
RUM**$_{apple\ iphone\ 4}$* ***=7.6+26.8+5.3+19.4+0+24.8+1.3=**85.2**

II. $\mathbf{RUM}_{\textbf{Nokia 100}}$=Price(low)+Internet(yes)+Battery length(long)+Keyboard(numerical)+Camera(low)+Brand(Nokia)+Application(othe r application)
RUM**$_{Nokia\ 100}$* ***= 0+26.8+9.7+0+0.7+7.2+0=**44.4**

9.2. Appendix 2 (Trial study 2)

9.2.1. Features and levels

As with trial study 1, the features and levels of a mobile phone were taken from the desktop research of a service provider website (3 website, 2012). In order to address some of the issues raised by the first trial study, this time the researcher simplified the features and levels by having fewer of them; placing emphasis on the most influential ones as follows.

Price (High, Medium, Low)

Internet & Application (Yes, No)

Battery Length (Long, Medium, Short)

Keyboard (Finger touch, Complete keypad, Numerical keypad, Combination F&K)

Camera Resolution (High, Medium, Low, No camera)

Brand (Apple, Samsung, HTC, LG, Nokia, BB, Sony, others)

9.2.2. RUM

Having acquired these features and levels, the RUM equation can be written as:

RUM=Price *(High, Medium, Low)* + ***Internet & Application*** *(Yes, No)* + ***Battery Length*** *(Long, Medium, Short)* + ***Keyboard*** *(Finger touch, Complete keypad, Numerical Keypad, Combination F&K)* + ***Camera Resolution*** *(High, Medium, Low, No camera)* + ***Brand*** *(Apple, Samsung, HTC, LG, Nokia, BB, Sony, others)*

9.2.3. Orthogonal design

The number of possible representative alternatives for the mentioned features and levels is 3*2*3*4*4*8=2304 so as stated earlier fractional factorial design (orthogonal design) was used. Once again, IBM SPSS 20 was employed to generate the fractional factorial design (orthogonal design) which elicited 32 profiles (appendix 4).

9.2.4. Data collection

The alternatives (profiles) were shown to the eight participants on a printed paper based survey (appendix 5) and they were asked to rate/score each of them out of 100. Once this data collection was completed, it was entered into SPSS and subsequently, the linear regressions were run to find the coefficients for each dummy variable. The table on the next page contains the coefficients for each part-worth.

9.2.5. Data analysis

The results from both methods are analysed here; first, the data analysis using SPSS syntax analysis and second, that using dummy variables (same method as trial study 1).

9.2.5.1. SPSS syntax analysis

Before, writing syntax for SPSS to analyse the data, the following few steps need to be carried out:

I. Determining the path to the dataset.
II. Determining which conjoint method to use in data collection "SEQUENCE, RANK, or SCORE", with score conjoint analysis being opted for.
III. Determining the type of factors present, which was "discrete" according to the SPSS manual explanations. However, this does give options for linear and quadratic relationships.

Finally, the syntax is written as:

```
CONJOINT PLAN='C:\Sim\Sim_CA_2.sav'
   /DATA='C:\Sim\Sim_Prtic_CA_2.sav'
   /SCORE=P1 TO P32
   /SUBJECT=ID
   /FACTORS=Brnd KEY I_A Batt Cam Price (DISCRETE)
   /PRINT=SUMMARYONLY.
```

The table below shows the part-worth utility outcome from the above syntax.

Utilities

		Utility Estimate	Std. Error
Price	Hi	-2.734	1.188
	Med	1.602	1.393
	Low	1.133	1.393
I_A	Yes	15.527	.891
	No	-15.527	.891
Batt	Lon	1.797	1.188
	Med	.469	1.393
	Shrt	-2.266	1.393
KEY	FT	5.176	1.544
	CK	1.582	1.544
	NK	-7.559	1.544
	CFK	.801	1.544
Cam	Hi	4.785	1.544
	Med	-.449	1.544

Brnd	Lo	1.348	1.544
	No	-5.684	1.544
	Apple	12.285	2.358
	Sony	-.840	2.358
	Samsung	-.527	2.358
	HTC	1.191	2.358
	BB	-3.652	2.358
	Nokia	.723	2.358
	LG	-.684	2.358
	Others	-8.496	2.358
(Constant)		42.480	.985

9.2.5.2. Dummy variables data Analysis

Prior to starting the data analysis, the dummy variables are created and in the regression below model the dummy variables have been written into the RUM.

Rating = B_0 + B_1price_high + B_2price_med + B_3I_A_yes + B_4 batt_long+ B_5 batt_med + B_6key_ft + B_7key_ck + B_8key_nk+ B_9cam_high + B_{10}cam_med + B_{11} cam_short + B_{12}Apple + B_{13} Sony + B_{14}Samsung + B_{15}HTC + B_{16}BB + B_{17} Nokia + B_{18}LG

The participants' ratings for each profile were used to run the regression, which provided the coefficients of the dummy variables.

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	12.441	4.084		3.046	.009
	Price_high	-3.867	2.183	-.107	-1.771	.100
	Price_med	.469	2.521	.011	.186	.855
	I_A_yes	31.055	1.782	.862	17.423	.000
	Batt_long	4.063	2.183	.113	1.861	.086
	Batt_med	2.734	2.521	.066	1.085	.298
	Key_FT	4.375	2.521	.105	1.736	.106
	Key_ck	.782	2.521	.019	.310	.761
	Key_nk	-8.359	2.521	-.201	-3.316	.006
	Cam_hi	10.469	2.521	.252	4.153	.001
	Cam_med	5.234	2.521	.126	2.077	.058
	Cam_low	7.031	2.521	.169	2.789	.015

apple	20.781	3.565	.382	5.829	.000
Samsung	7.656	3.565	.141	2.148	.051
HTC	7.969	3.565	.146	2.235	.044
LG	9.687	3.565	.178	2.718	.018
Nokia	4.844	3.565	.089	1.359	.197
BB	9.219	3.565	.169	2.586	.023
Sony	7.813	3.565	.143	2.192	.047

a. Dependent Variable: Average_rating

9.2.6. Results Comparison

After some data manipulation, the results from the SPSS syntax and the dummy variable regression are the same, as can be seen from this page and the previous tables. The underlined levels of utilities are the highest parts-worth possible. Therefore, we can write the RUM as.

Price: High= 0, <u>Medium=4.3</u>, Low=3.9

Internet: <u>Yes=31.1</u>, No=0

Battery Length: <u>Long=4.1</u>, Medium=2.7, Short=0

Keyboard: <u>Finger touch=12.8</u>, Complete keypad=9.2, Numerical keypad=0, Combination F&K=8.4

Camera Resolution: <u>High=10.5</u>, Medium=5.2, Low=7, No Camera=0

Brand: <u>Apple=20.8</u>, Samsung=7.7, HTC=8, LG=9.7, Nokia=4.8, BB=9.2, Sony=7.8, others=0

<u>Total Maximum Weight=4.3+31.1+4.1+12.8+10.5+20.8=83.6</u>

Scaling: Multiply all the parts-worth by (parts-worth*100/83.6) 1.2 to get a new scaled weight. For example, here is the scaled part-worth for RUM

Price: 4.3*1.2=5.2

Internet: 31.1*1.2=37.3

Battery Length: 4.1*1.2=4.9

Keyboard: 12.8*1.2=15.4

Camera Resolution: 10.5*1.2=12.6

Brand: 20.8*1.2=25

$RUM_{max}=U_{price}(5.2)+U_{Internet}(37.3)+U_{Battery\ Length}(4.9)+U_{Keyboard}(15.4)+U_{Camera\ Resolution}(12.6)+U_{Brand}(25)$

The SPSS syntax also gives the average importance of value out of 100.

Importance Values

Price	8.783
I_A	33.220
Batt	8.071
KEY	14.090
Cam	12.348
Brnd	23.489

Averaged Importance Score

9.2.7. Scaling All the Part-worth

By multiplying the each part worth to 1.196, the scaled part worth utility out of 100 is obtained, as follows:

Price: High= 0, Medium=5.2, Low=4.7

Internet: Yes=37.3, No=0

Battery Length: Long=4.9, Medium=3.2, Short=0

Keyboard: Finger touch=15.4, Complete keypad=11, Numerical keypad=0, Combination F&K=10

Camera Resolution: High=12.6, Medium=6.2, Low=8.4, No Camera=0

Brand: Apple=25, Samsung=9.2, HTC=9.6, LG=11.6, Nokia=5.8, BB=11, Sony=9.4, others=0

Having the above weights, any new possible random utility out of 100 can be written. For example:

I. **RUM**$_{\textbf{apple iphone 4}}$ =Price(high)+Internet(yes)+Battery length(short)+Keyboard(finger touch)+Camera resolution(high)+Brand(apple)+Application(apple store)
RUM**$_{\textbf{apple iphone 4}}$ =0+37.3+0+15.4+12.6+25=**90.3

II. **RUM**$_{\textbf{Nokia 100}}$=Price(low)+Internet(no)+Battery length(long)+Keyboard(numerical)+Camera(low)+Brand(Nokia)
RUM**$_{\textbf{Nokia 100}}$= 4.7+0+4.9+0+8.4+5.8=**23.8

9.3. Appendix 3 (Trial study 3)

9.3.1. Features and Levels

The Sawtooth demo used for this study does not allow users to have more than three features and there is a maximum of five participants. The features were defined as follows:

Price (High, Medium, Low)

Keyboard (Finger touch, Complete keypad, Numerical Keypad, Combination F&K)

Brand (Apple, Samsung, HTC, LG, Nokia, BB, Sony, others)

9.3.2. RUM

Having acquired the features and levels, the RUM below equation can be written as:

RUM=Price *(High, Medium, Low)* + ***Keyboard*** *(Finger touch, Complete keypad, Numerical Keypad, Combination F&K)* + ***Brand*** *(Apple, Samsung, HTC, LG, Nokia, BB, Sony, others)*

9.3.3. Orthogonal Design

The number of possible representative alternatives for the mentioned features and levels is 3*4*8=96, which is still too many for designing an experiment. Hence, random sampling algorithm by Sawtooth was used, which took 40 profiles out of 96.

9.3.4. Data Collection

The Sawtooth is automated software that uses an online platform for data collection. Five participants were asked to choose the most likely profile that they would buy in each set of alternatives. 40 profiles were presented comprising 10 sets of 4 choice possibilities+1 non choice option (Appendix 5).

9.3.5. Data Analysis

As can be seen in the table, Sawtooth generates automated outcomes by using a Multi-Nominal Logit (MNL) model. High standard errors were recorded due to the low number of participants.

Variable	Effect	Std Error	t Ratio
Price			
High	0.04237	2.65623	0.01595
Medium	-1.23933	2.78051	-0.44572
Low	1.19696	1.72335	0.69456
Keyboard			
Finger touch	-0.85713	2.89156	-0.29642
Complete keyboard	1.92288	2.95906	0.64983
Numerical Keyboard	-2.95662	3.26209	-0.90636
Both Finger touch and Complete	1.89087	3.34528	0.56523
Brand			
Apple	6.67337	3.79145	1.76011
Samsung	4.58458	3.55137	1.29093
HTC	-1.20479	4.17214	-0.28877
LG	1.59117	3.11191	0.51132
Nokia	-4.26449	4.63010	-0.92104
BlackBerry	1.46136	2.77109	0.52736
Sony	-3.42569	4.59884	-0.74490
Others	-5.41551	4.17517	-1.29708
NONE	-3.59671	4.04035	-0.89020

As stated earlier, the MNL probability model can be written as follows:

$$P_{in} = \frac{e^{V_{ni}}}{\sum_j e^{V_{nj}}}$$

V_{nj} is usually specified to be linear such that $V_{nj}=\beta X_{nj}$, where X_{nj} is a vector of the observed variable.

$$U_{nj} = V_{nj} + \varepsilon_{nj} = \beta X_{nj} + \varepsilon_{nj}$$

I. For example, the probability of purchasing an iphon4 can be written as:

$$P_{iphone4} = \frac{e^{V_{iphone4}}}{\sum_{40} e^{V_{all\ 40\ profiles}}}$$

The observed utility ($V_{iphone4}$) can be obtained through the following equations:

$\mathbf{V_{iphone4}}$= Price(high)+Keyboard(finger touch)+ Brand(apple)

$\mathbf{V_{iphone\ 4}}$ =0.042(1)-0.857(1)+6.673(1)=**<u>5.858</u>**

II. The probability of purchasing a Nokia 100 can be written as

$$P_{iphone4}= \frac{e^{V_{Nokia100}}}{\sum_{40} e^{V_{all\ 40\ profiles}}}$$

The observed utility ($V_{Nokia100}$) can be obtained through these equations

$\mathbf{V_{Nokia\ 100}}$=Price(low)+ Keyboard(numerical)+ Brand(Nokia)

$\mathbf{V_{Nokia\ 100}}$= 1.196(1)-2.96(1)-4.26(1)=-6.024

9.4. Appendix 4 (Orthogonal design trial studies)

9.4.1. Trial study 1 orthogonal design

Card List

	Card ID	Price	Internet	Battery	keyboard _	Camera_Resolution	Brand	Application_Store
1	1	Medium	No	Long	Finger touch	High	HTC	other_store
2	2	High	No	Short	Finger touch	High	Samsung	Andriod_store
3	3	High	Yes	Long	Combination F&K	High	Apple	No_application
4	4	Medium	Yes	Short	Combination F&K	Low	Sony	Andriod_store
5	5	High	No	Long	Complete keypad	Medium	LG	other_store
6	6	High	Yes	Medium	Numerical keypad	High	Others	Andriod_store
7	7	High	No	Long	Numerical keypad	High	Sony	Apple_store
8	8	High	No	Medium	Finger touch	Low	Nokia	Apple_store
9	9	High	Yes	Short	Complete keypad	High	Others	other_store
10	10	Low	No	Long	Finger touch	Low	Others	No_application
11	11	Low	Yes	Long	Numerical keypad	Medium	Samsung	No_application
12	12	Low	Yes	Medium	Finger touch	Medium	Sony	other_store
13	13	Medium	No	Medium	Complete keypad	Medium	Apple	Andriod_store
14	14	Low	Yes	Medium	Combination F&K	High	LG	Apple_store
15	15	High	No	Short	Combination F&K	Medium	Nokia	No_application
16	16	Medium	Yes	Long	Complete keypad	Low	Samsung	Apple_store
17	17	High	Yes	Short	Numerical keypad	Medium	HTC	Apple_store
18	18	Low	Yes	Long	Complete keypad	High	Nokia	Andriod_store
19	19	Low	No	Short	Complete keypad	High	BB	Apple_store
20	20	Low	No	Long	Combination F&K	High	HTC	Andriod_store
21	21	High	No	Medium	Combination F&K	High	Samsung	other_store
22	22	Medium	Yes	Long	Numerical keypad	High	Nokia	other_store
23	23	Low	No	Short	Numerical keypad	Low	Apple	other_store
24	24	Medium	No	Long	Combination F&K	Medium	Others	Apple_store
25	25	High	Yes	Long	Combination F&K	Low	BB	other_store
26	26	Medium	No	Medium	Numerical keypad	High	BB	No_application
27	27	Medium	Yes	Short	Finger touch	High	LG	No_application
28	28	High	Yes	Long	Finger touch	High	Apple	Apple_store
29	29	High	No	Long	Numerical keypad	Low	LG	Andriod_store
30	30	High	Yes	Long	Finger touch	Medium	BB	Andriod_store
31	31	High	Yes	Medium	Complete keypad	Low	HTC	No_application
32	32	High	No	Long	Complete keypad	High	Sony	No_application

9.4.2. Trial study 2 orthogonal design

Card List

	Card ID	Price	I_&_A	Batt	KEY	Cam	Brnd
1	1	Med	No	Lon	FT	No	Samsung
2	2	Hi	No	Shrt	FT	No	Sony
3	3	Hi	Yes	Lon	CFK	No	Apple
4	4	Med	Yes	Shrt	CFK	Lo	LG
5	5	Hi	No	Lon	CK	Med	HTC
6	6	Hi	Yes	Med	NK	Hi	Others
7	7	Hi	No	Lon	NK	No	LG
8	8	Hi	No	Med	FT	Lo	BB
9	9	Hi	Yes	Shrt	CK	No	Others
10	10	Low	No	Lon	FT	Lo	Others
11	11	Low	Yes	Lon	NK	Med	Sony
12	12	Low	Yes	Med	FT	Med	LG
13	13	Med	No	Med	CK	Med	Apple
14	14	Low	Yes	Med	CFK	No	HTC
15	15	Hi	No	Shrt	CFK	Med	BB
16	16	Med	Yes	Lon	CK	Lo	Sony
17	17	Hi	Yes	Shrt	NK	Med	Samsung
18	18	Low	Yes	Lon	CK	No	BB
19	19	Low	No	Shrt	CK	Hi	Nokia
20	20	Low	No	Lon	CFK	Hi	Samsung
21	21	Hi	No	Med	CFK	Hi	Sony
22	22	Med	Yes	Lon	NK	Hi	BB
23	23	Low	No	Shrt	NK	Lo	Apple
24	24	Med	No	Lon	CFK	Med	Others
25	25	Hi	Yes	Lon	CFK	Lo	Nokia
26	26	Med	No	Med	NK	No	Nokia
27	27	Med	Yes	Shrt	FT	Hi	HTC
28	28	Hi	Yes	Lon	FT	Hi	Apple
29	29	Hi	No	Lon	NK	Lo	HTC
30	30	Hi	Yes	Lon	FT	Med	Nokia
31	31	Hi	Yes	Med	CK	Lo	Samsung
32	32	Hi	No	Lon	CK	Hi	LG

9.5. Appendix 5 (Examples of Trial studies data collections)

9.5.1. Trial study 1 scoring survey

Profile Number 1

Card ID	Price	Internet	Battery	keyboard _	Camera_Resolution	Brand	Application_Store
1	Medium	No	Long	Finger touch	High	HTC	other_store

Profile Number 2

Card ID	Price	Internet	Battery	keyboard _	Camera_Resolution	Brand	Application_Store
2	High	No	Short	Finger touch	High	Samsung	Andriod_store

Profile Number 3

Card ID	Price	Internet	Battery	keyboard _	Camera_Resolution	Brand	Application_Store
3	High	Yes	Long	Combination F&K	High	Apple	No_application

Profile Number 4

Card ID	Price	Internet	Battery	keyboard _	Camera_Resolution	Brand	Application_Store
4	Medium	Yes	Short	Combination F&K	Low	Sony	Andriod_store

Profile Number 5

Card ID	Price	Internet	Battery	keyboard _	Camera_Resolution	Brand	Application_Store
5	High	No	Long	Complete keypad	Medium	LG	other_store

Profile Number 6

Card ID	Price	Internet	Battery	keyboard _	Camera_Resolution	Brand	Application_Store
6	High	Yes	Medium	Numerical keypad	High	Others	Andriod_store

Profile Number 7

Card ID	Price	Internet	Battery	keyboard _	Camera_Resolution	Brand	Application_Store
7	High	No	Long	Numerical keypad	High	Sony	Apple_store

Profile Number 8

Card ID	Price	Internet	Battery	keyboard _	Camera_Resolution	Brand	Application_Store
8	High	No	Medium	Finger touch	Low	Nokia	Apple_store

9.5.2. Trial study 2 scoring survey

Profile Number 1

Card ID	Price	I_&_A	Batt	KEY	Cam	Brnd
1	Med	No	Lon	FT	No	Samsung

Profile Number 2

Card ID	Price	I_&_A	Batt	KEY	Cam	Brnd
2	Hi	No	Shrt	FT	No	Sony

Profile Number 3

Card ID	Price	I_&_A	Batt	KEY	Cam	Brnd
3	Hi	Yes	Lon	CFK	No	Apple

Profile Number 4

Card ID	Price	I_&_A	Batt	KEY	Cam	Brnd
4	Med	Yes	Shrt	CFK	Lo	LG

Profile Number 5

Card ID	Price	I_&_A	Batt	KEY	Cam	Brnd
5	Hi	No	Lon	CK	Med	HTC

Profile Number 6

Card ID	Price	I_&_A	Batt	KEY	Cam	Brnd
6	Hi	Yes	Med	NK	Hi	Others

Profile Number 7

Card ID	Price	I_&_A	Batt	KEY	Cam	Brnd
7	Hi	No	Lon	NK	No	LG

Profile Number 8

Card ID	Price	I_&_A	Batt	KEY	Cam	Brnd
8	Hi	No	Med	FT	Lo	BB

Profile Number 9

Card ID	Price	I_&_A	Batt	KEY	Cam	Brnd
9	Hi	Yes	Shrt	CK	No	Others

Profile Number 10

Card ID	Price	I_&_A	Batt	KEY	Cam	Brnd
10	Low	No	Lon	FT	Lo	Others

9.5.3. Trial study 3 survey

Sawtooth Software - SSI Web Demo

Start

Please carefully chooce your best handset that is most likely you will be buying in following tasks.
Many thanks Semco

Sawtooth Software - SSI Web Demo

Mobile3_Random1

If these were your only options, which handset would you choose?
Choose by clicking one of the buttons below:

(1 of 10)

Price	Medium	Low	High	Low	NONE: I wouldn't choose any of these.
Keyboard	Both Finger touch and Complete	Both Finger touch and Complete	Finger touch	Complete keyboard	
Brand	BlackBerry	Samsung	Samsung	Others	
	Mobile3_Random1=1	Mobile3_Random1=2	Mobile3_Random1=3	Mobile3_Random1=4	Mobile3_Random1=5

0% 100%

Sawtooth Software - SSI Web Demo

Mobile3_Random3

If these were your only options, which handset would you choose?
Choose by clicking one of the buttons below:

(3 of 10)

Price	High	High	High	Low	NONE: I wouldn't choose any of these.
Keyboard	Complete keyboard	Complete keyboard	Complete keyboard	Complete keyboard	
Brand	LG	Apple	Sony	Others	
	Mobile3_Random3=1	Mobile3_Random3=2	Mobile3_Random3=3	Mobile3_Random3=4	Mobile3_Random3=5

0% 100%

9.6. Appendix 6 (Customers focus group questions)

I. <u>Mobile Phone Features</u>

1. What is your main concern when buying a mobile phone and why?
2. What are you looking for when buying a phone?
3. What is the most important criterion? if you want to name one
4. What features are most important?
5. Apart from brand, what other reasons are influence your choice of one phone over another? E.g. Apple over Blackberry or HTC over Samsung

II. <u>Changes of Features Over Time</u>

1. Did you have different criteria in the past when choosing your phone? what was that?
2. How have your criteria changed since your first, second phone?
3. What are the new criteria going to be in choosing your future phone?

9.7. Appendix 7 (Sales people focus group questions)

I. **<u>Mobile Phone Features</u>**

1. What kind of concerns did customers have when buying a mobile phone ? Why?
2. What are they looking for when buying a phone?
3. What is their most important criterion? (if you want to name one)
4. What features are most important?
5. Apart from brand, what other reasons are influence their choice of one phone over another? E.g. Apple over Blackberry or HTC over Samsung

II. **<u>Changes of Features Over Time</u>**

1. Did customers have different criteria in the past when choosing your phone? what was that?
2. How have their criteria changed?
3. What are the new criteria going to be in choosing their future phone in your opinion?

9.8. Appendix 8 (Focus group consent form)

Consent to Participate in Focus Group Study as Part of a Study on Sales Forecasting in Mobile Phone Industry

The purpose of the group discussion and the nature of the questions have been explained to me.

I consent to take part in a focus group about my opinions and reasons on topics related to Mobile phone, and the social reasons related to this. I also consent to be tape-recorded during this focus group discussion.

My participation is voluntary. I understand that I am free to leave the group at any time.

The research resulting from this study may be published at a future date, however none of my experiences or thoughts will be shared unless all identifying information is removed first. The information that I provide during the focus group will be grouped with answers from other people so that I cannot be identified.

__________________________________ ____________________

Your Name Date

____

Signature

____

Witness Signature

9.9. Appendix 9 (Orthogonal design main study)

9.9.1. Mobile phones

Mobile Phones Orthogonal Design

	Card ID	Brand	Price(£)	Camera Resolution (Mpix)	Memory Size(GB)	Display Size (inch)	Battery Life(Talking Hours)	Weight(g)
1	1	BlackBerry	‘150 to 299’	Normal '5 or Less'	High ‘More than 32’	Small ‘Less than 4’	Very High ‘More than 15’	Very Light ‘Less than 120’
2	2	Generic Brand	‘300 to 450’	Normal '5 or Less'	Small ‘Less than 16’	Medium ‘4 to 5’	High ’12 to 15’	Very Light ‘Less than 120’
3	3	HTC	‘More than 450’	No	High ‘More than 32’	Large ‘More than 5’	Medium ‘8 to 12’	Very Light ‘Less than 120’
4	4	Nokia	‘300 to 450’	No	Small ‘Less than 16’	Small ‘Less than 4’	Medium ‘8 to 12’	Light ‘120 to150’
5	5	Samsung	‘150 to 299’	No	Medium ’16 to 32’	Large ‘More than 5’	Short ‘Less than 8’	Medium ‘More than 150’
6	6	Apple	‘150 to 299’	Normal '5 or Less'	Medium ’16 to 32’	Medium ‘4 to 5’	Medium ‘8 to 12’	Light ‘120 to150’
7	7	Sony	‘More than 450’	Normal '5 or Less'	Small ‘Less than 16’	Large ‘More than 5’	Short ‘Less than 8’	Light ‘120 to150’
8	8	Apple	‘Less than 150’	Normal '5 or Less'	High ‘More than 32’	Small ‘Less than 4’	Medium ‘8 to 12’	Medium ‘More than 150’
9	9	Apple	‘300 to 450’	No	Small ‘Less than 16’	Large ‘More than 5’	Very High ‘More than 15’	Very Light ‘Less than 120’
10	10	Apple	‘Less than 150’	No	Small ‘Less than 16’	Small ‘Less than 4’	Short ‘Less than 8’	Very Light ‘Less than 120’

11	11	Samsung	‘More than 450’	Normal '5 or Less'	Small ‘Less than 16’	Small ‘Less than 4’	High ’12 to 15’	Very Light ‘Less than 120’
12	12	Apple	‘300 to 450’	High ' More than 5'	High ‘More than 32’	Large ‘More than 5’	High ’12 to 15’	Medium ‘More than 150’
13	13	HTC	‘300 to 450’	Normal '5 or Less'	Small ‘Less than 16’	Small ‘Less than 4’	Short ‘Less than 8’	Medium ‘More than 150’
14	14	Samsung	‘300 to 450’	No	High ‘More than 32’	Medium ‘4 to 5’	Very High ‘More than 15’	Light ‘120 to150’
15	15	Nokia	‘150 to 299’	No	Small ‘Less than 16’	Small ‘Less than 4’	High ’12 to 15’	Medium ‘More than 150’
16	16	Nokia	‘Less than 150’	Normal '5 or Less'	Medium ’16 to 32’	Large ‘More than 5’	Very High ‘More than 15’	Very Light ‘Less than 120’
17	17	Generic Brand	‘Less than 150’	No	High ‘More than 32’	Small ‘Less than 4’	Short ‘Less than 8’	Light ‘120 to150’
18	18	Nokia	‘More than 450’	High ' More than 5'	High ‘More than 32’	Medium ‘4 to 5’	Short ‘Less than 8’	Very Light ‘Less than 120’
19	19	Samsung	‘Less than 150’	High ' More than 5'	Small ‘Less than 16’	Small ‘Less than 4’	Medium ‘8 to 12’	Very Light ‘Less than 120’
20	20	Sony	‘300 to 450’	No	Medium ’16 to 32’	Small ‘Less than 4’	Medium ‘8 to 12’	Very Light ‘Less than 120’
21	21	Generic Brand	‘More than 450’	No	Medium ’16 to 32’	Small ‘Less than 4’	Very High ‘More than 15’	Medium ‘More than 150’
22	22	Generic Brand	‘150 to 299’	High ' More than 5'	Small ‘Less than 16’	Large ‘More than 5’	Medium ‘8 to 12’	Very Light ‘Less than 120’

23	23	Sony	‘Less than 150’	High ' More than 5'	Small ‘Less than 16’	Medium ‘4 to 5’	Very High ‘More than 15’	Medium ‘More than 150’
24	24	BlackBerry	‘More than 450’	No	Small ‘Less than 16’	Medium ‘4 to 5’	Medium ‘8 to 12’	Medium ‘More than 150’
25	25	HTC	‘150 to 299’	High ' More than 5'	Small ‘Less than 16’	Small ‘Less than 4’	Very High ‘More than 15’	Light ‘120 to150’
26	26	Sony	‘150 to 299’	No	High ‘More than 32’	Small ‘Less than 4’	High ’12 to 15’	Very Light ‘Less than 120’
27	27	BlackBerry	‘300 to 450’	High ' More than 5'	Medium ’16 to 32’	Small ‘Less than 4’	Short ‘Less than 8’	Very Light ‘Less than 120’
28	28	Apple	‘More than 450’	No	Small ‘Less than 16’	Small ‘Less than 4’	Very High ‘More than 15’	Very Light ‘Less than 120’
29	29	HTC	‘Less than 150’	No	Medium ’16 to 32’	Medium ‘4 to 5’	High ’12 to 15’	Very Light ‘Less than 120’
30	30	BlackBerry	‘Less than 150’	No	Small ‘Less than 16’	Large ‘More than 5’	High ’12 to 15’	Light ‘120 to150’
31	31	Apple	‘More than 450’	High ' More than 5'	Medium ’16 to 32’	Small ‘Less than 4’	High ’12 to 15’	Light ‘120 to150’
32	32	Apple	‘150 to 299’	No	Small ‘Less than 16’	Medium ‘4 to 5’	Short ‘Less than 8’	Very Light ‘Less than 120’

9.9.2. Laptops

Laptops Orthogonal Design

	Card ID	Brand	Price(£)	Display Size(inch)	Processor	Memory Size(GB)	Hard Drive	Weight
1	1	HP	‘400 to 699’	Small ‘Less than 12.9’	Normal	Small ‘Less than 4’	Very High ‘More than 1 TB’	Light ‘More than 2 Kg’
2	2	Samsung	‘Less than 400’	Large ’More than 16’	Normal	Small ‘Less than 4’	High ‘500 GB to 1 TB’	Light ‘More than 2 Kg’
3	3	Apple	‘More than 1000’	Small ‘Less than 12.9’	Normal	Small ‘Less than 4’	Medium ‘Less than 499GB’	Ultra-Light ‘Less than 2 Kg’
4	4	Toshiba	‘400 to 699’	Large ’More than 16’	Normal	High ‘More than 8’	High ‘500 GB to 1 TB’	Ultra-Light ‘Less than 2 Kg’
5	5	Sony	‘Less than 400’	Small ‘Less than 12.9’	Fast	Medium ‘4 to 8’	Very High ‘More than 1 TB’	Light ‘More than 2 Kg’
6	6	Generic Brand	‘Less than 400’	Medium ‘13 to 16’	High performance	Small ‘Less than 4’	High ‘500 GB to 1 TB’	Ultra-Light ‘Less than 2 Kg’
7	7	Toshiba	‘Less than 400’	Small ‘Less than 12.9’	High performance	Small ‘Less than 4’	Medium ‘Less than 499GB’	Light ‘More than 2 Kg’
8	8	Dell	‘More than 1000’	Medium ‘13 to 16’	Normal	High ‘More than 8’	Medium ‘Less than 499GB’	Light ‘More than 2 Kg’
9	9	Generic Brand	‘More than 1000’	Large ’More than 16’	Fast	Small ‘Less than 4’	Very High ‘More than 1 TB’	Ultra-Light ‘Less than 2 Kg’
10	10	Generic Brand	‘700 to 1000’	Small ‘Less than 12.9’	Normal	High ‘More than 8’	Medium ‘Less than 499GB’	Light ‘More than 2 Kg’
11	11	Samsung	‘700 to 1000’	Small ‘Less than 12.9’	High performance	Medium ‘4 to 8’	Medium ‘Less than 499GB’	Ultra-Light ‘Less than 2 Kg’

12	12	Toshiba	‘700 to 1000’	Medium ‘13 to 16’	Normal	Medium ‘4 to 8’	Very High ‘More than 1 TB’	Ultra-Light ‘Less than 2 Kg’
13	13	Apple	‘400 to 699’	Medium ‘13 to 16’	Fast	Medium ‘4 to 8’	High ‘500 GB to 1 TB’	Light ‘More than 2 Kg’
14	14	Sony	‘700 to 1000’	Medium ‘13 to 16’	Normal	Small ‘Less than 4’	Medium ‘Less than 499GB’	Ultra-Light ‘Less than 2 Kg’
15	15	Dell	‘Less than 400’	Large ’More than 16’	Normal	Medium ‘4 to 8’	Medium ‘Less than 499GB’	Light ‘More than 2 Kg’
16	16	Samsung	‘400 to 699’	Small ‘Less than 12.9’	Fast	High ‘More than 8’	Medium ‘Less than 499GB’	Ultra-Light ‘Less than 2 Kg’
17	17	HP	‘More than 1000’	Large ’More than 16’	High performance	Medium ‘4 to 8’	Medium ‘Less than 499GB’	Ultra-Light ‘Less than 2 Kg’
18	18	Dell	‘700 to 1000’	Small ‘Less than 12.9’	Fast	Small ‘Less than 4’	High ‘500 GB to 1 TB’	Ultra-Light ‘Less than 2 Kg’
19	19	Lenovo	‘700 to 1000’	Large ’More than 16’	Fast	Small ‘Less than 4’	Medium ‘Less than 499GB’	Light ‘More than 2 Kg’
20	20	HP	‘700 to 1000’	Small ‘Less than 12.9’	Normal	Small ‘Less than 4’	High ‘500 GB to 1 TB’	Light ‘More than 2 Kg’
21	21	Samsung	‘More than 1000’	Medium ‘13 to 16’	Normal	Small ‘Less than 4’	Very High ‘More than 1 TB’	Light ‘More than 2 Kg’
22	22	Dell	‘400 to 699’	Small ‘Less than 12.9’	High performance	Small ‘Less than 4’	Very High ‘More than 1 TB’	Ultra-Light ‘Less than 2 Kg’
23	23	Apple	‘700 to 1000’	Large ’More than 16’	High performance	High ‘More than 8’	Very High ‘More than 1 TB’	Light ‘More than 2 Kg’
24	24	Generic Brand	‘400 to 699’	Small ‘Less than 12.9’	Normal	Medium ‘4 to 8’	Medium ‘Less than 499GB’	Light ‘More than 2 Kg’

25	25	Lenovo	‘Less than 400’	Small ‘Less than 12.9’	Normal	High ‘More than 8’	Very High ‘More than 1 TB’	Ultra-Light ‘Less than 2 Kg’
26	26	Lenovo	‘400 to 699’	Medium ‘13 to 16’	High performance	Small ‘Less than 4’	Medium ‘Less than 499GB’	Light ‘More than 2 Kg’
27	27	Sony	‘400 to 699’	Large ’More than 16’	Normal	Small ‘Less than 4’	Medium ‘Less than 499GB’	Ultra-Light ‘Less than 2 Kg’
28	28	Apple	‘Less than 400’	Small ‘Less than 12.9’	Normal	Small ‘Less than 4’	Medium ‘Less than 499GB’	Ultra-Light ‘Less than 2 Kg’
29	29	Sony	‘More than 1000’	Small ‘Less than 12.9’	High performance	High ‘More than 8’	High ‘500 GB to 1 TB’	Light ‘More than 2 Kg’
30	30	Lenovo	‘More than 1000’	Small ‘Less than 12.9’	Normal	Medium ‘4 to 8’	High ‘500 GB to 1 TB’	Ultra-Light ‘Less than 2 Kg’
31	31	HP	‘Less than 400’	Medium ‘13 to 16’	Fast	High ‘More than 8’	Medium ‘Less than 499GB’	Ultra-Light ‘Less than 2 Kg’
32	32	Toshiba	‘More than 1000’	Small ‘Less than 12.9’	Fast	Small ‘Less than 4’	Medium ‘Less than 499GB’	Light ‘More than 2 Kg’

9.9.3. TVs

TVs Orthogonal Design

	Card ID	Brand	Price	Screen Size (inch)	Smart	3D	Freeview
1	1	Sony	‘200 to 400’	Very Large ‘More than 42’	Yes	Active	Yes
2	2	Generic Brand	‘Less than 200’	Large ‘25 to 42’	No	Passive	Yes
3	3	Sony	‘Less than 200’	Large ‘25 to 42’	Yes	Active	Yes
4	4	Toshiba	‘More than 400’	Medium ‘Less than 25’	Yes	No	No
5	5	Samsung	‘More than 400’	Medium ‘Less than 25’	No	Active	Yes
6	6	Generic Brand	‘200 to 400’	Medium ‘Less than 25’	Yes	Active	No
7	7	Panasonic	‘Less than 200’	Medium ‘Less than 25’	Yes	No	Yes
8	8	Samsung	‘200 to 400’	Large ‘25 to 42’	Yes	Passive	No
9	9	JVC	‘More than 400’	Very Large ‘More than 42’	No	Active	Yes
10	10	LG	‘More than 400’	Medium ‘Less than 25’	Yes	Passive	Yes
11	11	Panasonic	‘200 to 400’	Very Large ‘More than 42’	Yes	Passive	Yes
12	12	Sony	‘More than 400’	Large ‘25 to 42’	Yes	No	Yes
13	13	Sony	‘200 to 400’	Medium ‘Less than 25’	No	No	Yes
14	14	Sony	‘Less than 200’	Medium ‘Less than 25’	No	Passive	No
15	15	Generic Brand	‘More than 400’	Very Large ‘More than 42’	Yes	No	Yes
16	16	Toshiba	‘200 to 400’	Large ‘25 to 42’	Yes	Active	Yes
17	17	Sony	‘More than 400’	Very Large ‘More than 42’	Yes	Passive	No

18	18	LG	‘Less than 200’	Very Large ‘More than 42’	Yes	Active	No
19	19	Toshiba	‘Less than 200’	Very Large ‘More than 42’	No	Passive	Yes
20	20	Samsung	‘Less than 200’	Very Large ‘More than 42’	Yes	No	Yes
21	21	JVC	‘200 to 400’	Very Large ‘More than 42’	No	No	No
22	22	JVC	‘More than 400’	Large ‘25 to 42’	Yes	Passive	Yes
23	23	Panasonic	‘More than 400’	Large ‘25 to 42’	No	Active	No
24	24	LG	‘200 to 400’	Large ‘25 to 42’	No	No	Yes
25	25	JVC	‘Less than 200’	Large ‘25 to 42’	Yes	No	No
26	26	JVC	‘Less than 200’	Medium ‘Less than 25’	Yes	Active	Yes
27	27	JVC	‘200 to 400’	Medium ‘Less than 25’	Yes	Passive	Yes
28	28	JVC	‘Less than 200’	Medium ‘Less than 25’	Yes	Active	Yes

9.9.4. Fan Heaters

Fan Heaters Orthogonal Design

	Card ID	Brand	Price	Power (KW)	Type	Oscillating
1	1	Dimplex	less than 25	3 or more	Upright	No
2	2	Dimplex	50-75	2 to 2.9	Flat	Yes
3	3	Dyson	25-49	3 or more	Down Flow	Yes
4	4	DeLonghi	25-49	Less than 2	Flat	No
5	5	Dyson	less than 25	2 to 2.9	Flat	No
6	6	Dimplex	25-49	Less than 2	Flat	Yes
7	7	Dyson	More than 75	2 to 2.9	Upright	Yes
8	8	Challenge	50-75	3 or more	Flat	No
9	9	Generic Brand	50-75	Less than 2	Upright	Yes
10	10	DeLonghi	less than 25	Less than 2	Upright	No
11	11	Challenge	More than 75	Less than 2	Flat	Yes
12	12	DeLonghi	less than 25	2 to 2.9	Flat	Yes
13	13	Dyson	less than 25	Less than 2	Flat	Yes
14	14	Challenge	25-49	2 to 2.9	Upright	Yes
15	15	Generic Brand	less than 25	3 or more	Flat	Yes
16	16	Challenge	less than 25	2 to 2.9	Down Flow	No
17	17	Dyson	50-75	Less than 2	Upright	No
18	18	Generic Brand	More than 75	2 to 2.9	Flat	No
19	19	Dimplex	less than 25	2 to 2.9	Upright	Yes
20	20	DeLonghi	50-75	2 to 2.9	Down Flow	Yes
21	21	Dimplex	More than 75	Less than 2	Down Flow	No
22	22	Generic Brand	25-49	2 to 2.9	Upright	No
23	23	DeLonghi	More than 75	3 or more	Upright	Yes
24	24	Generic Brand	less than 25	Less than 2	Down Flow	Yes

9.10. Appendix 10 (Pilot study)

9.10.1. First experiment design scenario

Imagine that you are now choosing between the mobile phones with the features shown below. Which, if any, would you buy? (Please click at the bottom of screen)

Brand	BlackBerry	Others	HTC	Nokia	None of them
Price (£)	Medium 150 to 299	High 300 to 450	Very High More than 450	High 300 to 450	
Camera (Mpix)	Normal 5 or Less	Normal 5 or Less	No	No	
Memory (GB)	High More than 32	Small Less than 16	High More than 32	Small Less than 16	
Display (inch)	Small Less than 4	Medium 4 to 5	Large More than 5	Small Less than 4	
Battery (Hours)	Very High More than 15	High 12 to 15	Medium 8 to 12	Medium 8 to 12	
Weight (gr)	Very Light Less than 120	Very Light Less than 120	Very Light Less than 120	Light 120 to 150	

Next >>

qualtrics

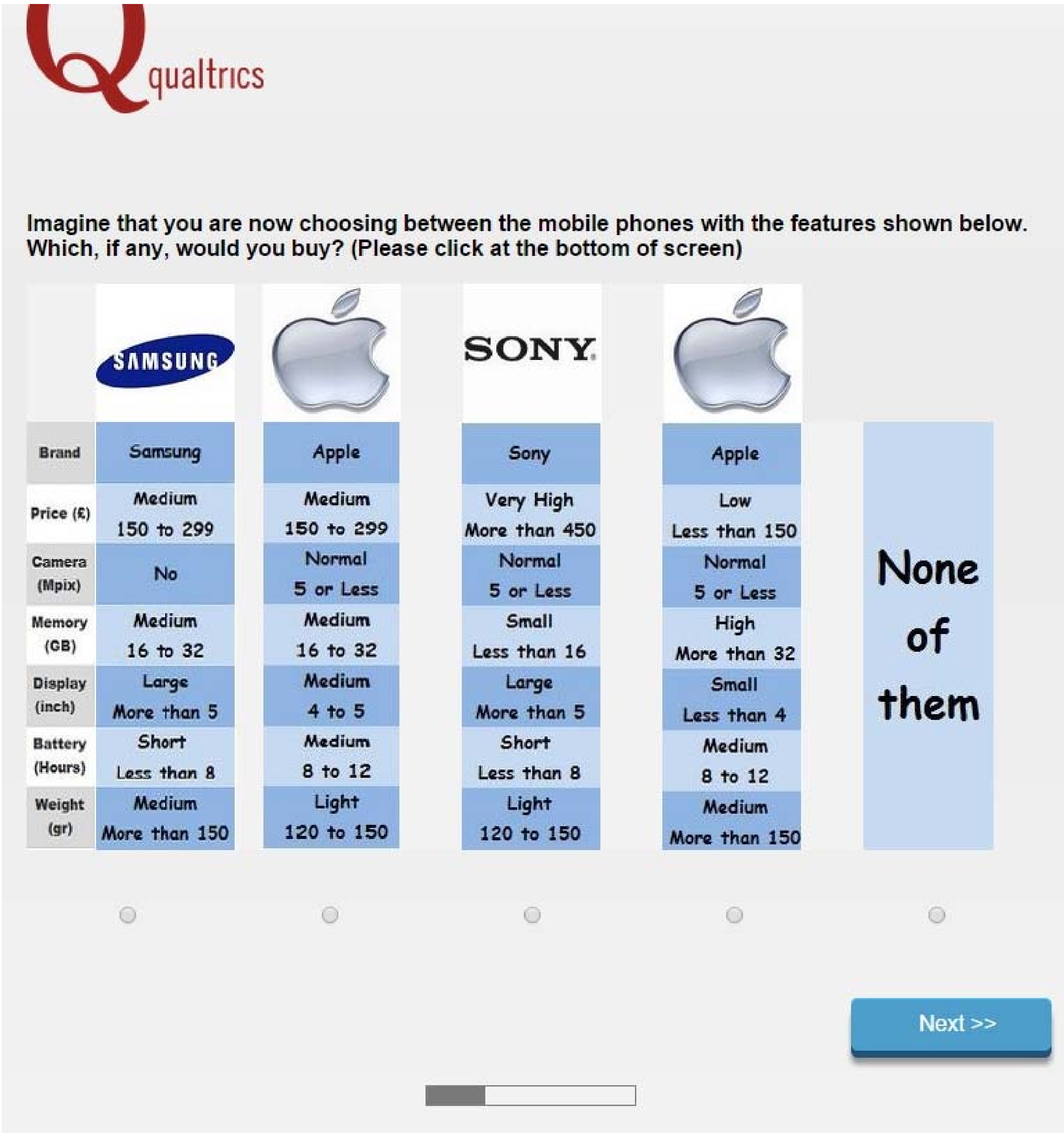
Imagine that you are now choosing between the Fan Heaters with the features shown below.
Which, if any, would you buy?




Brand	Dimplex	Dimplex	Dyson	DeLonghi	None of them
Price (£)	Low Less than 25	High 50 to 75	Medium 25 to 49	Medium 25 to 49	
Power (KW)	Very High 3 or more	High 2 to 2.9	Very High 3 or more	Medium Less than 2	
Type	Upright	Flat	Down Flow	Flat	
Oscillating	No	Yes	Yes	No	

Next >>

9.10.2. Second experiment design scenario



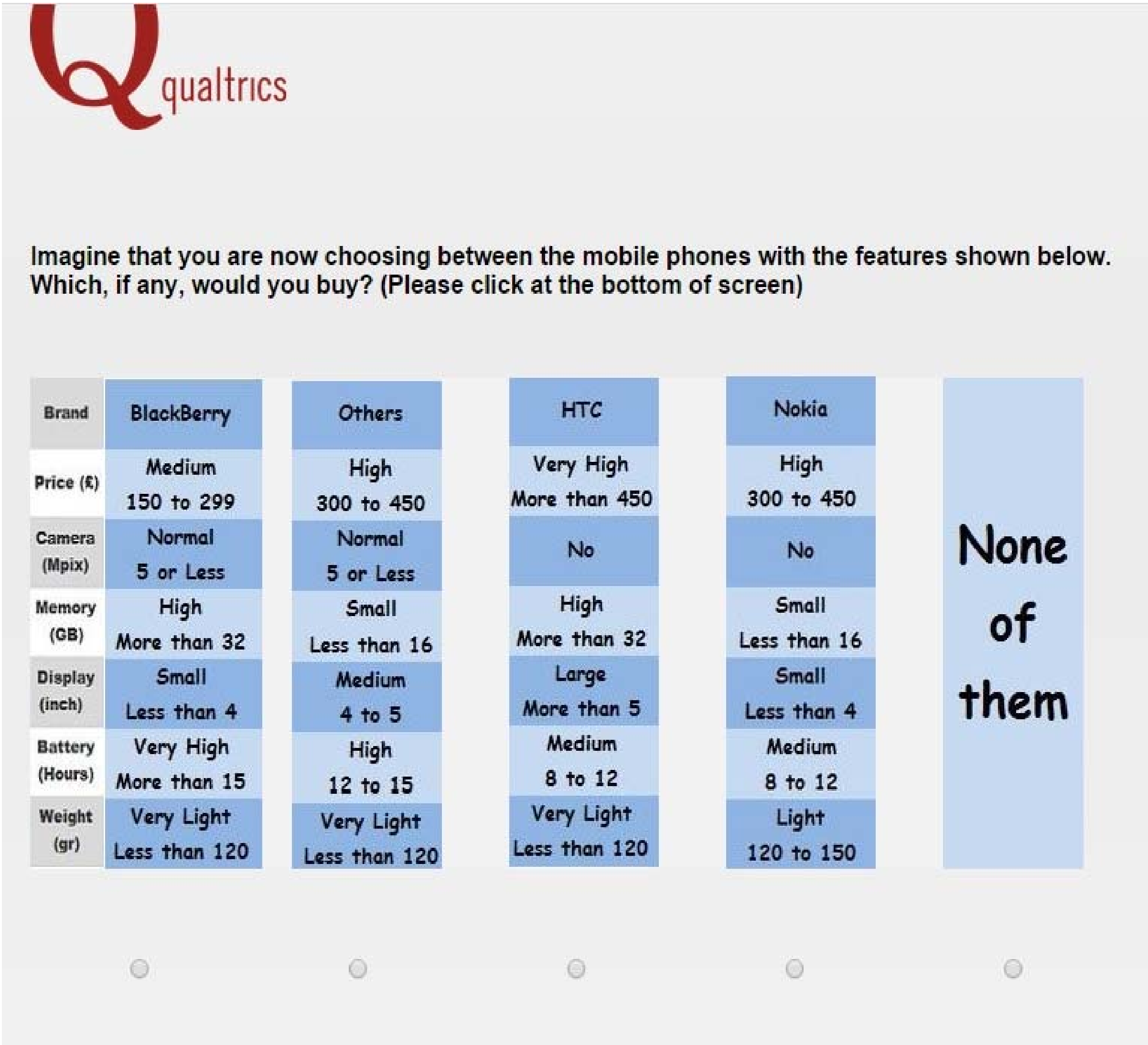
qualtrics

Imagine that you are now choosing between the mobile phones with the features shown below. Which, if any, would you buy? (Please click at the bottom of screen)

	SAMSUNG		SONY		
Brand	Samsung	Apple	Sony	Apple	None of them
Price (£)	Medium 150 to 299	Medium 150 to 299	Very High More than 450	Low Less than 150	
Camera (Mpix)	No	Normal 5 or Less	Normal 5 or Less	Normal 5 or Less	
Memory (GB)	Medium 16 to 32	Medium 16 to 32	Small Less than 16	High More than 32	
Display (inch)	Large More than 5	Medium 4 to 5	Large More than 5	Small Less than 4	
Battery (Hours)	Short Less than 8	Medium 8 to 12	Short Less than 8	Medium 8 to 12	
Weight (gr)	Medium More than 150	Light 120 to 150	Light 120 to 150	Medium More than 150	

Next >>

9.10.3. Third experiment design scenario



qualtrics

Imagine that you are now choosing between the mobile phones with the features shown below. Which, if any, would you buy? (Please click at the bottom of screen)

Brand	BlackBerry	Others	HTC	Nokia	None of them
Price (£)	Medium 150 to 299	High 300 to 450	Very High More than 450	High 300 to 450	
Camera (Mpix)	Normal 5 or Less	Normal 5 or Less	No	No	
Memory (GB)	High More than 32	Small Less than 16	High More than 32	Small Less than 16	
Display (inch)	Small Less than 4	Medium 4 to 5	Large More than 5	Small Less than 4	
Battery (Hours)	Very High More than 15	High 12 to 15	Medium 8 to 12	Medium 8 to 12	
Weight (gr)	Very Light Less than 120	Very Light Less than 120	Very Light Less than 120	Light 120 to 150	

9.11. Appendix 11 (Experiments snapshots)

UNIVERSITY OF BATH
SCHOOL OF MANAGEMENT

Time Tracked Product Choice Survey

This is the first round of a survey into what drives people's choices of consumer electronic goods. It has been developed as part of my PhD research at the University of Bath. The 2nd and 3rd round link will be sent in June and August respectively to the email address you provided. It is really important for the success of the research that you complete all three rounds fully and carefully. The questions are not sensitive, your participation is voluntary and you can pull out at any time by closing the browser. All of the information that you provide will be treated anonymously and confidentially. Data will not be personally identifiable and only used for academic purposes.

The survey is easy to complete, you simply indicate which product you would buy from the selection presented. You will be asked to make 29 choices relating to four categories of products (Mobile Phones, Fan Heaters, TVs and Laptops). The experiment will take approximately 8 minutes. As a token of thanks for your participation, a donation will be made to the charity of your choice on your behalf once you completed all three rounds of survey. Please do not hesitate to contact me, should you have any questions.

N.B. Please do not use any phone, tablet or PDA to complete the survey as it ruins the structure of it!

Thank you for your participation! This is much appreciated.

Semco Jahanbin
Doctoral Researcher
School of Management
University of Bath

S.Jahanbin@bath.ac.uk

Please indicate your preferred charity (Please click):

- Cancer Research UK
- British Heart Fondation
- The Trussell Trust - Food Bank Charity
- Mahak Charity - Society to support childern suffering from Cancer

Next >>

qualtrics

Please enter a preferred user name so that we can track your choices:

Please enter your email address so that I can send you the 2nd (June) and the 3rd (August) round of this survey:

What is your gender? (Please click)

Male	Female
○	○

How old are you?

Under 18	18-30	31-45	46-60	Over 60
○	○	○	○	○

What is your highest level of education to date?

Did not complete Secondary School	Secondary School	Undergraduate degree	Postgraduate degree
○	○	○	○

Which of the following best describes your current main occupation?

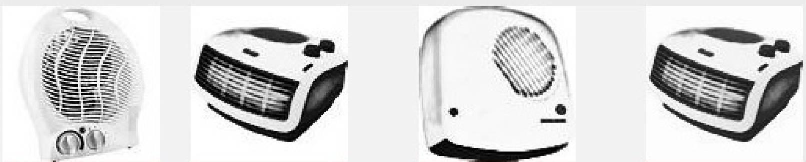
Unemployed	Student	Full-time employee	Part-time employee	Self-employed	Housewife Househusband	Retired
○	○	○	○	○	○	○

Next >>

1. Imagine that you are now choosing between the mobile phones with the features shown below. Which, if any, would you buy? (Please click at the bottom of screen)

Brand	BlackBerry	Generic Brand	HTC	Nokia	None of them
Price (£)	£150 to £299	300 to 450	More than £450	£300 to £450	
Camera (Mpix)	Normal 5 or Less	Normal 5 or Less	No	No	
Memory (GB)	High More than 32	Small Less than 16	High More than 32	Small Less than 16	
Display (inch)	Small Less than 4	Medium 4 to 5	Large More than 5	Small Less than 4	
Battery (Hours)	Very High More than 15	High 12 to 15	Medium 8 to 12	Medium 8 to 12	
Weight (gr)	Very Light Less than 120	Very Light Less than 120	Very Light Less than 120	Light 120 to 150	

9. Imagine that you are now choosing between the Fan Heaters with the features shown below. Which, if any, would you buy?



Brand	Dimplex	Dimplex	Dyson	DeLonghi	None of them
Price (£)	Less than £25	£50 to £75	£25 to £49	£25 to £49	
Power (KW)	Very High 3 or more	High 2 to 2.9	Very High 3 or more	Medium Less than 2	
Type	Upright	Flat	Down Flow	Flat	
Oscillating	No	Yes	Yes	No	

15. Imagine that you are now choosing between the TVs with the features shown below. Which, if any, would you buy?

					
Brand	Sony	Generic Brand	Sony	Toshiba	None of them
Price (£)	£200 to £400	Less than 200	Less than £200	More than £400	
Screen Size (inch)	Very Large More than 42	Large 25 to 42	Large 25 to 42	Medium Less than 25	
Smart	Yes	NO	Yes	Yes	
3D	Active	Passive	Active	No	
FreeView	Yes	Yes	Yes	NO	

22. Imagine that you are now choosing between the Laptops with the features shown below. Which, if any, would you buy?

					
Brand	HP	Samsung	Apple	Toshiba	None of them
Price (£)	'£400 to £699'	'Less than £400'	More than £1000	'£400 to £699'	
Display (inch)	Small 'Less than 12.9'	Large 'More than 16'	Small 'Less than 12.9'	Large 'More than 16'	
Processor	Normal	Normal	Normal	Normal	
Memory Size (GB)	Small 'Less than 4'	Small 'Less than 4'	Small 'Less than 4'	High 'More than 8'	
Hard Drive	Very High 'More than 1 TB'	High '500 GB to 1 TB'	Medium 'Less than 499GB'	High '500 GB to 1 TB'	
Weight	Light '2 Kg or More'	Light '2 Kg or More'	Ultra-Light 'Less than 2 Kg'	Ultra-Light 'Less than 2 Kg'	

9.12. Appendix 12 (Examples of Difference between features weights)

FH B	Differences R2-R1	Differences R3-R2	Differences R3-R1
Brand_Challenge	-0.15	0.17	0.03
Brand_Dimplex	0.17	0.13	0.30
Brand_DeLonghi	0.37	-0.05	0.32
Brand_Dyson	0.21	0.07	0.29
Price_Low	0.12	-0.01	0.11
Price_Med	0.07	-0.02	0.05
Price_Hi	-0.20	-0.19	-0.39
Power_Hi	-0.06	0.00	-0.06
Power_VeryHi	0.26	-0.26	0.00
Type_Upright	-0.11	0.04	-0.07
Type_Flat	-0.13	-0.05	-0.18
Oscillating_Yes	0.34	0.10	0.44
Constant	-0.28	-0.04	-0.32

Laptop B	(Difference R2-R1)^2	(Difference R3-R2)^2	(Difference R3-R1)^2
Brand_Apple	0.22	0.02	0.11
Brand_Samsung	0.19	0.00	0.19
Brand_HP	0.16	0.04	0.35
Brand_Sony	0.22	0.00	0.20
Brand_Dell	0.27	0.02	0.43
Brand_Lenovo	0.35	0.02	0.55
Brand_Toshiba	0.46	0.00	0.54
Price_Low	0.00	0.01	0.02
Price_Med	0.02	0.00	0.02
Price_Hi	0.01	0.02	0.06
Dis_S	0.02	0.00	0.01
Dis_M	0.01	0.00	0.01
Proc_Fas	0.06	0.02	0.01
Proc_Hi	0.09	0.00	0.06
Mem_M	0.02	0.00	0.04
Mem_H	0.02	0.00	0.01
HDD_Hi	0.02	0.03	0.09
HDD_VerHi	0.01	0.01	0.00
Weight_UltraL	0.03	0.00	0.03
Constant	0.04	0.00	0.06

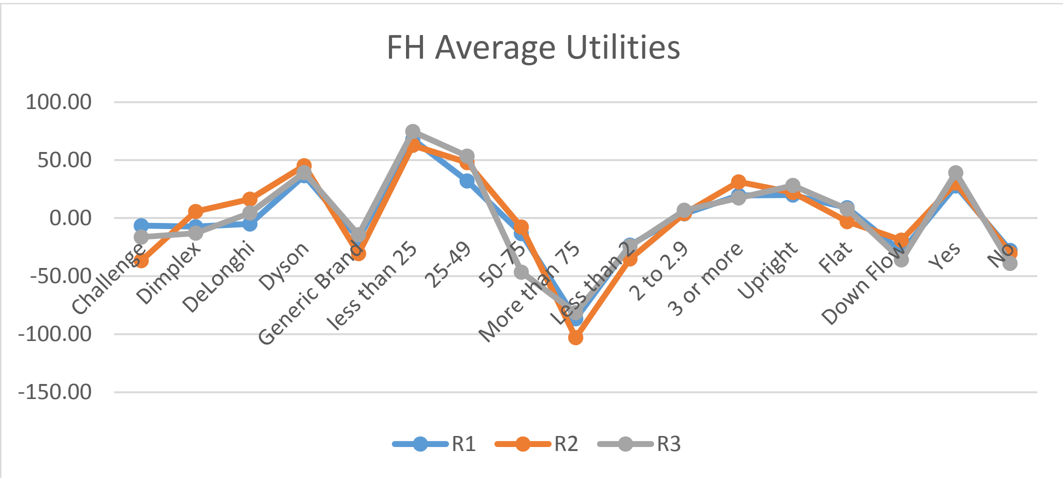
Mobile B	| Difference R2-R1|	| Difference R3-R2|	| Difference R3-R1|
Brand_Apple	0.69	0.26	0.95
Brand_Samsung	0.35	0.22	0.58
Brand_Nokia	0.68	0.05	0.73
Brand_HTC	0.46	0.50	0.96
Brand_Sony	0.86	0.37	1.23
Brand_BB	1.08	0.24	1.32
Price_Low	0.10	0.02	0.12
Price_Med	0.03	0.03	0.00
Price_Hi	0.04	0.12	0.17
Cam_Norm	0.27	0.20	0.07
Cam_Hi	0.25	0.17	0.08
Mem_M	0.20	0.03	0.17
Mem_H	0.23	0.02	0.21
Dis_S	0.25	0.28	0.02
Dis_M	0.22	0.01	0.20
Batt_M	0.31	0.24	0.07
Batt_H	0.00	0.25	0.25
Batt_VerHi	0.22	0.32	0.10
Weight_VerL	0.21	0.18	0.03
Weight_Li	0.34	0.05	0.29
Constant	0.55	0.20	0.74

TV B	(Difference R2-R1)^2	(Difference R3-R2)^2	(Difference R3-R1)^2
Brand_JVC	0.15	0.02	0.07
Brand_Sony	0.12	0.03	0.28
Brand_Panasonic	0.02	0.00	0.02
Brand_Samsung	0.11	0.00	0.12
Brand_LG	0.00	0.00	0.00
Brand_Toshiba	0.45	0.10	0.12
Price_Low	0.00	0.00	0.00
Price_Med	0.00	0.01	0.01
Screen_L	0.01	0.01	0.04
Screen_VeryL	0.00	0.04	0.02
Smart_Yes	0.01	0.06	0.02
ThreeD_Act	0.00	0.02	0.01
ThreeD_Pass	0.03	0.00	0.01
FreeV_Yes	0.00	0.00	0.01
Constant	0.14	0.20	0.00

9.13. Appendix 13 (Average Utilities using HB)

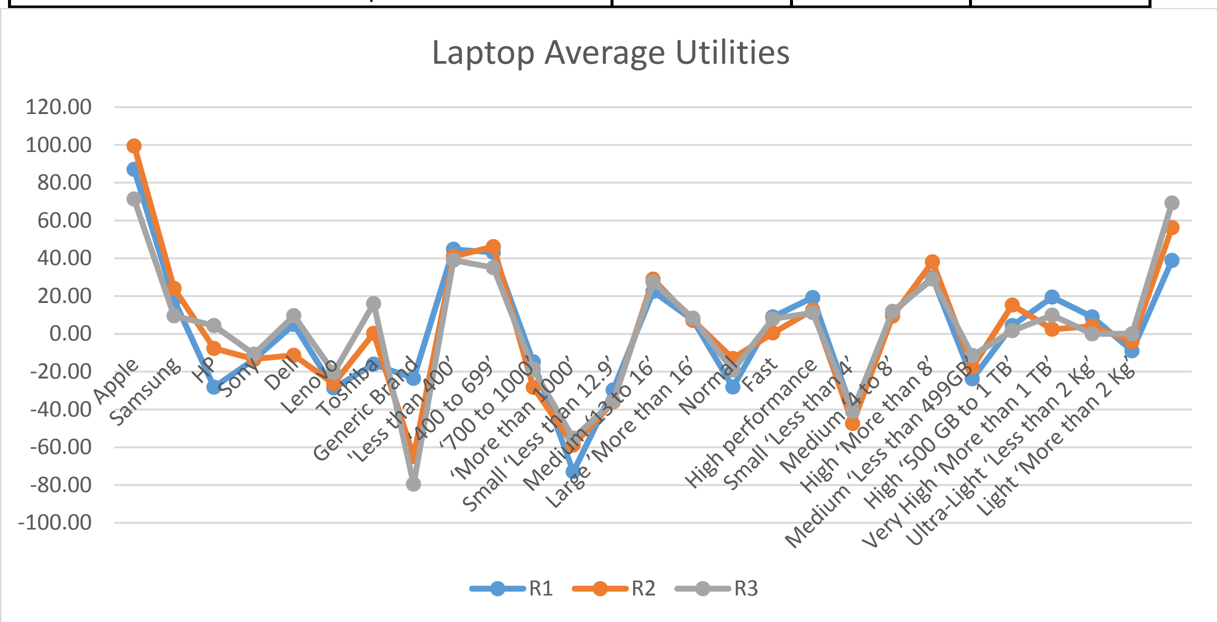
9.13.1. Fan Heaters

	FH Average Utilities	R1	R2	R3
Brand	Challenge	-6.53	-36.62	-16.33
	Dimplex	-7.39	5.72	-12.99
	DeLonghi	-5.00	16.33	4.43
	Dyson	36.60	45.17	39.25
	Generic Brand	-17.68	-30.59	-14.36
Price	less than 25	67.93	62.74	74.59
	25-49	32.03	47.93	53.43
	50-75	-13.29	-7.69	-46.56
	More than 75	-86.67	-102.98	-81.46
Power	Less than 2	-23.33	-35.19	-24.10
	2 to 2.9	3.76	3.95	6.73
	3 or more	19.57	31.23	17.37
Type	Upright	19.87	22.05	28.13
	Flat	8.98	-2.99	7.76
	Down Flow	-28.85	-19.05	-35.89
Oscillating	Yes	27.79	30.32	39.01
	No	-27.79	-30.32	-39.01
None Choice Option		50.00	15.88	26.04



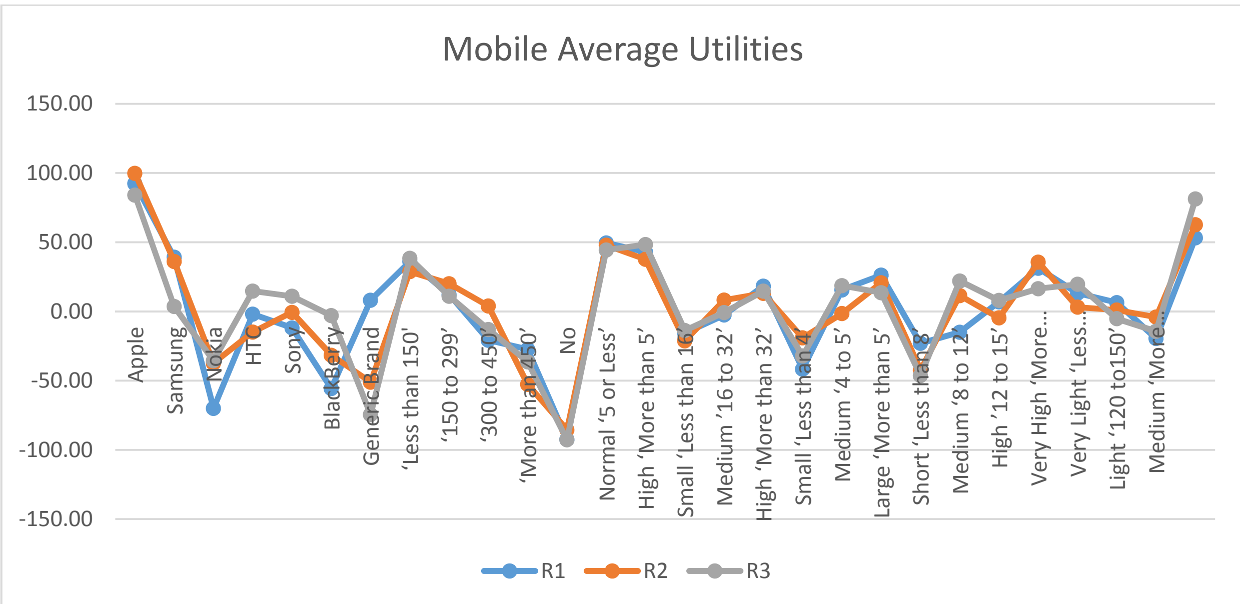
9.13.2. Laptops

	Laptop Average Utilities	R1	R2	R3
Brand	Apple	87.05	99.39	71.34
	Samsung	18.06	24.04	9.55
	HP	-28.21	-7.70	4.34
	Sony	-13.60	-13.27	-10.76
	Dell	4.98	-11.34	9.59
	Lenovo	-28.67	-26.39	-20.50
	Toshiba	-16.07	0.25	16.02
	Generic Brand	-23.54	-64.99	-79.57
Price (£)	'Less than 400'	44.73	41.01	39.01
	'400 to 699'	43.10	46.13	35.04
	'700 to 1000'	-14.87	-28.28	-18.78
	'More than 1000'	-72.96	-58.87	-55.27
Display Screen (inch)	Small 'Less than 12.9'	-29.72	-36.00	-35.71
	Medium '13 to 16'	22.45	28.91	27.44
	Large 'More than 16'	7.26	7.09	8.27
Processor	Normal	-28.18	-13.05	-19.17
	Fast	8.97	0.44	7.95
	High performance	19.21	12.60	11.23
Memory Size(GB)	Small 'Less than 4'	-41.05	-47.45	-40.91
	Medium '4 to 8'	11.27	9.36	11.92
	High 'More than 8'	29.78	38.09	29.00
Hard Drive	Medium 'Less than 499GB'	-23.82	-17.63	-11.49
	High '500 GB to 1 TB'	4.38	15.24	1.63
	Very High 'More than 1 TB'	19.44	2.39	9.86
Weight	Ultra-Light 'Less than 2 Kg'	8.97	4.11	0.01
	Light 'More than 2 Kg'	-8.97	-4.11	-0.01
None Choice Option		38.88	56.22	69.25



9.13.3. Mobile

	Mobile Average Utilities	R1	R2	R3
Brand	Apple	92.34	99.76	84.00
	Samsung	39.13	36.08	3.53
	Nokia	-70.03	-37.45	-35.63
	HTC	-1.98	-14.94	14.71
	Sony	-11.88	-0.70	10.92
	BlackBerry	-55.67	-31.67	-3.02
	Generic Brand	8.09	-51.07	-74.53
Price(£)	‘Less than 150'	35.95	28.74	38.40
	‘150 to 299’	12.17	20.04	11.01
	‘300 to 450’	-20.78	3.90	-13.03
	‘More than 450’	-27.34	-52.68	-36.38
Camera Resolution (Mpix)	No	-92.42	-85.49	-92.68
	Normal ‘5 or Less’	49.48	47.83	44.34
	High ‘More than 5’	42.94	37.66	48.34
Memory Size(GB)	Small ‘Less than 16’	-15.67	-21.27	-13.81
	Medium ’16 to 32’	-2.60	8.19	-0.81
	High ‘More than 32’	18.27	13.08	14.62
Display Size (inch)	Small ‘Less than 4’	-41.69	-19.10	-32.15
	Medium ‘4 to 5’	15.51	-1.56	18.63
	Large ‘More than 5’	26.18	20.66	13.52
Battery Life (Talking Hours)	Short ‘Less than 8’	-23.04	-42.37	-46.35
	Medium ‘8 to 12’	-15.01	11.47	21.97
	High ’12 to 15’	6.89	-4.67	7.96
	Very High ‘More than 15’	31.16	35.58	16.41
Weight(g)	Very Light ‘Less than 120’	13.19	3.07	19.59
	Light ‘120 to150’	6.36	1.01	-5.21
	Medium ‘More than 150’	-19.56	-4.08	-14.38
None Choice Option		53.12	62.69	81.27



9.13.4. TV

	TV Average Utilities	R1	R2	R3
Brand	JVC	-23.42	-31.36	-30.47
	Sony	36.09	35.90	38.31
	Panasonic	39.56	29.60	35.09
	Samsung	17.38	24.31	32.40
	LG	12.80	2.04	1.58
	Toshiba	-53.50	1.43	-32.37
	Generic Brand	-28.91	-61.92	-44.55
Price(£)	'Less than 200'	24.13	36.40	29.18
	'200 to 400'	31.15	21.94	19.78
	'More than 400'	-55.29	-58.34	-48.95
Screen Size (inch)	Medium 'Less than 25'	-59.67	-61.02	-59.28
	Large '25 to 42'	43.17	30.36	33.41
	Very Large 'More than 42'	16.50	30.66	25.87
Smart	Yes	34.83	38.69	32.98
	No	-34.83	-38.69	-32.98
3D	Active	26.17	19.70	18.68
	Passive	-11.34	-2.72	-9.04
	No	-14.83	-16.97	-9.64
Freeview	Yes	32.28	21.73	30.16
	No	-32.28	-21.73	-30.16
None Choice Option		59.87	69.71	74.87