Assessing Preference Elicitation Methods in Choice Experiments: A Case Study of Tourism Facilities at Kenyir Lake, Malaysia

by

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A thesis submitted to the Newcastle University for the degree of Doctor of Philosophy

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May 2018

Abstract

The aim of this thesis is to explore methodological issues in a choice experiment (CE); to ascertain how they might be used to improve the reliability of valuation estimates. Three methodological issues are explored; whether the status quo (SQ) is relevant as one of the alternatives in the CE choice sets; whether respondents ignore any of the attributes presented in the choice set, and the implications this has for estimating willingness to pay; and the effect of different distributional assumptions of random parameters in the Mixed Logit Model: does it matter what distributional assumption is employed?

These issues were explored through a study of recreational visitors to Kenyir Lake in Malaysia. Currently, no entrance fee is charged to visitors using Kenyir Lake. But there are government plans to develop Kenyir Lake which involve public investment. Public authorities need to understand visitors' preferences towards facilities, and whether the benefits of improving these facilities justify the cost.

The main findings are: 1) including the SQ on choice card does not affect the results substantially, 2) it is important to account for attribute non-attendance, and 3) except for the lognormal distribution, different specifications of the mixing distribution do not make that much difference in WTP values.

This study delivers two fundamental contributions. Firstly, it demonstrates the importance of taking into account methodological issues in a CE, and in the analysis of the CE models. The study also provides methodological recommendations for future CE studies. Secondly, it investigates visitors' preferences for tourist facilities and offers policy recommendations regarding the improvement of these facilities. Accounting for methodological issues in a choice experiment is shown to help and provide a deeper understanding regarding the challenges of applying this method; and this thesis offers recommendations on how to apply CE in the future.

Acknowledgments

First and foremost, I would like to express my deep gratitude to my supervisor, Emeritus Professor Dr Ken Willis, for all his excellent guidance and supervision.

I wish to express my warm and sincere thanks to my second supervisor, Dr Neil Powe, for being very helpful and encouraging.

I would also like to extend my thanks to the Malaysian Ministry of Higher Education and University Putra Malaysia (UPM) for granting the scholarship and study leave that enabled this study to take place. Thanks also to Newcastle University for providing excellent facilities and environment to complete this study.

To my loving husband, Ahmad Marwan A Manan, thank you so much for your support, patience, encouragement and understanding in enduring this journey together. My hugs and kisses to my children, Nur Ammara Iris, Aqil Uqashah and Aryan Noah, who braced themselves for all the challenges abroad. May this piece of work be the inspiration for your knowledge quest in the future.

Finally, an honourable mention goes to my extended family and my friends for their prayers and support in completing this research.

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Acronyms

AIC	Akaike Information Criteria
ANA	Attribute Non-Attendance
ASC	Alternative Specific Constant
ASM	Academy of Sciences Malaysia
BIC	Bayesian Information Criteria
BG	Bidding Game
CE	Choice Experiment
CL	Conditional Logit
CM	Choice Modelling
CRk	Contingent Ranking
CRt	Contingent Rating
CVM	Contingent Valuation Method
DB	Double Bounded
DC	Dichotomous Choice
DD	Demand curve
ECL	Error Component Logit
ESRS	Exogenously Stratified Random Samples
HPM	Hedonic Pricing Method
IIA	Independence from Irrelevant Alternatives
IID	Independently and Identically Distributed
INA	Inferred Non-Attendance
KETENGAH	The Central Terengganu Development Authority
LCM	Latent Class Model
LLR	Log-likelihood Ratio
ML	Maximum Likelihood
MNL	Multinomial Logit
MXL	Mixed Logit
NOAA	National Oceanic and Atmospheric Administration
NSQ	No Status Quo
OE	Open-Ended
OLS	Ordinary Least Squares
Pc	Pair-wise Comparison

PC	Payment Cards
RM	Ringgit Malaysia
RP	Revealed Preference
RPL	Random Parameter Logit
RUT	Random Utility Theory
SAS	Statistical Analysis System
SB	Single Bounded
SHS	Standard Halton Sequences
SLL	Simulated Log Likelihood
SNA	Stated Non-Attendance
SP	Stated Preference
SQ	Status Quo
SRS	Simple Random Samples
TCM	Travel Cost Method
TIC	Tourist Information Centre
UF	Unforced
WTA	Willingness to Accept
WTP	Willingness to Pay

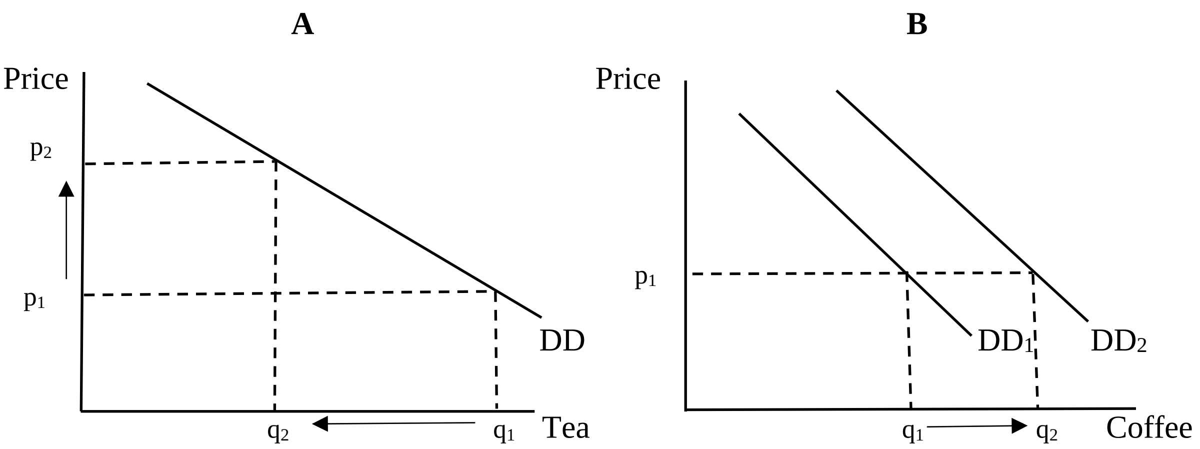
Chapter 1: Introduction

1.0 Background of Study

In economics, demand is described as a desire of the consumer and a willingness to pay the price or charge for an individual product or service. The demand for a product or service is influenced by several factors, amongst these are: price, consumer tastes and preferences, the level of income of the consumer and the quality of the product. Price is regarded as the most important element which affects the demand for a product. According to the law of demand, the price and the quantity demanded are inversely correlated (other things remain constant for normal goods) and as a result, the change in price and the change in the quantity demanded of particular goods move in opposite ways (McEachern, 2012). Thus, when the price of a product increases, the quantity demanded decreases, and *vice-versa*.

The quantity demanded for a certain product may also be influenced or determined by prices of other products. For example, for the complimentary good like cars and petrol, an increase in petrol price may cause a reduction in the quantity demanded for cars. Meanwhile, for substitute goods such as coffee and tea, an increase in the price of tea may cause a reduction in the quantity demanded for tea (law of demand) while the quantity demanded for coffee could increase. The demand (DD) curve shows the relationship between the quantities of goods that consumers are willing to buy and the price of those goods. Figure 1.1 shows that, when the price of tea rises from p_1 to p_2 in graph A, the demand for tea falls from q_1 to q_2. The demand curve for tea remains unchanged. In graph B, with coffee remaining at the same price, the demand for coffee increases due to the increase in the price of tea and the demand curve moves from DD_1 to DD_2.

Figure 1.1: The Example of Demand Curve



Changes in consumer tastes and preferences may also affect the demand for a particular product. As an example, announcing that a study has indicated that grilled red meat causes cancer might change consumer preferences. As a consequence, a consumer might buy less grilled red meat and more fish or chicken; all other things being equal. Although the price of grilled red meat and fish remain the same, quantity demanded has changed due to consumer tastes and preferences have changed. Thus, this situation involves a movement in the demand curve whilst the price remains unchanged.

In general, the demand curve approaches involve eliciting the demand for a particular product by regressing the quantity purchased on the factors noted (e.g. price, income, taste and preferences). The demand curve approaches are able to provide welfare measures in economics. Estimation of the demand curve can be divided into two techniques: 1) Stated Preference (SP) Techniques, and 2) Revealed Preference (RP) Techniques. The main differences between the SP techniques and RP techniques are the origin of the data and the method of collecting the data. Revealed preference techniques infer an individual's willingness to pay (WTP) value for goods or products by examining their actual or observed behaviour in existing markets or in the consumption of the product itself. In other words, RP data reflects actual choices of the individual. The most well-known RP techniques are the Hedonic Pricing Method (HPM) and the Travel Cost Method (TCM).

In contrast, SP techniques are questionnaire-based techniques that collect data through a survey by presenting the respondents with hypothetical choice situations. The most well-known SP techniques are the Contingent Valuation Method (CVM) and the Choice Experiment (CE) Method. These techniques have primarily emerged from a desire to understand the consumer demand for goods and services; where it is unfeasible to use the revealed preference data on the actual choices made by individuals since the goods are not traded on the real market (Mangham, Hanson and McPake, 2009). Examples of goods which are not traded on the market (non-market goods) include clean air and water, wetland systems, wildlife population and open access recreation from ecotourism sites where the economic values of these goods cannot be directly obtained from the market. According to Alpizar, Carlsson and Martinsson (2003), markets fail to exist for certain goods either because they are public goods, or because these goods simply do not currently exist, for example, a new product or service under development. Thus, the SP techniques have the advantage of examining individual's responses to situations that do not exist yet.

Over time, SP techniques have become a well-established mechanism to elicit individual's preferences for non-market goods or goods without a market price. Specifically, the discrete choice experiment, also known as conjoint analysis, has experienced considerable development over the last decade, since it has a strong theoretical foundation and is able to measure individual's preferences for various aspects of goods. The attraction of this method lies in the analyst's ability to estimate values for changes in several attributes along with multiple changes in attribute levels. Respondents in the choice experiment are presented with choice situations described by a combination of different attributes and levels in a hypothetical market situation. They are asked to make trade-offs between attributes levels presented and state the choice which maximises their utility. The responses to the choices are then directly translated to marginal WTP values through a discrete choice model estimation which reflects the trade-offs between the attributes in a manner consistent with the random utility theory (Bateman et al., 2002).

The CE method is used to a growing extent to explore the behavioural response of consumers, households or even organisations and can be identified in various applied fields such as: environmental economics (e.g. Adamowicz, Louviere and William, 1994; Hanley, Wright and Adamowicz, 1998b; Jamal, Bennet and Blamey, 2004; Garrod, Ruto, Willis and Powe, 2014; Tawfik and Turner, 2014), health economics (e.g. Mangham et al., 2009; Clark, Determann, Petrou, Moro and de Bekker-Grob, 2014), food studies (e.g. Carlsson, Frykblom and Lagerkvist, 2007; Loureiro and Umberger, 2007), transportation (e.g. Puckett and Hensher, 2008; Rose and Hess, 2009; Hess and Hensher, 2010) and many more.

Interestingly, most of the CE studies aim to provide policy makers with detailed information regarding public preferences relating to particular goods or services. In other words, the purpose of CE study is to obtain policy-useful information in order to achieve better management and allocation of resources in the future. Since preferences can be quantified in economic terms, the costs and benefits of different policy designs can also be compared. For example, Hanley, MacMillan, Patterson and Wright (2003) applied CE in order to explore public preferences for a design of wild goose conservation policy in Scotland. The policy attributes used by Hanley et al., (2003) included species, means of control and location. The purpose of the set of attributes chosen was to capture features of the goose management problem which the government has a probability of influencing, through policy design, along with the costs of policy to the taxpayer.

In environmental economics field, Birol, Karousakis and Koundouri (2006) estimated the economic values of wetland in Greece, using the CE method. The aim was to assist policy makers in formulating efficient and sustainable wetland management policies in line with the

European Union Water Framework Directive. A further field of study by Loureiro and Umberger (2007) investigated the relative value that consumers in the United States placed on several relevant beef attributes. They aimed to provide industry and policy makers with further information regarding the need for country-of-origin labelling versus animal traceability based on consumer interests. Meanwhile, Willis, Scarpa and Acutt (2005) conducted a study that assessed benefits to water company clients of changes across 14 water service factors in the United Kingdom. The finding from this study was directly relevant to policy for the regulation of water industry in the United Kingdom. This identifies how the use of CE supports policy makers in their decision making process, particularly for non-market goods.

Even though the application of CE is a well-established method for eliciting individual preferences for non-market goods in a wide range of fields, there are a number of research issues currently being deliberated regarding how to improve the design of CE and how to improve the estimation of the CE models. Designing a CE question involves several important decisions, for example, determining the number of choice tasks and determining how complex each choice task is going to be, where each decision will affect the choice responses. Therefore, the major challenge for researchers in a choice experiment study is how to design statistically practical experiments in order to provide sufficient information for accurately eliciting individual preferences, thus achieving the most accurate measure of welfare estimates in the CE models.

In different fields of study where the choice experiment is used, there has been research on how different designs of choice experiment questions can affect the results. These studies have among other things been focused and concerned with;

1) ***the choice and number of attributes*** (e.g. DeShazo and Fermo, 2002; Caussade, Ortuzar, Rizzi and Hensher, 2005; Hensher, 2006a; Islam, Louviere and Burke 2007; Gao, House and Yu, 2010; Meyerhoff, Oehlmann and Weller, 2015; Vanniyasingam, Cunningham, Foster and Thabane, 2016).
2) ***the number of attribute levels and level ranges*** (e.g. Caussade et al., 2005; Rose, Hensher, Caussade, de Dios Ortùzar and Jou, 2009; Mørkbak, Christensen and Gyrd-Hansen, 2010; Meyerhoff et al., 2015).
3) ***the number of alternatives*** (e.g. DeShazo and Fermo, 2002; Arentze, Borgers, Timmermans and DelMistro, 2003; Caussade et al., 2005; Volinskiy, Adamowicz, Veeman and Srivastava, 2009; Rolfe and Bennet, 2009; Meyerhoff et al., 2015).

4) ***the number of choice tasks*** (e.g. Hensher, Stopher and Louviere, 2001; Boxall, Adamowicz and Moon, 2009; Bech, Kjaer and Lauridsen, 2011; Meyerhoff et al., 2015).
5) ***whether to include a status quo or other constant alternative in the choice sets*** (e.g. Breffle and Rowe, 2002; Boyle and Ozdemir, 2009).
6) ***the experimental design effects*** (Viney, Savage and Louviere, 2005; Hess, Smith, Falzarano and Stubits, 2008; Louviere, Islam, Wasi, Street and Burgess, 2008b; Bliemer and Rose, 2011).

The number of attributes, attributes levels and levels ranges

The effect on error variance of varying the number of attributes has been investigated by many studies, amongst these, Caussade et al., (2005) revealed that the number of attributes had a noticeable detrimental effect on a respondent's competency to choose, which subsequently contributed to a higher error variance. Specifically, the error variance in the utility function tends to increase when the number of attributes or levels increases. As noted by DeShazo and Fermo (2002), respondents may make an error when they try to process a more extensive information set that results in a sub-optimal preference ordering. Moreover, the respondents may alter their information processing strategies as the number of attributes increases. They may also apply simplified decision rules or heuristics that are based on the only partial information. Another significant effect was also found by Meyerhoff et al., (2015), who varied the number of attributes between four and seven. Meyerhoff et al., (2015) revealed that the probability of the respondents of abandoning the survey significantly increased with the number of attributes.

Not only are the number of attributes important in the design of a CE, but also the varying number of levels, whether wide or narrow levels ranges are offered, how many levels differ across alternatives, etc. As stated by Hensher (2006a), the less the number of levels per attribute, the more the number of attributes that might be considered by the respondents. Meanwhile, Caussade et al., (2005) found that the higher number of levels contributes to the higher error variance. With regard to the effect on WTP value, Rose et al., (2009) reveal that the attribute level range seems to have a significant influence on results, whose sign is different based on the attribute and country selected.

The number of alternatives and the number of choice tasks

The number of alternatives is a fundamental element in the design of CE questions. Providing a large number of alternatives ostensibly increases the information that can be gained from a limited sample size. However, previous studies suggest that a large number of alternatives increases the complexity of CE questions as the respondents are exposed to more and varied decision tasks (Caussade et al., 2005; Boxall et al., 2009). In this situation, the respondents is dealing with not only which alternative to choose but also how many alternatives to consider. A study by Arentze et al., (2003) comparing the use two and three alternatives (without a constant alternative) did not find a statistically significant difference in error variance. Contrary to this, DeShazo and Fermo (2002) found a quadratic relationship among the number of alternatives and the variance of the error component. Specifically, they argued that the error variance first decreased due to an improved match of preferences and then increased due to an escalation in task complexity, with three or more hypothetical alternatives. Meanwhile, Meyerhoff et al., (2015) found that the drop-out rate was higher in a design with five alternatives compared to one with three alternatives. In relation to the number of choice tasks, the empirical evidence from Bech et al., (2011) revealed a U-shaped pattern for the error variance. A similar pattern was found by Meyerhoff et al., (2015). They claimed that the error variance at the beginning decreased as a result of learning, prior to increasing due to subsequent fatigue effects. Meanwhile, an empirical comparison of the single choice (status quo + one alternative) versus multiple choice format is given by McNair, Bennet and Hensher (2011), who found differences in WTP arising after the first task.

The effects of experimental design

Several strategies have been proposed in order to design the CE question, and it has been shown in academic findings that different experimental designs lead to differences in results. For example, Hess et al., (2008) applied two orthogonal designs; with random blocking and non-random blocking for all alternatives, identifying significant differences in model results. In particular, random blocking techniques resulted in poor performance and an overestimation of WTP values. Previously, Viney et al., (2005) investigated the impact of three different experimental designs on coefficient estimates, i.e. an orthogonal main effects design, a utility balanced design and a random design. The results revealed that different experimental designs did not influence the coefficient estimate. However, unexplained variance was found to be higher in a utility balanced design. In a more recent study, Bliemer and Rose (2011) empirically examined whether D-efficient designs were competently producing more reliable coefficient estimates as promoted in the literature, with smaller sample sizes. To be specific, they compared one orthogonal design and two D-efficient experimental designs all with a different number of choice situations. The empirical findings advocate the use of D-efficient experimental designs as these designs produced more reliable estimates and lower standard errors.

Summarising, the majority of studies discovered that the design dimensions of the CE question matter to the results and this became an important methodological issue in the choice experiment. In many cases, varying designs of CE influence the error variance and welfare estimates. The most worrying effect is related to biased welfare estimates, since the results from the valuation studies are commonly used to inform policy makers in their design and implementation of more effective actions in the future. In other words, results and policy implications may be distorted if the methodological issues in the application of CE are not properly examined and explored. Therefore, failing to take into account the methodological issues in CE could have profound policy consequences because the provision of goods or services may not reflect the true benefits.

1.1 Motivation of this study

There are two motivating factors for the research conducted in this thesis. The first motivation of this study is to explore the methodological issues in the choice experiment technique and how it can be used to improve the valuation estimates. Recent advances in the use of CE have revealed that different methodological issues affect welfare estimates. Therefore, analysing these emerging issues in CE may help to improve models and produce unbiased results. Most importantly, the validity and reliability of the results are vital for policy recommendations. Currently, research on the methodological issues in the application of CE is still limited, and this situation requires greater study to be carried out in relation to this issue. Among several methodological issues discussed in literature related to CE, there are three issues that are the main focus of interest to this study, namely; the status quo (SQ) effect, the effect of attribute non-attendance (ANA), and the influence of different distributional assumptions of random parameters in the mixed logit model (MXL).

Specifically, the emerging issues in CE that need to be examined and answered are:

1. Is the status quo relevant as one of the alternatives in the choice set?
2. Are the effects of attribute non-attendance important in welfare estimation?

3. How far do different distributional assumptions of random parameters affect welfare estimates?

The second motivation of this study is to enable the use of the choice experiment with the aim of providing policy makers with detailed information about public preferences relating to particular goods or services. With this in mind, this study addresses the lack of valuation estimates on the economic benefits of improving the quantity and quality of tourist facilities attributes. Therefore, the evaluation of the visitors' preferences for the tourist facilities attributes is conducted with a view to informing policy makers about the future provision of such attributes. An outcome of this study is to assist policy makers in planning and implementing more effective policies for the improvement of future recreation services.

1.1.1 Status Quo

Status quo is an alternative that presents the current scenario as an option on the choice card. The inclusion of status quo as one of the alternatives in the CE studies is believed to create an unforced situation with the goal of deriving unbiased welfare measures. Evidence from the environmental economics literature (Freeman, Herriges and Kling, 2014) and transport economics literature (Bateman et al., 2002) clearly state that to derive and obtain reliable welfare estimates of compensating variation some form of status quo or opt-out is needed. However, there is an ongoing academic debate regarding the necessity for offering status quo alternative in CE question. Johnson and Desvousges (1997) have suggested that the CE choice sets need not be restricted or constrained by the requirement of SQ in each alternative. Carson et al., (1994) have also discussed the question of incorporating a constant alternative (e.g. status quo, opt-out) in the context of choice experiment. They note that there are empirical advantages and disadvantages of including or excluding the constant alternative and this question remains an open research issue.

Offering status quo may not be a realistic action when the respondents are asked to make a choice for attribute improvement (Breffle and Rowe, 2002). Furthermore, the inclusion of the SQ alternative may produce biased responses: with information on trade-offs between attributes, it is easy for the respondents to choose the SQ alternative and ignore the complex hypothetical alternatives (Samuelson and Zeckhauser, 1988). In addition, when the SQ is chosen too often by the respondents, less information is obtained regarding the trade-off between attributes. A review of relevant literature indicates that not all attribute-based CE studies have included the SQ option. An alternative is to provide a forced choice for respondents between two or more hypothetical options.

Interestingly, the inclusion or exclusion of the status quo has been debated regarding whether it provides a significant impact on the preference parameter and WTP estimate. For example, a respondent who receives a forced choice question (without the status quo option) may feel compelled to answer, choosing an option, even though this alternative would reduce their utility compared with the status quo or no change situation. Thus, the outcome can lead to the estimation of a biased preference parameter such that E(d) > ɠ, where d is the estimated parameter for an attribute and ɠ is the real value. Overestimation arises since the forced choices reveal an increase in utility when in reality utility is actually decreases, and leading to a biased welfare estimate. As such, it is pertinent for this study to compare the effect of offering and not offering a SQ option in relation to welfare estimates in CE models. In Chapter 8, the effect of status quo is explored through a split sample design of a CE question. A split sample is used to evaluate the actual visitor's preferences of tourist facilities provided at a recreational site. The first design presents the CE question in which the status quo option is included whilst the second design offers only two hypothetical choice situations without the status quo option. These split samples enable a comparison of the results from the forced and unforced situations presented to the respondents. The Conditional Logit (CL), Mixed Logit (MXL) and Latent Class (LCM) models are used in the analysis. The results are then used to develop policy recommendations for improving attributes linked to better tourist facilities provision.

1.1.2 Attribute non-attendance

One of the fundamental assumptions in discrete choice theory is that respondents do consider all attributes and alternatives given to them. However, in some cases, this assumption may not be true. In a choice experiment, the repeated choices, the different combination of choice tasks, and the number of attributes and levels under consideration are among the factors that contribute to the complexity of the task. Research has shown that human decision strategy appears to be contingent on a wide range of task and context variables which are related to the particular values of the choice objects (Payne, Bettman and Johnson, 1988). Thus, the complex choice task leads to the adoption of decision strategies applied by individuals to solve decision problems. One such strategy is ignoring, or not attending to, certain attributes. In other words, respondents only consider a subset of attributes and ignore the rest.

Ignoring attributes indicates non-compensatory behaviour or non-compensatory strategy, as the given attribute level improvement fails to compensate for the reductions of levels of other attributes (Scarpa, Gilbride, Campbell and Hensher, 2009). Consequently, choices that are made using non-compensatory strategies cannot be represented as preferences over a utility function. This has important implications on the accuracy of welfare estimates. In recent times, a growing number of studies have explored how attribute non-attendance affects welfare estimation and how it could be accounted for in the choice experiment (e.g. Campbell, 2008; Alemu, Mørkbak, Olsen and Jensen, 2013). One of the interesting findings is that, from all of the respondents who claimed to have ignored an attribute, only some of them actually ignored it. Thus, the common method of dealing with ignored attribute in academic finding seems to be flawed. This finding has driven further investigations within this study in order to determine if attribute exclusion was a characteristic of the split sample CE design used in Chapter 8, whilst determining whether the respondents who claimed to have ignored an attribute really did so, through the introduction of a new method which encompasses how to deal with attribute non-attendance. The results are presented in Chapter 9.

1.1.3 Different Distributional Assumptions of Random Parameters

Stated preference data has been widely analysed using the MXL model to estimate respondents' willingness to pay for the goods being valued. Each respondent in the MXL model is considered as being one segment - hypothetically each person has unique tastes. The purpose of the estimate is to find the parameters of the distribution from which respondents' tastes are drawn. An interesting element of this model is that the analyst is required '*ex ante*' to define the functional form of this distribution. In the literature, the vast majority of the MXL studies employ the normal distribution of random parameters (e.g. Revelt and Train, 1998; Train, 2000; McFadden and Train, 2000; Sándor and Wedel, 2002; Ascani, Crescenzi and Iammarino, 2016). Some random parameters are also restricted to a specific distribution such as lognormal with the purpose of getting a non-negative sign parameter (e.g. Sillano and Ortuzar, 2005; Hess, 2010) and many other distributions can be applied to the coefficients which are not restricted in sign.

However, it is noticeable from the CE literature that insufficient attention is typically paid to the choice of random parameter distributions in MXL model. This is problematic given that the different distributional assumptions of random parameters chosen in the analysis of MXL model can have a major impact on resulting WTP estimates. With this in mind, some studies point out the importance of testing different distributions when developing the MXL model (e.g. Train and Weeks, 2005; Ghosh, Maitra and Das, 2013). Therefore, this research estimates four types of random distribution in the MXL (normal, lognormal, uniform and triangular) and the results of these different distributions towards welfare estimates are compared and presented in Chapter 10.

Summarising, it is important that the three issues discussed above are investigated further, since effect of these issues on welfare estimates has not been adequately explored. Most importantly, understanding more about these issues enables the researcher to undertake choice experiment studies correctly, thereby achieving a more accurate measure of WTP estimates which in turn is intrinsic to policy implementation.

1.2 Research Objectives

Four research objectives are defined for this study. Together they aim to achieve the overall goal of providing more representative estimates (for instance willingness to pay values). Reliable valuation estimates produce relevant information which is important for policy implementation. The specific objectives of the study are both methodological and policy orientated.

Methodological:

1) To examine the effect of offering and not offering the status quo option in discrete choice experiment questions on visitors' trade-offs and values for attributes.

2) To examine the effect of attribute non-attendance on attribute values.

3) To examine the different distributional assumptions of random parameters on attributes values and to determine which assumption produces the best model estimate.

Policy:

4) To evaluate the visitors' preferences for the tourist facilities attributes, and on the basis of these, to develop policy recommendations about the facilities and amenities to those involved in the management of the recreational lake.

Examining the methodological objectives along with the objectives to identify the visitor preferences for tourist facilities attributes is a step towards better policy management decisions for the development of tourist facilities in the future.

1.3 Kenyir Lake as a Case Study Area

Since the 1980s, tourism has become one of the important industries in Malaysia (Tan, 1991). Indeed, tourism is regarded as a vital sector in raising the national income of many countries in the world including Malaysia. Based on Malaysia's Economic Transformation Program (2010), the tourism industry is expected to contribute RM103.6 billion in gross national income by 2020, with tourist arrivals increasing from 24 million in 2009 to 36 million in 2020. This prediction would mean the industry will continue to play a significant role in the country's growth.

In general, the successful operation of tourism is mainly dependent on the accessibility of publically provided tourism facilities and infrastructures. Strictly speaking, these facilities support or facilitate visitation without generating any income to tourism operators. It is regarded as a complementary factor, adding value to the tourist's experience besides the other readily available resources (e.g. natural attraction). Indeed, the strong growth effect is a combination of the complement between natural and built amenities rather than occurring from just the natural ones (Partridge and Olfert, 2011). For example, in Budderoo National Park, New South Wales, Australia, the construction of tourist facilities has been identified as a factor that boosted the number of visitors[1] by nearly 100% within three years (Bushell, 2003).

Kenyir Lake is among the popular ecotourism sites in Malaysia. This lake offers a wide range of recreational benefits to the visitors and it charges zero money for the entrance fee (see Figure 1.2). However, with only a small budget from the government, maintenance of the facilities provided are not carried out effectively or regularly, and this can impact on the quality of the facilities provided to the visitors, especially those surrounding the main entrance point of the lake, called Gawi Jetty. Poor facilities, whether provision or maintenance, make a trip less pleasant, increases dissatisfaction and discouraging visitors in the long term.

[1] The term visitors can be divided into two categories; (1) tourist – those who spend the night at the destination, and (2) same-day visitors – those who spend only the day at the destination (Lickorish and Jenkins, 2011). Therefore, the terms tourists and visitors are used interchangeably in this study.

In addition, the overwhelming increase in visitors to this lake every year generates additional or excessive use of the tourist facilities. For example, whilst in 2003 Kenyir Lake was visited by around thirty to forty thousands of visitors, this number has increased on a yearly basis, and in 2008 the number of visitors reached one hundred thousand (see Table 1.1). In 2013, the total number of visitors was 467,678, reaching nearly half a million. Meanwhile, in 2014 and 2015, the total number of visitors reached over half a million. This increasing trend now poses a serious challenge to the lake management, who must cater for and fulfil the needs of the tourists while ensuring that the economics, ecotourism sustainability and recreational benefits are balanced and well-organized. The Central Terengganu Development Authority (KETENGAH) is one of the government agencies responsible for developing and maintaining the jetty in accordance with the needs of tourism here.

Figure 1.2: Map of Kenyir Lake

Source: Malaxi (http://www.malaxi.com/terengganu/terengganu_map.html)

Table 1.1: Number of Visitors to Kenyir Lake

Year	Domestic Visitor	International Visitor	Total of Visitors
2003	35,423	1864	37,287
2004	39,760	2093	41,853
2005	48,274	2541	50,815
2006	57,505	3027	60,532
2007	87,589	4610	92,199
2008	126,891	6678	133,569
2009	179,919	9469	189,388
2010	214,291	11,279	225,570
2011	261,479	13,762	275,241
2012	377,155	19,850	397,005
2013	444,294	23,384	467,678
2014	616,924	32,470	649,394
2015	670,912	35,311	706,223

Source: Department of KETENGAH (2016)

Having an adequate quantity and quality of facilities is crucial to meet the present and future demands of tourism. Otherwise, it act as a deterrent to tourists. For example, a short supply in facilities such as toilets can lead to congestion and overuse of the services that result in inconvenience and a poor experience for the visitors. Although the presence of public toilets or other facilities is unlikely to influence a visitor's decision on whether to spend their leisure time at particular destination, it can have a bearing on the value of their experience and their willingness to return. Ashley, Rose and Goodwin (2001) have identified the cleanliness aspect and the provision of adequate numbers of bathroom facilities amongst the issues for tourism destinations. Meanwhile, Hall and Lew (2009) give an example of deteriorating restroom facilities over time leading to visitor complaints and environmental risks. Swarbrooke and Page (2002) have noted that the facilities at tourist sites become one of the benchmarks for judging attractions in the minds of visitors. Taking into account these reasons, it is essential to maintain, and where possible, improve the basic services and facilities that underpin the visitor's experience.

One of the issues in providing and maintaining tourist facilities relates to financial concerns, as the money comes from the federal government. The money is often not adequate enough to cover the operational cost of a tourist area. Even though the government is the responsible body for providing or developing tourist facilities as a "public good[2]" which can be used for free,

[2] The common or collective benefits provided by the government are regarded as a "public good" (Olson, 2002). An example of pure public good is open-access to a recreational park which provides a wide range of tourist

dependency on government funding is not necessarily the best option for the future. As an alternative, attention towards applying a charging fee could be considered. According to Willis (2003), an entrance fee can be introduced for public parks in order to defer the high costs of maintenance in an era where the public funding is limited, provided access points are limited in number. The collection of an entrance fee at a tourist area would be hypothecated for management purposes to provide improved facilities for the tourists.

In Malaysia, the implementation of an entrance fee system is not a new matter since it has been applied in nature parks, national parks and some of the recreational forests to support the management and operation of the parks. Table 1.2 presents the list of popular tourist areas in Malaysia and their current entrance fees (in 2016). However, most of the tourist areas in Malaysia currently do not collect an entrance fee at all.

Table 1.2: The Popular Tourist Areas in Malaysia and their Entrance Fee

Location	Entrance Fee/ Conservation Charge (in Ringgit Malaysia 2016)	Source
Redang Island Marine Park, Perhentian Island	RM 5 - Adults RM 2 - Students, school children, retirees, and senior citizens (55 year and above). Children below 6 years old are free.	Department of Marine Park Malaysia
Taman Negara National Park	RM 1	Department of Wildlife and National Parks
Malaysian Agriculture Park	RM 3 – Adult (12 – 54 years) RM 1 – Children (6 – 11 years) RM 1 - Senior citizens (55 years and above)	Malaysian Agriculture Park
Forest Research Institute Malaysia	RM 5/car	Forest Research Institute Malaysia, Ministry of Natural Resources and Environment

Examining the impact of the implementation of an entrance fee to a tourist area that currently does not collect a fee, such as Kenyir Lake, may provide important evidence about the practicality of collecting entrance fees from tourists. In this regard, this study aims to examine some of the methodological issues in the choice experiment by assessing visitors' preferences

facilities and services without imposing any entrance fee, while impure public good could be a recreational park that only allows entrance following the payment of an entry charge.

towards tourist facilities attributes at Gawi Jetty, Kenyir Lake, and the values of these facilities through a proposed entrance fee. The entrance fee would be used for the development and maintenance of visitors' facilities surrounding the jetty. By assessing actual visitors' preferences toward the facilities provided and proposed, the information gathered could help the government to implement the relevant action to enhance the quality of the services in the future.

In Malaysia, the use of the choice experiment as a mechanism to analyse preferences of the individual has been applied by some researchers in order to provide responsible bodies with an added perspective in their decision making. For example, Pek and Jamal (2011) used CE to reveal consumer preferences and WTP for the improvement of solid waste disposal options in Selangor. This study aims to assist the relevant bodies in identifying a superior waste disposal management strategy. A different study by Yacob, Shuib and Mamat (2009) employed CE to estimate visitors' preferences towards ecotourism facilities and services in the Redang Island Marine Park. The results obtained from the study were important in helping policy makers in the management and improvement of ecotourism facilities and services in Marine Park. Othman, Bennet and Blamey (2004) estimated the non-market values obtained under various management options in Matang Mangrove Wetland to aid decision makers in determining the optimal wetland management strategy. Meanwhile, Hasan-Basri and Karim (2016) applied CE to investigate benefit transfer and to determine the public preferred attributes in recreational parks in Kuala Lumpur and the Malaysia Agricultural Park in Selangor.

Briefly, choice experiments have been increasingly used in Malaysia to inform policy evaluation and project appraisal in many sectors such as forest, tourism, wetland, park, coastal system, marine environment. However, there has been no CE study in Malaysia which has focused on valuing recreational site attributes, particularly the attributes of tourist facilities. As a result, this study attempts to employ CE to estimate the WTP in order to inform the policy maker how best to improve the provision of tourist facilities attributes in Malaysia. This allows different attributes to be included in the CE study.

The choice of Kenyir Lake is a suitable case study area for the investigation of the methodological issues discussed in this study, for several reasons. Firstly, Kenyir Lake is actively being enhanced and developed as a tourism destination which offers a wide range of benefits to visitors. Several development plans have been proposed and implemented by KETENGAH department based on the budget provided by the government. One of the ongoing projects is to turn the lake into a duty free area to become the top holiday destination in

Southeast Asia. The project includes the improvement of the infrastructure at Gawi Jetty which is the main entrance point of the lake. Thus, the central question here is whether a ‘do nothing’ option is a realistic policy alternative which should be offered to the respondent when the improvement of infrastructure provided at Kenyir Lake might be undertaken in the future. Kenyir Lake attracts a diversity of visitors who come from various backgrounds. Thus, visitors with different backgrounds might have differing preferences and perceptions on the status quo option, which could in turn help this study to affirm whether the status quo is relevant as one of the alternatives in the CE choice sets or not.

Secondly, this study focuses on the improvement of the tourist facilities often used by tourist at any tourism area. When the respondents are already familiar with the attributes, do they still have a tendency to ignore any of the attributes presented in the choice cards? Even though responding to the CE choice cards is a complex task for respondents to undertake and can cause them to ignore some of the attributes, it is expected that they are less likely to miss out the attributes that they are already familiar. Thus, the choice of scenario at Kenyir Lake is suitable to examine whether the respondents still employ the attribute processing strategies when they are faced with a non-complex task. Meanwhile, different types of visitors who come to the lake use different types of tourist facilities, and this situation might contribute to the possibility of some attributes being ignored in the choice cards. In other words, it is plausible to assume that only a subset of tourist facilities attributes is of behavioural relevance to some respondents. Thus, the effects of attribute non-attendance towards welfare estimation could be examined in this study.

Lastly, different types of visitors to Kenyir Lake might exhibit a different taste variation: what is known in the CE literature as heterogeneity in preferences, since their background and perceptions differ. Visitors with dissimilar preferences are a suitable vehicle to explore the effect of various preference distributional assumptions (e.g. whether preferences are normally distributed, uniformly distributed and so on). This situation requires the use of the MXL model specification which allows for random taste variation, and thus the effect of different distributional assumptions of random parameters towards welfare estimates could be examined in this study.

1.4 Contribution of Research

This study contributes to the CE literature by outlining the importance of correctly conducting CE research, empirically revealing differences in welfare estimates when methodological issues are taken into consideration, as compared with standard practise. In achieving the four research objectives previously described, this study delivers four contributions which are innovative in a number of dimensions.

Contribution 1: This study uses a split sample design in the choice experiment to examine the effect of status quo on welfare estimation and tests the data using the logit family of CE models (e.g. conditional logit, mixed logit). The application of split sample designs to examine the issue of status quo is lacking in the literature. Thus, there is a scope for more split sample studies to explore this methodological issue, and this research assists in contributing to this gap. In addition, no single study applying a split sample design has been undertaken in Malaysia for the valuation of non-market goods. This study also introduces a new supplementary question at the end of the choice task in order to elicit the respondents' opinion regarding the choice card design. The follow-up questions are helpful in identifying if any bias of choice occurs as a result of presenting two different versions of discrete CE questions to respondents, in which the respondents are randomly assigned to the forced or unforced CE questions. For example, respondents who answer a CE question without the status quo alternative presented on the choice card might prefer to respond to the CE question which provides the SQ alternative and *vice versa.* Thus, the bias of not presenting the CE question, with the SQ option given in the choice card, to respondents who might want to have this option, can be examined. From the review of the literature, this study is the first study that uses a supplementary question to identify a bias of choice that might occur as a result of applying a split sample design of CE questions.

Contribution 2: With the aim of identifying and incorporating procedures for dealing with attribute processing strategies, this study proposes unique extension to the current standard way of ANA elicitation approach by introducing a new method of how information can be elicited from the respondents. Previous studies on this issue have mostly asked respondents which attribute they ignored when making their decision, and the parameter of the ignored attributes are set to zero in the analysis. However, recent evidence suggests that the standard way of assigning a zero value for the ignored attributes in the analysis is inappropriate and might create biased results. One of the reasons this suggestion has been raised is due to respondents who have stated that they ignore a certain attribute but may in fact just find the attribute of lesser importance. Thus, this study aims to contribute to this growing area of research by introducing a new supplementary question that can help respondents to differentiate which attributes they ignore and which attributes are less important to them when making their decision. In addition, this study test and compares four different specifications of MXL model to account for ANA in the analysis.

Contribution 3: This study tests the MXL model with different types of random parameter distributions, namely the normal, the lognormal, the triangular and the uniform distributions. So far, little research has explored and discussed the effect of these different distributions towards welfare estimates. The results from this study reveal that, whilst there are some similarities in results between some of the distributions, in relation to one of the distributions, there are quite significant dissimilarities.

Contribution 4: To help develop policy recommendations for tourist facility attributes through the evaluation of the CE results, and to enhance these recommendations by the application of recent methodological advances in the choice experiment. Briefly, this research provides detailed information on the value of improvements to the tourist facilities attributes at Kenyir Lake. So far, there is no quantitative study undertaken on tourist preferences at Kenyir Lake, or in general, in Malaysia. Therefore, this adds significantly to the ways decisions can be improved through having a more rigorous method. In addition, one of the main benefits of the choice experiment method for drawing practical policy recommendations, is the information on the explicit trade-off between attributes.

Summarising, this study contributes significantly to the non-market valuation literature mainly on Choice Modelling (CM) by examining three main methodological issues in CE; the status quo, the attribute non-attendance, and the different distributions of the random parameter. In addition to the issues discussed above, in the valuation and assessment of tourist facilities from the perspective of tourists, it is important to realise that the provision of such facilities fulfils their preference.

1.5 Achieving the Objectives: The Thesis Structure

The remainder of this thesis is set up as follows:

Chapter 2: Stated Preference Approaches to Valuing Non-Market Goods

This chapter provides an overview of two main approaches in stated preference technique to valuing non-market goods, namely, the contingent valuation method and the choice experiment method. The strengths and drawbacks of each method are discussed along with its suitability for valuing recreational site attributes.

Chapter 3: Literature Review of Choice Experiment

This chapter reviews the literature on choice experiments. The review begins with the summary of the previous choice experiment studies in non-market valuation, followed by the discussion of the design process of choice experiment which includes the assignment of attributes and levels, the choice of experimental design, CE questionnaire design and sampling strategy. The data collection techniques in CE are also discussed in this chapter. This is followed by the overview of the theory behind the CE method and the derivation of the conditional logit (CL) model, the mixed logit model (MXL) and the latent class model (LCM). The last section discusses the welfare measurement used in this study, which is the willingness to pay (WTP) value estimate.

Chapter 4: Literature Review of the Status Quo Issue, Attribute non-attendance and the Different Distributional Assumptions of Random Parameters in the Mixed Logit Model

This chapter provides the discussions from the previous literature related to the research issues that were explored in this study, namely; (1) the status quo, (2) the attribute non-attendance, and (3) the different distributional assumptions of random parameters. This chapter also serves as a point of reference for the analysis carried out in Chapters 8, 9 and 10.

Chapter 5: Study Area Description

This chapter presents the information related to Kenyir Lake, Malaysia, which is the research study area. It begins with the presentation of background information about Malaysia and types of lakes accessible in Malaysia. This chapter continues with the presentation of a general profile of Kenyir Lake; geography, history, climate, flora and fauna. Furthermore, the establishment of Kenyir Lake and the available attractions offered are also discussed. Information regarding the management and administration of Kenyir Lake is presented in the final part of the chapter.

Chapter 6: Research Methodology

This chapter provides an explanation of the research methodology that was applied in this study. Methods to determine the attributes and levels to be used in this study are discussed, along with a description of the chosen attribute level and the construction of the experimental design. This chapter also provides the description of each section of the final questionnaire survey administered in the study. Finally, the sampling and implementation of the survey are described.

Chapter 7: Descriptive Analysis

This chapter discusses the finding of the descriptive analysis of the study. The first section of the chapter presents the analysis of the socioeconomic profiles of the respondents, including gender, age, nationality, household numbers, occupation and monthly gross household income. This is followed by the analysis of the travel information of the respondents and the analysis of the attitudes and perception of the respondents towards Kenyir Lake.

Chapter 8: Status Quo Analysis

This chapter presents the empirical results of the split sample design and their interpretation of the status quo issue. The first section presents the analysis of the choice card responses, followed by the analysis of the effect of status quo option on the share of hypothetical alternatives and the discussion of the Conditional Logit Model results. The Mixed Logit Model and the Latent Class Model, two models that consider the heterogeneity in preferences, are then discussed. This chapter then presents the results of the willingness to pay estimate as a welfare measurement used in this study. Finally, summary and discussion for future research are considered.

Chapter 9: Attribute Non-Attendance Analysis

This chapter presents the empirical results of the attribute non-attendance issue. The first section presents the results of the attribute responses followed by the cross tabulation analysis between attribute responses and respondents' characteristics. The summary of attribute attendance and non-attendance, for both forced and unforced samples and the results of the MXL model estimations, are then presented and discussed. This chapter then presents the effects of the attribute non-attendance towards the estimation of willingness to pay value. Finally, summary and discussion for future research are considered.

Chapter 10: Different Distributional Assumptions of Random Parameters Analysis

This chapter presents the empirical results of the four distributional assumptions of random parameters in the MXL model. The first section presents the results for the forced sample, followed by the results for the unforced sample (with and without the specification of status quo). The effects of different types of distributions towards the estimation of willingness to pay value are then presented and discussed.

Chapter 11: Conclusion

This final chapter summarises the main contributions of the thesis and recommends the direction for future research.

Chapter 2: Stated Preference Approaches to Valuing Non-Market Goods

2.0 Introduction

This chapter discusses the stated preference approaches for valuing non-market goods. It begins with Section 2.1 and the introduction of the two main methodological approaches used in the economic valuation study for valuing non-market goods and services, namely, the stated preference techniques and the revealed preference techniques. Stated preference techniques are detailed in Section 2.2, which includes the discussion of; (1) the elicitation techniques and the problems and biases in the application of contingent valuation method; and (2) the variants in the choice modelling method. Section 2.3 compares advantages and disadvantages of both contingent valuation and choice modelling methods. This section also identifies a method which is suitable to be applied in this study. Finally, concluding remarks are presented in Section 2.4.

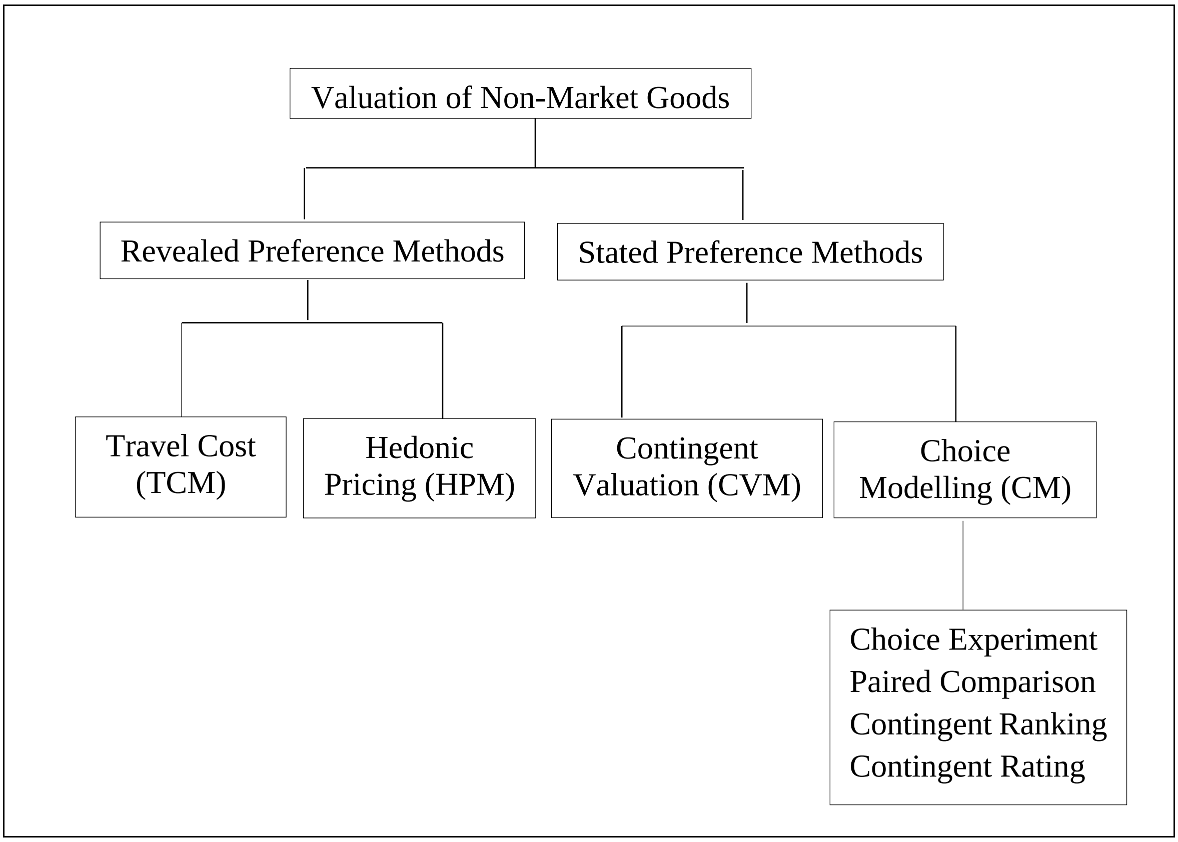
2.1 Approaches to Valuation

Methodological approaches for measuring the economic values attached to non-market goods and service, including recreational sites, can be classified into two main groups. Firstly, non-market stated preference techniques and secondly, market-based revealed preference techniques (see Figure 2.1). In general, the reveal preference techniques have the advantage of data being based on the actual decision or observed behaviour of the consumers, according to the real market situation. In other words, the reveal preference techniques identify the ways in which the non-market goods influence actual markets for other goods, i.e. value is revealed through a proxy or surrogate market. For that reason, the data from revealed preference techniques are often said to be more accurate (Willis, 2014).

Revealed preference techniques comprise of two components; hedonic pricing method and travel cost method. The hedonic price method evaluates the environmental services quality by observing prices of houses, land or other marketed goods. This method tries to identify how much of the price of a property, such as a house, varies as the quality of closely related environmental goods changes. For example, by looking at the existence of an environmental quality such as air pollution or noise level that are considered to affect house prices (e.g. houses located in noisy areas are expected to be cheaper than similar houses in quieter but otherwise comparable areas). This relationship is used to assess public natural resources that do not have a price or market price does not exist. For instance, Leggett and Bockstael (2000) examined the impact of water quality on residential land prices, Lansford and Jones (1995) considered the recreational and aesthetic value of water, i.e. whether fluctuation in water level of a lake had a statistically significant effect on residential property values, while Garrod and Willis (1992) studied the effect of countryside characteristics on property values.

Conversely, the travel cost method has been widely used to value the recreational benefit provided by a specific recreational site (Mitchell and Carson, 1989; Garrod and Willis, 1999). The travel cost method uses the travel expenses incurred to gain access to the particular recreational site as a surrogate for the “price” paid by that visitor for a site visit. Generally, this method explains how the demand for environmental goods and services is inversely correlated to the travel expenses incurred to gain access to them, i.e. the demand for a particular site decreases when the cost that an individual incurs to travel to the site increases. The method takes into account data on visitation rates to the recreational site, the expenses of individuals who visit the site (e.g. admission fee, travel cost, the cost of fishing permit) and the distance travelled to visit the site. The total cost of travel is substituted for the amount an individual is willing to pay for the services of that site.

Figure 2.1: Non-market Valuation Method



Though HPM and TCM seem relatively straight forward and easy to apply, there are several problems with the methods in practice. For example, one of the problems in TCM is the multi-purpose visit journeys or multi-activity trip, and it is contrary to the assumption in TCM application, i.e. a trip taken by the visitors to a specific recreational site is for a single purpose or undertaking only a single recreational activity (Garrod and Willis, 1999). Therefore, the value of the site may be overvalued when a trip has more than one purpose. Meanwhile, Hanley and Knight (1992) point out that it is difficult to differentiate day-visitors from 'meanderers' and 'holidaymakers' with the travel cost method.

In addition, Willis (2003) envisages the problem of estimating the demand for urban sites through TCM due to the variation in travel costs, i.e. the distance most visitors travel to urban site tends not to differ that much and only involved a time cost of access as compared to the travel and time cost incurred when visiting more distant site in rural areas. This method also requires a reasonably large data set and a large amount of information for every respondent to be effective and reliable (Koetse, Brouwer and van Beukering, 2015). As a result, the cost of conducting the surveys are usually expensive and take a long time to complete. The other problems in TCM are substitute sites and non-paying visitors (Turner, Pearce and Bateman, 1994; Randall, 1994; Garrod and Willis, 1999). Finally, the TCM is restricted to the use values. Consequently, the estimated benefits will be underestimated if site preservation is also important to non-users.

Meanwhile, problems usually related to HPM include data collection problems and statistical difficulties. For instance, though all relevant characteristics should be incorporated in the hedonic price functions to avoid biased parameters, this commonly results in important multicollinearity problems (Hoevenagel, 1994). As stated by Garrod and Willis (1992), multicollinearity is the common problem in hedonic price functions and is regularly ignored. If multicollinearity problem is serious, it can cause unreliable and unstable coefficient estimates. The HPM is useful mainly for long-term environmental changes since these are expected to affect property value. Hence, in the case of an incident that causes a temporary effect only, the HPM is considered unsuitable to apply. In addition, the application of hedonic price to the environmental functions of public natural resources (e.g. wetland) necessitates that these values are reflected in the proxy market. In some situations, the method may be limited, for example, where markets are distorted by the government interventions (Hoevenagal, 1994) or choices are constrained by income (Barbier, Acreman and Knowler, 1997). The other problems in HPM are: measurement error, user unfriendliness and market segmentation (Hanley and Spash, 1993; Garrod and Willis, 1999).

Though there are several studies applied the Hedonic Travel Cost Method (e.g. Mendelsohn and Brown Jr., 1983; Englin and Mendelsohn, 1991; Pendleton and Mendelsohn, 2000) which is the combination of HPM and TCM, the method is cumbersome to be apply (Smith and Kaoru, 1987). Since this study aims to measure specific attributes of non-market goods and investigates the changes for each attribute, the HPM and TCM are not suitable valuation methods.

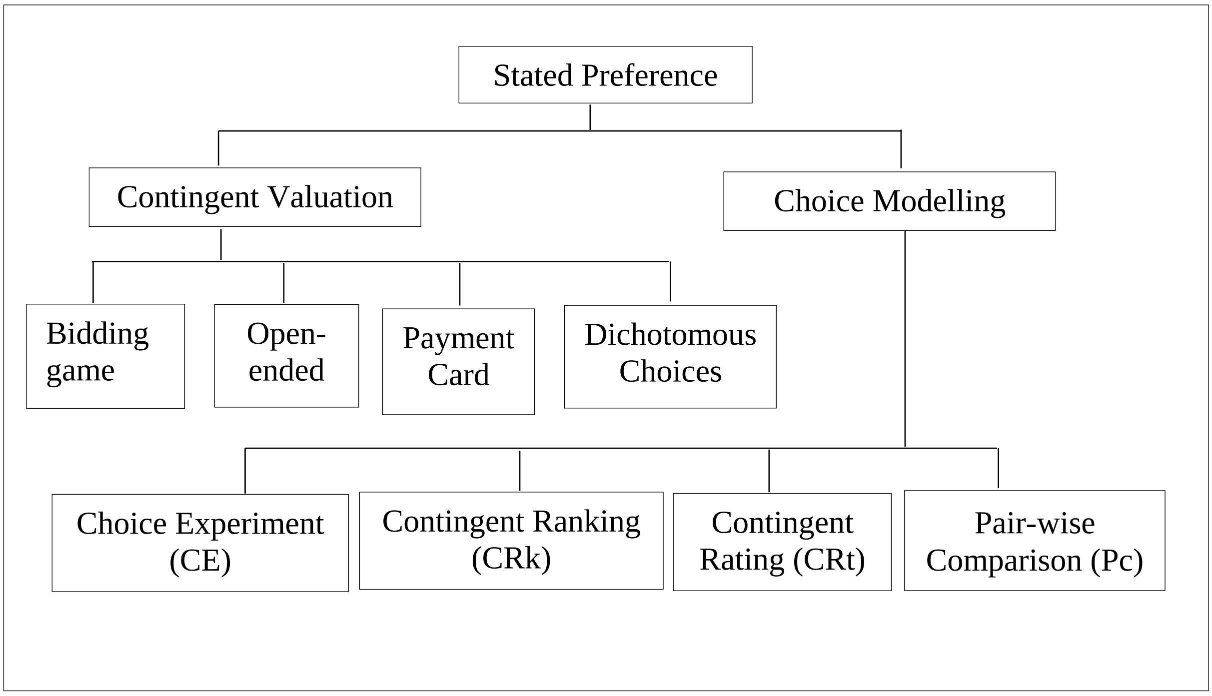
Consequently, research in the area of valuation of non-market goods has seen an enormous interest in another branch, namely stated preference techniques or direct methods. The use of this method has been extensively discussed in the literature on economic valuation of environmental goods and services (e.g. Garrod and Willis, 1999; Adamowicz, Boxall, Williams and Louviere, 1998).

2.2 Stated Preferences Techniques

Of the numerous valuation techniques available, stated preference techniques or direct methods are being used and applied to a growing extent. These techniques assess the value of non-market goods and also potential 'marketed' goods by asking the individual to express their preferences for a hypothetical option presented in the questionnaire. In other words, the stated preference data is collected through a questionnaire survey that tries to find out what are the individuals' preferences for goods, or for the attributes of a certain goods, that are being valued. Fundamentally, stated preference techniques elicit the WTP of the respondents directly by asking a question in the form of "How much are you willing to pay?" or "Are you willing to pay RM *x* amount of money?" or by asking respondents to express their preferences through some set of hypothetical alternatives. Two popular techniques used to value the benefits of recreational sites with direct methods are the contingent valuation method and choice modelling method (see Figure 2.2). The choice modelling method was developed at the same time as CVM was developed, after recognising the possible biases in CVM in the valuation of non-market goods (Hanley, Mourato and Wright, 2001).

Stated preference techniques were initially promoted by the work of Davidson (1973) and Louviere and Hensher (1983) who discovered how analysts could investigate trip-makers responses to hypothetical combinations of attributes and levels for travel modes. Stated preference techniques are suitable to be used where the WTP information that is looked-for cannot be inferred from the market because there is no existing market for those goods, for instance, recreational sites. As mentioned by Willis (2002), stated preference techniques are needed because revealed preference techniques cannot be used to value all environmental goods, for example, a good which has not yet to be formed, or a good which people might value, but they have never used or seen. In addition, stated preference data are less constrained than revealed preference data and allow the researchers to look at possible changes (Swait, Louviere and William, 1994).

Figure 2.2: The Family of Stated Preference Technique



The process of estimating non-market values by the use of stated preferences has four main steps (see Table 2.1). In step A, critical decisions are made regarding the objective of the study and how that objective will be fulfilled. The objective of the study should answer the policy question of interest. For instance, if the question is whether the national forest area should be designated as wilderness area, the objective might be to evaluate the economic benefits of designation. In step B, the survey tool and sampling strategy are considered. The design of the survey tool includes identifying the goods or attributes to be valued (e.g. a careful depiction of the proposed wilderness area) and any independent variables to be collected in the survey (e.g. education, income), the administration method (e.g. mail survey), and other important details. In step C the survey is conducted and administered while in step D the data is cleaned and analysed, including scaling the responses to estimate the magnitudes on the measurement of interest (e.g. binary choices are transformed to an estimate of mean WTP).

Table 2.1: Process of Evaluating Values using Stated Preference Techniques

Step A - Plot out the valuation approach by identifying the following: 1. measurement objective to respond to the policy question 2. targeted population to be sampled 3. theoretical construct that fulfils the measurement objective 4. valuation technique that suits the theoretical concept 5. response mode of the valuation question(s) 6. measure of value 7. statistical model used to scale the valuation responses Step B - Design the survey tool and sampling strategy by identifying the following: 1. goods or attributes to be valued 2. monetary amounts to be used (necessary for some methods, such as dichotomous choice contingent valuation) 3. independent variables (if any) to be measured 4. administration method (e.g. phone, mail) 5. other details of the instrument, such as background information about the good, information about substitutes, the order of the questions, and use of graphics 6. the sample 7. details of sampling, such as method of contacting respondents, method of boosting response, and schedule of activities. Step C - Administer the survey Step D – Clean and analyse the data

Source: Adapted from Brown (2003)

2.2.1 Contingent Valuation Method (CVM)

The contingent valuation method refers to a technique that uses a survey question to elicit respondents' WTP for non-market goods contingent upon the supply or particular improvement in the goods being valued. For instance, respondents could be asked directly to state their maximum WTP for an admission fee to the public park. Thus, this method is aimed at eliciting respondents' WTP in the monetary terms. The CVM also can be used to elicit people's preferences for private goods, and is one of the obvious strengths of this method (Sugden, 1999). For example, Willis and Powe (1998) compared contingent valuation estimates of willingness to pay with actual payments for a private good, i.e. entrance charge to Warkworth Castle, a historical site in northern England.

Historically, the CVM was proposed by Ciriacy-Wantrup (1947) in the discussion evaluating capital returns from soil conservational program. Nevertheless, Davis (1963) was the first to apply the CVM empirically when he used a questionnaire to value the benefits of outdoor recreation in a Maine backwoods area. Afterwards, the popularity of the CVM increased and has been widely used by the researchers around the world for valuating services of natural resources, including recreation. For example, Daubert and Young (1981) adapted the CVM to assess the recreational demands of maintaining instream flows, based on three activities; trout fishing, white-water boating (rafting and kayaking), and streamside recreation (e.g. picnicking, camping, or hiking). Meanwhile, Lee and Han (2002) explored the recreational values of five national parks in South Korea using CVM.

2.2.1.1 Elicitation Techniques in CVM

The different kinds of elicitation techniques that have commonly been used in the CVM are a bidding game (BG), an open-ended (OE) WTP or willingness to accept (WTA) question, payment cards (PC) and a dichotomous choice (DC) format. The next sub-section discusses the advantages and disadvantages of each of the elicitation techniques used in CVM.

2.2.1.1.1 Bidding Game (BG)

The bidding game is the oldest elicitation method in the CVM, and it has been widely used by researchers (Mitchell and Carson, 1989). In brief, this approach poses a series of questions to the respondent and the process is continued until the maximum amount a respondent is willing to pay is found. A particular bid from a range of predetermined bids would be randomly assigned to the respondent, and they will be asked to say ‘yes’ or ‘no’ to that particular bid. If they say ‘no’, they will be assigned with a lower bid value. In contrast, if they say ‘yes’ for the starting bid amount, then they will be asked whether they are willing to pay a higher bid amount and this process would continue until the highest bid is recorded.

The main advantage of the BG method is that it offers a more flexible alternative to the respondent (Howard, Chave, Bakir and Hoque, 2006). Meanwhile, a major disadvantage of the bidding game is related to the starting point bias, for example, the final WTP amount can be influenced by the starting bid value (Alberini and Cooper, 2000). Also, this method would not be appropriate for a postal survey because of the need to wait for each yes or no answer before continuing to the next bid level.

2.2.1.1.2 Open-Ended (OE)

The open-ended format involves directly asking the respondent what is the maximum amount that he/she would be willing to pay for the public goods being valued. Due to this, OE questions are considered to be the easiest and most straightforward format in the application of the CVM. An example of such a question is ‘How much are you willing to pay as a conservation fee for the National Park?’ and the respondent is expected to give his/her open-ended value based on this question. Some of the advantages of using this format are that it is convenient to apply and free of any starting point bias (Mitchell and Carson, 1989).

Meanwhile, one of the disadvantages of this method is that it is difficult for the respondents to complete or to provide a spontaneous value for the public goods because they are not familiar or have never thought about evaluating changes in public goods before. Furthermore, instead of stating maximum WTP values, most regular market transactions involve deciding whether or not to buy products at fixed price (Bateman et al., 2002).

2.2.1.1.3 Payment Card (PC)

The payment card is an approach that displays a list of monetary values for goods in question on a card and respondents are required to pick the amount that best represents their maximum willingness to pay. By using this approach, the respondent only has to bid once from the range of values provided and their choice is final. An example of a question asked could be ‘Based on the prices listed on this card, could you please tick the highest price that you would be willing to pay?’.

As stated by Mitchell and Carson (1989), some researchers prefer to use the PC format because of two reasons; (1) to maintain a direct approach for eliciting the respondents’ WTP, and (2) to increase the response rates. Moreover, the PC approach may avoid starting point bias and reduce the number of outliers compared to other elicitation formats (Bateman et al., 2002). One of the disadvantages of this format is that it is exposed to bias in relation to the range of the numbers presented on the card, that is, the minimum and/or maximum price has an influence on the result (Heinzen and Bridges, 2008). Furthermore, the respondents tend to restrict their declared WTP to the value presented on the card (Alberini and Cooper, 2000).

2.2.1.1.4 Single Bounded (SB) and Double Bounded (DB) Dichotomous Choices

The single bounded dichotomous choice format was originally introduced by Bishop and Heberlein (1979). This format is the most frequently used for CVM studies. In this format, each respondent faces a single question of the form ‘Are you willing to pay X?’ where “X” is an amount of money that being varied across the subject. The application of double-bounded format is similar to the SB format in which the respondents are presented with a price, but after giving their choice, they are offered another price and again the respondents are asked whether they are willing or not to pay that amount. The second price is set based on the respondent’s responses to the first price. If the respondent replies "yes" the first time, the amount of the second price is higher than the first price; if the first answer is "no," the second price is a lower amount.

The SB format simplifies the cognitive task faced by the respondents, since it offers the situation in a similar way as the consumers decide whether or not to purchase goods and services at a certain price. However, the DB format is well known to be more efficient than the SB format, as more information about each respondent’s willingness to pay is elicited (Bateman et al., 2002) and produces a less biased estimate (Hanemann, Loomis and Kanninen, 1991).

Dichotomous choice formats have several drawbacks, for example, larger samples are required since less information is available from the respondents. Moreover, use of the DB format leads to a potential loss of incentive incompatibility due to the fact that the second question may not be regarded by the respondents as exogenous to the choice situation (Bateman et al., 2002).

2.2.1.2 Problems and Biases in the CVM

Despite the wide use of CVM for the valuation purpose, this method has been criticised by some analysts, especially in relation to the accuracy and consistency of the results and the effects of several biases and errors (Freeman et al., 2014). The criticism is also related to the ability of CVM to provide reliable willingness to pay estimates (Weber, 2015). The application of the CVM suffers from some potential errors and biases. To name a few, strategic bias, starting point bias and non-response bias are among the biases in the CVM which are usually found in the SP techniques.

Strategic bias occurs when the respondents give WTP values that differ from their true WTP in an attempt to influence the provision of the goods (Bishop and Romano, 1998). For example, the respondents may understate their WTP values when they think that their bids will be collected. On the other hand, the respondents may overstate their WTP values if they believe that their bids are hypothetical.

Starting point bias occurs when the initial amount proposed at the beginning of a bidding game has a significant influence upon the final bid stated by the respondents (Turner, Georgiou, Clark and Brouwer, 2004). Meanwhile, non-response bias arises when there is only a small number of valid responses obtainable from the total sample (Fredman, 1999).

Despite the fact that the CVM has the potential to measure the recreational attributes values in this study, problems and biases encourage the employment of another branch of SP technique, namely, the choice modelling approach. Hanley et al., (2001) pointed out the increased interest among valuation practitioners in applying choice modelling rather than the CVM in order to avoid some of the potential biases in the CVM approach.

2.2.2 Choice Modelling (CM) Techniques

Choice modelling techniques, which is sometimes called 'Conjoint Analysis', can be used to assess value for choice or preferences that are not revealed in market transactions (Rolfe, 2006). CM techniques are based on the idea that all goods can be described in terms of its attributes and levels (Bateman et al., 2002) and each attribute and level gives value to those goods (Alpizar et al., 2003; Green and Srinivasan, 1978). For example, a recreational park can be described in terms of its recreational facilities, natural attractions and the level of information provided to visitors.

In this technique, various alternatives which comprise different combinations of attributes and attributes levels are presented to the respondents (Hanley et al., 2001). Analyses in CM may be undertaken using four main variants; contingent ranking (CRk), contingent rating (CRt), pair-wise comparison (Pc), and choice experiment (CE). Hence, these approaches are reviewed to select the best method and are discussed in the next sections.

2.2.2.1 Contingent Ranking (CRk)

Respondents in CRk technique are asked to rank a set of alternatives given to them according to their preferences (Bateman et al., 2002; Garrod and Willis, 1999). In this technique, respondents face a sequential choice process whereby they first choose their most preferred alternatives, followed by the second preferred alternative out of the remaining alternatives and so on (Hanley et al., 2001). Bateman et al., (2002) showed an example of a CRk question which could be presented to respondents in Figure 2.3.

CRk technique has been used widely in the valuation of environmental goods and services including: river water quality improvement (Smith and Desvousges, 1986), biodiversity conservation (Garrod and Willis, 1997), estimation of amenity loss for recreational users (Garrod and Willis, 1998), recreational benefits (Isangkura, 1998), estimation of the impacts of pesticide usage in the United Kingdom (Foster and Mourato, 2000) and measuring the economic value of a marine park (Rawi, 2012).

This technique presents a simple task to the respondent in terms of producing a ranking alternative, rather than stating their WTP for unfamiliar goods. In other words, respondents do not have to state their WTP, but they are asked to indicate and report their most preferred alternatives in sequence. Moreover, some studies have shown that respondents feel more content when choosing and ranking alternatives with cost and benefits assigned, rather than assigning an explicit price for the goods being valued (Smith and Desvouges, 1986).

Despite the wide use of CRk in the assessment of environmental goods and services, the application of this method can be prone to several biases also found in CVM techniques such as payment vehicle bias (Morrison, Blamey, Bennet and Louviere, 1997). Moreover, a study by Foster and Mourato (2002) who tested the consistency of responses to CRk surveys found that almost half of the respondents failed to provide consistent responses. A possible factor of this failure is related to the inability of respondents to cope with ranking task due to not having an opportunity to express their indifference towards the alternatives and also due to the task complexity.

Figure 2.3: Example of Contingent Ranking Question

Rank the alternative policy option below according to your preferences, assigning 1 to the most preferred, 2 to the second most preferred and 3 to the least preferred.

	Choice A	Choice B	Choice C
Native woodland	500 ha protected	100 ha protected	700 ha Protected
Heather moorland	1200 ha protected	600 ha protected	No protection
Lowland hay meadow	300 ha protected	No protection	300 ha Protected
Cost per household per year in additional taxes	£25	£5	£15

Your ranking 1…….2…….3…….

Source: Bateman et al., (2002)

2.2.2.2 Contingent Rating (CRt)

In the CRt approach, respondents are presented with a series of alternatives and are then asked to rate each one individually on a semantic or numeric scale. These ratings are usually analysed using the Ordinary Least Squares (OLS) method which implies a strong assumption regarding the cardinality of the rating scales (Hanley et al., 2001). A scale from 0 to 10 is one of the examples of a measuring scale used for the rating purpose (Morrison et al., 1997; Hanley et al., 2001). The lowest level of the scale usually reflects the least preferred alternatives, and is contrasted with the highest level which reflects the most preferred alternatives. Figure 2.4 presents an example of CRt question which may be offered to the respondents.

Mackenzie (1993) used the CRt approach to value hunters' preferences for recreational hunting. The CRt is found to be most efficient when compared to the other methods used in the study (e.g. contingent ranking, paired comparison) based on its ability to deliver information on preference intensities, whilst specifically representing respondent indifference or ambivalence. However, there are some disadvantages to CRt application in the valuation of non-market goods. For example, the method does not produce a consistent welfare estimate (Bateman et al., 2002) and suffers from metric bias because of the use of a rating scale (Morrison et al., 1997). Furthermore, this method suffers from estimation bias since OLS procedures are shown to be biased and inefficient when used with discrete data. Finally, the valuation estimates derived by the CRt approach are only relative because individuals are incapable of expressing their opposition to payment (Mackenzie, 1993).

Figure 2.4: Example of Contingent Rating Question

Wetland Management Survey

Please circle one of the numbers below to show your preferences for the following alternatives

Water quality	Fair
Number of waterbirds	50,000
Area of wetlands	60,000ha
Household cost	RM40

1	2	3	4	5	6	7	8	9	10
Weakly preferred									Strongly preferred

(Source: Morrison et al., 1996)

2.2.2.3 Pair-wise Comparison (Pc)

The pair-wise comparison approach asks respondents to choose their most preferred alternative from a set of two choices, and to indicate the strength of their preferences in a numeric or semantic scale. The combination of the elements of ‘choosing the most preferred alternative’ and ‘rating the strength of the preferences’ in this approach reflects the CE method (Bateman et al., 2002). Paired comparison is also known as rated or graded pair comparison (e.g. Hanley et al., 2001, Bech, Gyrd-Hansen, Kjær, Lauridsen and Sørensen, 2007). Data from Pc has been analysed with the OLS procedure (Magat, Viscusi and Huber, 1988; Cameron and Huppert, 1989) and ordered logit and probit procedures (Johnson and Desvousges, 1997).

The Pc approach is very popular among marketing practitioners, particularly after the introduction of computerised interviewing techniques and the development of specialised computer software (e.g. Adaptive Conjoint Analysis) which determines attributes, levels and pair-wise comparison, tailor-made for each respondent (Bateman et al., 2002). One of the advantages of the Pc approach is that it generates more accurate and reliable data as it can identify minimal differences in preferences (Courcoux and Semenou, 1997).

In addition, the rating task stimulates thinking concerning marginal trade-offs, which is the basis of welfare measurement. Even though the Pc task is more challenging compared to ranking or discrete-choice formats, the rating response produces more statistical information for a particular sample size (Johnson and Desvousges, 1997). The disadvantage of Pc approach is that the number of pair-wise comparisons that need to be completed may become very large and thus the task becomes lengthy (Macharis, Springael, Brucker and Verbeke, 2004).

Figure 2.5: Example of Paired Comparison Question

WHICH ROUTE WOULD YOU PREFER TO VISIT IN THE SUMMER, GIVEN THE TWO ROUTES DESCRIBED BELOW?

Characteristics of route	Route A	Route B
Length of climb	150 metres	50 metres
Approach time	3 hours	2 hours
Quality of climb	3 stars	1 star
Crowding at route	Not crowded	Not crowded
Scenic quality of route	Not at all scenic	Very scenic
Distance of route from home	200 miles	110 miles

1	2	3	4	5	6	7	8	9	10
Strongly prefer route A							Strongly prefer route B		

(Source: Hanley et al., 2001)

2.2.2.4 Choice Experiment (CE)

The most recent method used among the CM approaches is the choice experiment. The CE was initially introduced by Louviere and Woodworth (1983) and originated in the field of transportation and marketing. The different attributes of the goods, as well as the whole value of the goods, can be valued using this technique (Willis, 2002). Based on a hypothetical market situation, respondents are presented with a series of alternatives described by different attributes-levels combinations, from which they are required to choose their most preferred alternatives. If the price is included as one of the attributes, this enables the estimation of economic values associated with other attributes (Boxall, Adamowicz, Swait, Williams and Louviere, 1996). In every choice set presented, a status quo or a baseline alternative reflecting the current situation is also typically included (Pearce, Atkinson and Mourato, 2006). Adamowicz et al., (1994) became one of the first to apply a CE in a non-market valuation study. Since then there have been many applications within the field of non-market valuation (e.g.

Boxall et al., 1996; Hanley et al., 1998b). Table 2.2 presents an example of CE choice card used in this study.

Table 2.2: Choice Experiment Choice Card

An example of a choice card is presented below. Two possible development options for the tourism facilities at Gawi Jetty are presented. If you would like to see an additional jetty, medium toilets and superior tourist information centre; but you are happy with the existing car parking slots and a small children's play area, and are willing to pay an entrance fee of RM 1 per person you should choose <u>Option 1</u>.

If you would like to see a large children's play area, medium information centre, an additional jetty, more car parking slots; but you are happy with the existing toilet conditions and are willing to pay an entrance fee of RM 7.50 per person, then you should choose <u>Option 2</u>.

Alternatively, if you are happy with the current situation at Gawi Jetty or you do not want to pay an entrance fee then you should choose the <u>Current situation</u> option.

Please tick √ which option you prefer.

Facilities	**Option 1**	**Option 2**	***Current Situation***
Toilet	Medium	Basic	*Basic*
Jetty	Two	Two	*One*
Car Park	30 slots	100 slots	*30 slots*
Tourist Information Centre	Superior	Medium	*Basic*
Children's Playground	Small	Large	*Small*
Entrance Fee	RM 1	RM 7.50	*RM 0*
Your Option			

Consequently, the construction of a CE involves substantial effort in the identification of the important attributes levels which affect people's preferences with the related scenarios, and the use of suitable experimental design techniques (Adamowicz et al., 1998). In short, this technique, by presenting repeated choice situations and varying attribute levels to the respondents, produces four pieces of information for the researchers (Hanley et al., 1998a); (1) which attributes significant influence choice, (2) the implied ranking of these attributes, (3) the marginal WTP for an increase or decrease in any significant attribute, and (4) implied WTP for a programme that changes more than one attributes simultaneously.

To date, vast and increasing attention has been devoted to the application of CE compared to other attribute-based methods because it can mimic actual market behaviour, and is consistent with the random utility theory (Adamowicz et al., 1998; Louviere, 2001; Holmes and Adamowicz, 2003). Moreover, the application of a CE gives the researcher a chance to break down the attributes and by doing so, the preferences over the attributes can be determined (Garrod and Willis, 1999).

The other techniques in choice modelling such as CRt and Pc are found to have a weak theoretical basis and do not produce economically valid valuation estimates compare to CE (Morrison et al., 1996). Thus, the CE technique appears to be the most suitable method for valuing recreational site attribute in this study compared to other CM methods.

2.3 Contingent Valuation Method versus Choice Experiment – Which method is Superior?

The choice experiment method possesses several advantages relative to the contingent valuation method. Hanley et al., (2001) discussed three attractions of choice experiment approach as follows:

1) CE is mostly suitable to deal with circumstances where changes in particular goods or services are multidimensional and the trade-off between them is of particular interest. Though CVM can also be used to estimate multidimensional changes, for instance by including a series of contingent valuation scenario in the questionnaire, or by doing a series of CVM studies, this method is clearly very costly and produces cumbersome alternatives. Moreover, Adamowicz et al., (1998) explained that it would be challenging to maintain a degree of orthogonality in the design and administration of the questionnaire if a large number of CVM exercises are needed.

2) The CE approach is more formative than the CVM because respondents in a CE have several chances to express their preferences for the goods being valued over a range of payment amounts from a number of alternatives. This is supported by Adamowicz et al., (1998), where the researchers preferred applying the CE for valuing public goods

such as recreational sites since the CE helps us to understand the respondents' preferences over the attributes of a scenario instead of a specific scenario.

3) Unlike the CVM, the CE commonly avoids asking respondents about their WTP values directly. The WTP amount that respondents choose comes together with other combination of attributes in the alternative presented. Thus, the CE approach may reduce some of the response difficulties in the CVM (e.g. starting point bias, yea-saying, protest bid, etc.) when the WTP is asked directly.

To conclude, even though in the CVM is possible to examine multiple recreational attributes in this study, it might be very cumbersome to apply. Instead, the CE approach has the ability to estimates multi-attributes options and marginal changes for each individual attribute. Therefore, the CE method is the most suitable method to estimate the recreational attributes values in this study.

2.4 Conclusion

This chapter has provided an overview of the stated preferences techniques that are available and suitable for valuing the recreational site's attributes. By looking at these techniques, it has been possible to consider the potential use of each technique in order to value recreational site attributes. There are several potential methods which are relevant to value recreational site attribute developments such as the TCM, CVM and CM. Nevertheless, the TCM is questionable in this case in terms of its suitability to value attribute development and is therefore considered inappropriate. This method has limitations in measuring specific recreational attributes as well as in examining the changes in each of the attributes.

Even though the CVM technically can be applied to value multiple recreational attributes, its application is time-consuming and involves a high cost as explained in Section 2.3. Since this study is designed to explore the visitors' preferences for the tourist facility attributes available at the recreational site, and to estimate the trade-off between attributes as well as the WTP value for attributes, the CE approach is believed to be more suitable for these type of preferences, compared to the CVM. In fact, the CE is increasingly used as an alternative to the CVM (Boxall et al., 1996; Adamowicz et al., 1998).

In addition, CE is interesting due to its welfare-consistency estimates (Bateman et al., 2002). Four reasons in favour of its use are: (1) the method forces the respondents to trade-off the changes in attribute levels against the costs of making these changes; (2) status quo as one of the options allows respondents to choose a current situation at zero (additional) cost; (3) econometric model derived from this technique is consistent with the theory of probabilistic choice; and (4) the technique permits the benefits of public goods and services to be estimated through measures of both compensating and equivalent surplus (Bateman et al., 2002). Further information about the CE method is provided in the following chapter.

Chapter 3: Literature Review of Choice Experiment

3.0 Introduction

This chapter reviews the application of the choice experiment method in a non-market valuation study, particularly in recreation related issues, in Section 3.1. Following this, the design process of the choice experiment which involved important issues such as the assignment of attributes and levels, the choice of experimental design and the choice experiment questionnaire design is discussed in Section 3.2. The theoretical background of the discrete choice experiment is discussed and derived in Section 3.3. The primary model used for analysing the stated preference data from the choice experiment is the conditional logit model as presented in Section 3.4. However, this model has been recognised as having a major drawback related to the homogeneous preferences assumption across respondents (except this can be represented using interaction with socioeconomic variables). Therefore, this study also employs the mixed logit model in Section 3.5 and the latent class model in Section 3.6 in order to capture underlying heterogeneity within responses to discrete choice experiment questions. The procedure for computing the willingness to pay value as a welfare measure used in this study is explained in Section 3.7. Finally, concluding remarks are presented in Section 3.8.

3.1 Choice Experiment for Valuing Recreational Benefit

A number of studies in the field of outdoor recreation research have applied the choice experiment method as a tool to help determine individuals' preferences relating to recreation-related issues. According to previous research, Adamowicz et al., (1994) employed the CE in order to evaluate the recreationists' preferences for the Little Bow and Highwood rivers in southwestern Alberta, Canada. The attributes used in this study were: terrain, fish size, fish catch rate, water quality, camping facilities, swimming, beach, distance, water feature, fish species, boating and an entrance fee to maintain facilities. Choice sets were constructed for two river categories, i.e. running water and standing water. Respondents were presented with 16 choice sets, and in each situation, they were asked to choose either a standing water or running water site, or non-water (to decide to choose not to be involved in something water-based). A multinomial logit discrete choice model was specified and estimated. The results showed that the water quality, distance, the availability of boating, fishing success, the presence of swimming areas, and the presence of beaches were significant factors influencing site choice. The per trip welfare measures varied from $4.33 to $8.06.

In contrast to the above study, Boxall et al., (1996) reported the results of a CE applied to recreational moose hunting in the province of Alberta, Canada. Specifically, this study aimed to measure a number of characteristics of the stalking experience to determine the value that amateur stalkers attach to the attributes surveyed. The attributes included in the CE design were: the moose population (evidence of more or less than one moose per day), hunger congestion, access within hunting area, forestry activity, quality of road access and distance from home to a hunting area. Each respondent was presented with 16 pairs of alternatives, and in each pair of alternative, the option of not choosing any alternative (do not go hunting) was also presented. The conditional logit model was estimated for the data. Results in the CL model indicated that all attributes except forestry activity and levels of road quality were significant and according to the expected sign. The WTP per trip for an increased moose population was $3.46.

Adamowicz et al., (1998) used a CE to evaluate the protection of old-growth forests in west-central Alberta, Canada, from the perspective of preserving caribou populations (an endangered species in Alberta). The CE questionnaire contained alternative woodland designs described in terms of five attributes, i.e. caribou and moose population, the area of wilderness (forest management agreement), forest industry employment, recreational restrictions and a change in provincial income tax level. The orthogonal main effects design resulted in 32 choice sets, and these choice sets were blocked into four versions of the questionnaire. Thus, each respondent received eight choice sets, and in each choice set, the respondents were asked to choose among the current situation and two hypothetical alternatives. The respondents consisted of residents of Edmonton. Based on the results from the linear CE model, the caribou population and wilderness area showed significant positive coefficients.

Meanwhile, in a study that evaluated preferences for deer stalking trips and landscape change in the Scottish Highlands, Bullock, Elston and Chalmers (1998) asked the respondents to rank the two hypothetical trips, giving a ranking of the hypothetical trips besides the status quo after they had compared two hypothetical recreational hunting trips with the last trip they had taken (status quo option). The attributes selected were the number of stalking success, quality of stags, alternative activities, landscape (the proportion of native forest and open moor) and the price paid for stalking. The questionnaires were posted to associates of 38 different organisations including sporting estates, agencies and associations, since there is no licencing of hunters in the United Kingdom.

A study by Juutinen et al., (2011) used a CE to assess different trade-offs which evolved in park development scenarios. Specifically, this study focused on biodiversity and recreational services provided by Oulanka National Park, Finland. The visitors' preferences, which are amongst the potentially conflicting management priorities at this national park, were evaluated. The attributes used in the design of the CE were: biodiversity, resting places, expected number of visitors, information boards, and entrance fee. The data was analysed using conditional logit, random parameter logit and latent class models. The result revealed that an increase in biodiversity was the most highly valued attribute by the respondents. Furthermore, protecting the biodiversity of national parks while also permitting access to them for recreational and tourism purposes can lead to conflicting welfare effects unless it is managed appropriately.

Another study, carried out in Helsinki, Finland (Horne, Boxall and Adamowicz, 2005), used a spatially explicit CE to examine visitors' preferences for forest management at five adjacent municipal recreation sites. The design of the CE in this study accounted for changes in biodiversity and scenery indices in the forest environment generated from forest management practices. The attributes used in this study were: species richness at each site, average species richness, the scenery at each site, the variance of species richness and change in municipal taxes. Every respondent received six CE choice sets, each with two forest management options and the present situation. On-site interviews were conducted as a method of data collection and a total of 431 questionnaires were used to estimate Finnish recreationists' preferences. Results showed that respondents had a strong preference for scenic beauty and the preservation of species richness.

Christie, Hanley and Hynes (2007) employed a CE alongside contingent behaviour methods to estimate a range of improvements to recreational facilities in forest and woodlands in Great Britain. There were eight attributes used in this study: types of trails, optional trail obstacles, showers, bike wash facilities, general facilities (e.g. car park, toilet, picnic area, play areas), information, surroundings and distance. Interestingly, travel distance was used as a proxy for the costs of travelling. In several CE studies involving environmental quality changes to recreational behaviour, travel costs have been used in place of the price attribute (e.g. Hanley, Wright and Koop, 2002; Czajkowski, Hanley and LaRiviere, 2013). Four groups of forest users were targeted in this study: cyclists, nature watchers, horse riders and general forest visitors. The data was estimated using the conditional logit model, and the results revealed that a heterogeneity of preferences existed within each group of forest users. Specifically, more specialist forest user groups preferred higher values for improvements compared to general users.

Scarpa, Thiene and Train (2008) surveyed 858 members of the local division (Veneto Region) of the Italian Alpine Club regarding the site choice in the Alps. The recreational attributes used in this study were the degree of difficulty of the available trail itineraries, “ferrata” which was the number of trails equipped with safety ropes, alpine shelters which were the quantity of equipped alpine shelters available in the destination area, and the percentage of easy trails and the percentage of hard trails. Interestingly, Scarpa et al., (2008) compared two methods for estimating the distribution of consumers’ WTP in the discrete choice modelling. The first method, “preference space” was applied by estimating the utility coefficients of the trail attributes, and then WTP was derived as the ratio of the utility and price coefficients. The second method, called “WTP space” was applied by estimating the distribution of WTP directly. In the WTP space model, the model was re-parameterized such that the parameters were the WTP for each attribute rather than the utility coefficient of each attribute. Scarpa et al., (2008) estimated the models by both Hierarchical Bayes estimation and maximum simulated likelihood. The results from this particular study revealed that the “WTP space” method fitted the data better, reduced the incidence of extremely large estimated WTP values, and provided the researcher with better control in identifying and testing the distribution of WTP. On the other hand, there is some evidence that models in “preference space” fit the data better than models in “WTP space” (e.g. Hole and Kolstad, 2012; Train and Weeks, 2005). Meanwhile, Hensher and Greene (2011) revealed that the gap between the evidence in preference space and WTP space narrowed significantly when scale heterogeneity was taken into account.

In Malaysia, there have been very few published works on the use of the CE method to estimate individuals’ preferences in relation to recreation issues. For example, Othman et al., (2004) applied a CE to assist policy makers in determining the optimal management strategy for the Matang Mangrove Wetlands, Perak state. They assessed the values for environmental attributes, for instance the area of environmental forest protected, the recreation use of the area and the number of bird species protected, as well as the value of the non-market attribute (i.e. the employment of local people in wetland-based extractive industries). The estimation of household consumer surplus showed that the households were willing to pay RM -11.80 to RM 13.40 per annum for management of the wetland, contingent on the alternative management scenario and estimation method employed (multinomial logit or nested logit models). The negative WTP indicated that the households experienced negative utility from reduced employment and therefore, demand compensation.

Other research by Shuib, Jaafar and Wah (2006) applied a CE to estimate preferences for outdoor recreation attributes in Taman Negara Malaysia. The attributes included: types of accommodation, visitor congestion level, the permitted period of stay in Taman Negara per entry permit, and the entrance fee per visitor. The choice probability model was estimated, and the results revealed that types of accommodation, specified by differences in room rates, and congestion levels were the two significant attributes affected visitors' preferences for the ecotourism resources. Another study by Kaffashi, Radam, Shamsudin, Yacob and Nordin (2015a) employed a CE to analyse users' preferences and WTP to enhance improved management of Penang National Park for the dual aim, i.e. conservation and recreation. The attributes selected for this study were ecological management, provision of information, recreational facilities and conservation charge. The analysis of the random parameter logit model revealed that visitors placed the highest value on having adequate information about Penang National Park, followed by improvements in the park's ecological management.

Hasan-Basri and Karim (2016) analysed benefit transfer in the case of recreational parks in Kuala Lumpur and the Malaysia Agricultural Park in Selangor, using the CE technique. The attributes used in this study were: amenities, recreational facilities, informational attributes, natural attractions and price. Overall, the results from the multinomial logit model showed that respondents in Kuala Lumpur had the highest preference for recreational facilities and this was followed by visitor amenities, natural attractions and information. In contrast, the order of preference for the Malaysia Agricultural Park was recreational facilities, followed by visitor amenities and information.

3.2 Design Process of the Discrete Choice Experiment

The design process for a CE study basically involves four steps (Hoyos, 2010); (1) classification of attributes and levels of provision, (2) experimental design, (3) development of the questionnaire, and (4) sampling strategy. Responses from the different steps are sequentially combined in the final design of the CE.

In a CE application, respondents are required to choose their preferences from several alternatives presented on a given choice card. These alternatives present the various hypothetical scenarios that might be used to describe the goods that are being valued, such as environmental goods or services. Each alternative consists of possible combinations of various attributes, and the attributes consist of different levels in order to describe a wide range of scenarios. The number of alternatives or profiles in the choice cards depends on the total number of attributes and their levels (Garrod and Willis, 1999). For example, a total of eight alternatives, or possible combinations, can be generated using three two level attributes.

Designing and employing a CE requires an appropriate survey design. Certain questions may arise at this point; for instance, what alternatives, attributes and attributes levels should be incorporated to describe a scenario to respondents? How many alternatives or options should be presented to respondents? How many choice tasks should the design consist of? Should a status quo option be presented in the choice sets? These questions are discussed in the next sections.

3.2.1 Assignment of Attributes and Levels

Since the CE design is based on particular attributes and their levels, it is not surprising that issues of selection, and the description of attributes and their levels, are a crucial stage in building a CE (Garrod and Willis, 1999). Furthermore, a misspecification of attributes levels could produce erroneous results which then leads to inappropriate policy implementation.

When determining attributes two criteria need to be considered (Bennet and Blamey, 2001), namely: (1) selected attributes are significant to the policy-making process, and (2) the attributes used must be relevant to the respondent who will answer the questionnaire. Having said this, the selection of attributes need to consider both sides; the end-user and the resource managers. Presenting the relevant attributes to the respondent is important in order to reduce the likelihood of invalid responses or a low response rate. Moreover, attributes presented should not only be easily identifiable but produce policy-relevant information.

Various methods have been applied to the development of CE attributes. These include focus group discussion, pilot surveys, literature reviews, consultation with experts, and discussions with the responsible management authority. To avoid confusing respondents, Pearmain, Swanson, Kroes and Bradley (1991) suggested an upper limit of 6 or 7 attributes to be used within a CE study, or fewer if several attributes are unfamiliar to respondents or are difficult to define. Some of the attributes can be quantitative (e.g. how many jetties are available at the lake) and some may be qualitative (e.g. how is the water quality). A monetary value attribute is typically included to allow the estimation of willingness to pay.

After identifying attributes to be used in the experiment, the next step is to derive attribute levels. Levels are defined as the levels assigned to an attribute as part of the experimental design process (Hensher, Rose and Green, 2015). The levels used must be plausible and varied over a relevant range (Street and Burgess, 2007). The levels are not randomly interpreted. Similarly to attributes, the ranges of levels can be identified through literature review, discussion with the responsible management authority, discussion with focus groups of respondents, or any other methods that is suitable for the case study.

3.2.2 Choice of Experimental Design

The experimental design is a vital part in the development of a choice experiment method (e.g. Kuhfeld, 2005; Johnson et al., 2013). Considered an important part of choice experiment studies, the experimental design is usually used to generate a number of specific combinations of alternative scenarios that respondents assess in a choice question. The design is formulated from the number of factors or attributes and the number of levels for each attribute. The larger the number of attributes levels, the larger the experimental design will be (Bateman et al., 2002). The attributes chosen in the experimental design must be attributes that influence a respondent's choices.

Conceptually, experimental designs may be viewed as the systematic arrangement in matrices of the values that researchers use to describe the attributes representing the alternative policy options of the hypothetical choice sets (Scarpa and Rose, 2008, p. 254). Two forms of experimental design are typically employed, namely a full factorial design and fractional factorial design. A full factorial design comprises all possible combinations of attributes and levels used in the study. This design allows researchers to estimate main effects and all interaction effects. Main effects can be explained as responses generated from the movement of one level to the other level of a particular attribute, while the level of all other attributes remains the unchanged (Garrod and Willis, 1999). Meanwhile, interaction effects occur when the preference for the level of a particular attribute is dependent on the levels of other attributes in the design (Hensher et al., 2015).

The total number of alternatives that could be generated will depend on the number of attributes and levels assigned. Garrod and Willis (1999) indicated that the total number of alternatives can be obtained by using the simple mathematical expression of x^n, where x is the number of levels and n is the number of attributes. Take as an example, if there are six attributes altogether, three of them have two levels, and three of them have three levels ($2^3 \times 3^3$), therefore, the total number of possible alternative produced from this order is 216 (e.g. 2 x 2 x 2 x 3 x 3 x 3). Five attributes specified at three levels each yields a total of $3^5 = 243$ different alternatives. Given this kind of combinatorial explosion, a reduced number of alternatives is required in practice.

Therefore, alternatives strategies are required and the fractional factorial design is another option.

Fractional factorial designs take only a subset of all possible combination. For example, the 27 options from full factorial designs (3 attributes with 3 levels each) can be reduced to 9 options only, using fractional factorial designs. These designs are offered through specialised software such as the IBM SPSS Statistic and Statistical Analysis System (SAS). Hence it becomes easier for the respondent to evaluate a small number of choice alternatives, compared to the full combination alternatives. In addition, a smaller number of choice alternatives could reduce respondents fatigue and could decrease the number of incomplete questionnaire surveys.

According to Louviere, Hensher and Swait (2000), there is a drawback in the application of fractional factorial designs which is associated with some loss of statistical information. The use of fractional factorial designs will terminate thousands of possible combinations; hence, the efficiency of the model is being reduced (Street and Burgess, 2007). However, there is a need to make a trade-off between practicality and complexity of choice tasks in CE; therefore, fractional factorial designs are conventionally used (Blamey, Louviere and Bennet, 2001; Kuhfeld, 2005; Street and Burgess, 2007). Another reason for the use of fractional factorial designs is that particular effects of interest (particular subsets or samples) can be efficiently estimated (Louviere et al., 2000). Experimental designs can be defined as orthogonal or efficient where both have different features. These are discussed in the next section.

3.2.2.1 Orthogonal Design

An experimental design is said to be orthogonal when it has the property of zero correlation between attributes (Bliemer and Rose, 2006; Johnson et al., 2013) and the frequency for pair levels are balanced (Kuhfeld, 2005). Traditionally, CE designs have relied on orthogonal fractional factorial design (Rose and Bliemer, 2009; Scarborough and Bennet, 2012). However, this design is unable to measure interaction effects. Consequently, it could produce a biased result if an interaction effect is not being tested in the model, and is significant.

An orthogonal design is believed to be practical for main-effects models when the number of factors and the number of levels for each factor is small. However, in certain circumstances, an orthogonal design might not be feasible. These include; (1) unrealistic combinations of attribute levels, (2) the desired number of runs is not available in an orthogonal design, and (3) an interaction model is being used (Kuhfeld, 2005). When the orthogonal design is not practical to apply, some analysts have proposed using an efficient design.

3.2.2.2 Efficient Design

Fundamentally, efficient design tries to maximise the information from each choice situation (Rose and Bliemer, 2009), subject to the total number of attributes, the attribute levels and other characteristics of the survey, for instance, the cost of the survey (Carlsson and Martinsson, 2003). Efficient designs are balanced and orthogonal which means that the frequency of each level appearing within an attribute is likely to be the same, and each pair of levels appears equally often across all combinations of attributes.

In the efficient design there is a chance to reduce the confidence intervals for parameters of interest in choice models, or to reduce the required number of sample sizes. Furthermore, with an equal or lower sample size, an efficient design will still be able to produce reliable parameter estimates compared to less efficient designs (Louviere et al., 2008a; Rose and Bliemer, 2009).

D-efficiency is a commonly used approach to measuring the efficiency of experimental designs (Ferrini and Scarpa, 2007; Kuhfeld, 2005). This form of design aims to maximise the amount of information an experiment can capture from the attributes levels combination (Grisolia and Willis, 2016). It has the advantage that the ratio of two D efficiencies for two competing design is invariant under different coding schemes (Willis, 2014). D-efficient designs minimise the D-error, which is an aggregate measure constructed from the variances and covariance of the estimated utility function parameters.

3.2.3 Questionnaire Design

When designing the questionnaire, there are several aspects that need to be considered for example; (1) whether the status quo (current situation) option needs to be included, (2) how to present the alternatives in the choice cards, (3) the optimum number of attributes to be included in choice alternatives, (4) the suitable number of alternatives in each choice card, and (5) the ideal number of choice cards to be presented to respondents. A questionnaire can be organised into different sections which include choice experiment questions, travel information and background information of respondents.

As shown in Table 3.1, previous CE studies have included a status quo option in the choice sets. Status quo is typically defined in terms of those attribute levels that are currently experienced by the respondents (Scarpa, Willis and Acutt, 2005b) and are familiar to the respondents (Willis, 2014). The inclusion of a status quo option can be regarded as a way of ensuring an unforced situation where the respondents have the right to ‘do nothing’, or to reject all the hypothetical alternatives presented to them. Having said this, the status quo option gives the respondents the opportunity to stay with the present situation.

In some cases however, the inclusion of status quo may lead to several problems. For example, respondents have a tendency to choose the status quo option when faced with a complex decision (Nicolle, Fleming, Bach, Driver and Dolan, 2011). The example of a complex decision is when the respondents are presented with two alternatives where the pay-offs of these two alternatives are very close. This situation requires more cognitive effort from the respondents in making their choice. Consequently, to avoid making a difficult decision, respondents are likely to choose the status quo option. A detail description regarding the status quo issue is presented in Chapter 4.

Table 3.1: Selected Choice Experiment Questionnaire Designs

Author(s)	Experimental Design	No. of Attributes	No. of Alternatives in Choice Sets	No. of choice sets	Data Collection	Sample size
Adamowicz et al., (1994)	Fractional factorial design	13	2 + status quo	64 (Blocking into 4 blocks, 16 choice sets for each block)	Mail survey	413
Boxall et al., (1996)	Fractional factorial design	6	2 + status quo	32 (Blocking into 2 blocks, 16 choice sets for each block)	Meeting	271
Bullock et al., (1998)	Fractional factorial (1/3 of the full factorial)	5	2 + status quo	6	Mail survey	854
Hanley et al., (1998b)	Orthogonal main effects design	6	2 + status quo	8	Face-to-face interview	256
Christie et al., (2006)	Fractional factorial experimental design	5	2 + status quo	25 (Blocking into 10 blocks, 5 choice sets for each block)	Personal interview	741
Willis (2009)	Fractional factorial design	6	2 + status quo	24 (6 versions of questionnaire, 4 choice sets for each questionnaire)	Face-to-face interview	149
Garrod et al., (2014)	Fractional factorial design	5	2	28 (4 choice cards for each questionnaire)	Interview	1180
Grisolia and Willis (2016)	D-efficient experimental design	7	4	10	Post	353

Other fundamental issues in designing a CE question is how to present the alternatives in the choice sets; whether in a generic (unlabelled) or labelled format (Blamey, Bennett, Louviere, Morrison and Rolfe, 2000). For example, based on generic format, each alternative in the choice set is assigned as 'Alternative A', 'Alternative B' and 'Alternative C'. On the other hand, the labelled format, known as the alternative-specific format, is related to the designation of information, either directly or indirectly, which could reflect the alternatives. For instance, Hensher et al., (2015) use car and plane as the labels for modes of travel. Meanwhile, Grisolia and Willis (2016) use drama, comedy, opera and musical as the labels for basic shows.

The use of a labelled format can make the task look easier and straightforward. The format, however, appears to reduce the attention respondents give to the attributes (Blamey et al., 2000). The generic design is selected by Hensher (2006a) to avoid perplexing the effect of the number of alternatives with the labelling.

Various suggestions have been made in CE literature relating to the number of attributes to include in choice options. For example, Carson et al. (1994) proposed the use of seven attributes per alternative, while Abiiro, Leppert, Mbera, Robyn and Allegri (2014), Willis (2009) and Boxall et al., (1996) used six attributes per alternative. Other researchers used three, four and five attributes (e.g. Scarborough and Bennett, 2012; Blamey et al., 2000; Christie et al., 2006; Garrod et al., 2014).

Regarding the number of alternatives presented in each choice card, Carson et al., (1994) suggested four alternatives per choice card. Rolfe and Bennett (2009) compared the results using two and three alternatives, and they finally found that three alternatives constructed more robust results. However, most applications of the CE studies use only two hypothetical alternatives per choice card.

The number of choice cards employed in the questionnaire differs across CE studies. For instance, Mourato, Ozdemiroglu, Atkinson, Newcombe and Garis (2006) suggest not more than eight choice cards, while Carson et al., (1994) recommend only four choice cards. Caussade et al., (2005) propose that discrete CE with nine to ten choice cards seem to be optimal in the matter of minimising error variance, supporting the hypothesis of an inverse U-shaped relation between choice situations and the scale parameter. However, Caussade et al., (2005) also point out that the importance of the number of choice cards is smaller compared to the number of attributes and number of alternatives.

3.2.4 Sampling

Sampling is the procedure of selecting individuals from a target population of study. Sampling comprises of specific consideration such as identifying a target population from which the sample will finally be drawn (or known as sampling frame) and determining the sampling design and sample size. There are cases where a reliable sample frame is hard to obtain from the target population, and the implementation of another sampling approach is needed (Bateman et al., 2002).

An example of non-list sampling is when the target population is visitors to a particular recreational park. In this case, the interviewer may need to stay at the site in order to sample people who show up at the park. According to Bateman et al., (2002), such intercept surveys pose several implications, for instance, more people may show up at some times than others, and the composition of visitors may depend according to different periods of the year (for example during school holiday or weekend versus others time). Hence, in the case of intercept surveys, it is effective to sample people either as they arrive or as they leave (Bateman et al., 2002). However, this method of survey can also lead to on-site sampling bias, i.e. over-sampling frequent visitors, but, perhaps not a problem at Kenyir Lake.

There are two main sampling designs; non-probabilistic design and probabilistic design, presented in Table 3.2. The difference between these designs is that non-probabilistic designs do not involve random selection and probabilistic designs do.

Table 3.2: Taxonomy of Sampling Design

Non-probabilistic designs	Convenience samples
	Judgement samples
	Quota samples
Probabilistic designs	Simple-random sampling
	Systematic sampling
	Stratified sampling
	Cluster sampling

Source: Bateman et al., (2002)

The common sampling strategies applied in CE are simple random samples (SRS) and exogenously stratified random samples (ESRS) (Louviere et al., 2000). In the SRS, each component of the sample frame has the same chance of being selected, while, in the ESRS, the sample frame is separated into distinct subpopulation or strata. By using the random sampling, separate samples are selected from each stratum in the ESRS.

Another important procedure is to determine an appropriate sample size that represents the population because this will affect the accuracy of the results in CE estimation. Too small a sample may lead to inaccurate estimation while a sample that is too large may waste money, time and resources. Bateman et al., (2002, p. 107) highlighted three consideration factors in choosing an optimal sample size:

1) The smallest subgroup within the sample for which estimates are needed.
2) The precision with which estimates are needed – how much sampling error can be tolerated.
3) How much variation there is in the target population with respect to the characteristic of interest.

The technique presented by Louviere et al., (2000) is considered in determining the minimum sample size for a repeated choice study. Though it is unlikely that the repeated choices from the respondent are independent, practice has shown that a well-designed choice task that encourages respondents to view each choice scenario as unrelated to the previous one will yield parameter vectors that are proportional to those derived from models estimated on single choice from each respondent (Louviere et al., 2000, p. 263).

Table 3.3: Choice Probability Estimation

P	**Minimum number of choices required**	**Minimum number of respondents (for r = 8)**	**Minimum number of respondents (for r = 6)**
0.10	3457	432	576
0.20	1537	192	256
0.30	896	112	149
0.40	576	72	96
0.50	386	48	64
0.60	256	32	43
0.70	165	21	28
0.80	96	12	16

Source: Adopted from Table 9.2 of Louviere et al. (2000, p. 264)

Table 3.3 is an adaptation of Table 9.2 in Louviere et al., (2000, p. 264) which was formed to estimate the choice probability for several p values, in a real market situation, with a relative accuracy of 10 percent of p with probability of 0.95 (α = 0.95) and requires every respondent to assess eight replications using the formula below:

$$n \geq \frac{q}{rpa^2} \Phi^{-1}\left(\frac{1+\alpha}{2}\right) \tag{3.1}$$

Where a is the relative accuracy, p is the true proportion, q is 1- p, r is the number of replications or choice tasks each respondent faces and $\Phi^{-1}$is the inverse cumulative normal distribution function. The number can be used as a guideline to decide the sample size required for any valuation study.

Another guideline for estimating the suitable sample size for stated choice experiments is based on the biggest number of levels for any one attribute (*NLVE*), the number of choice cards given to each respondent (*NREP*), and the number of alternatives on the choice card (excluding the status quo alternative) (*NALT*) as follows:

$$N \geq 500 \ . \ \frac{NLVE}{NALT.\ NREP} \tag{3.2}$$

Where N is the total number of respondents (Johnson, Kanninen, Bingham and Ozdemir, 2006).

3.2.5 Data Collection

There are several data collection techniques that can be used in CE studies. According to Bateman et al., (2002), data collection can be done with the standard survey modes, either self-administered or interview-administered. These include self-completion questionnaires through mail surveys, such as in Savage and Waldman (2008), face-to-face interviews identified in Willis (2009) and Meyerhoff and Liebe (2009a), telephone interviews (Mueller et al., 2016), and mixed modes, for example in Veldwijk et al., (2016). Each survey method has its own strengths and weaknesses.

For example, as stated by Snowball and Willis (2011), in some situations a self-completion questionnaire produces more reliable valuation results compared to a face-to-face interview method because respondents are given more time to think. Moreover, self-completion surveys enable respondents to record their answers directly and involve a lesser cost compared to other data collection methods.

The self-completion questionnaire, through a mail survey, is done by sending the questionnaires to the respondents via mail. A stamped-addresses envelope is provided, so that the respondent can fill in the questionnaire and return it back to the researchers. The questionnaire can also be distributed to the respondent at a site (e.g. a recreational park) where they are asked to fill it in and return it at the exit gate.

However, one of the disadvantages of the self-completion method is that respondents tend to not to answer several pieces of information requested in the questionnaire (Snowball and Willis, 2011), particularly income and other sensitive socioeconomic questions. Moreover, the researcher does not have any opportunity to clarify the details of the information presented to the respondent. Consequently, the response rates tend to be lower and thus requires a larger number of people to be contacted in order to achieve the target sample size (Amaya-Amaya, Gerard and Ryan, 2008).

The strengths and weaknesses of the other survey modes are summarised in Table 3.4. However, having discussed possible approaches for data collection, the most suitable technique for collecting information from respondents in any stated preference study, including CE, as stated by National Oceanic and Atmospheric Administration (NOAA) panel report, is face-to-face interviews (Portney, 1994).

Table 3.4: Strengths and Weaknesses of Survey Modes

Type	Strengths	Weaknesses
1) Self-completion • On site • Residential • Street	- low cost - filled out by respondents at their own convenience time - less interview bias	- cannot identify who actually completes the survey - some questions might be not answered - low data reliability - the low response rate - must collect back all the questionnaires that have been distributed either by a person or mail
• Mail survey	- low cost - no interview bias - filled out by respondents at their own convenience time	- no pressure to complete the questionnaires leads to low response rates - low data reliability - some questions might be not answered - cannot identify who actually completes the survey - unable to ask the follow-up questions and explain questions

Table 3.4 (continued): Strengths and Weaknesses of Survey Modes

Type	Strengths	Weaknesses
2) Telephone interviews	- cheaper than face-to-face interviews - quicker and save time - can emphasis on a particular geographic area	- the complexity of questions is the constraint - people may hang up the phone
3) Face-to-face Interviews • On site • Residential • Street	- fewer incomplete questionnaires - direct contact - the high response rate - effective for long and complex interview questionnaire - able to ask the follow-up questions and explain questions	- high cost - time consuming - low data reliability
4) Mixed modes • Drop off survey (mail + face-to-face) • Mail + telephone surveys	- initial personal contact - completed by respondents at their own convenience time	- survey may be lost in the interval - have some limitation like mail surveys - costly

Source: Bateman et al., (2002) and Babbie (2008)

3.3 Theoretical Background of the Discrete Choice Experiment

Discrete choice modelling forms the theoretical foundation of the discrete choice experiment[3] method. This model has its foundation in classic economic consumer theory. Furthermore, it is based on two main theoretical extensions: the Theory of Value by Lancaster (1966) and Random Utility Theory (RUT) by Manski (1977). A brief outline of the main concepts of economic consumer theory is provided in this section along with the elaboration of the two theoretical extensions, in order to demonstrate how they come together to form the theory behind discrete choice modelling.

The objective of economic consumer theory is to deliver the means for the transformation of assumptions about consumer's desires into a demand function expressing the consumer's behaviour, under given circumstances (Ben-Akiva and Lerman, 1985). In this theory, the fundamental assumption about the consumers is that they are the rational decision makers. As rational decision makers, when faced with a choice situation comprising of possible

[3] The 'discrete choice experiment' method has been referred to as 'choice experiment method', 'attribute-based stated choice', 'choice-based conjoint', 'choice modelling' and 'discrete choice model' in literature. The terms 'discrete choice experiment', 'choice experiment method' and 'discrete choice model' have been used interchangeably in this study.

consumption bundles of goods, they assign preferences to each of the various bundles and then select their most preferred bundle of goods. In the process of selecting goods, there are some axioms of choice involved, for example:

reflexivity	-	any bundle is as good as itself. For example, for any q element in Q, $q \geq q$
completeness	-	consumers are able to compare any pair of alternatives in the economy, $q^i \geq q^j$ or $q^j \geq q^i$
continuity	-	two bundles of goods are close to each other. For example, for any bundle q^1, define X(q^1) the "at least as good as q^1 set" and Y(q^1) the "no better than q^1 set" by X(q^1) = {q|q $\geq q^1$} and Y(q^1) = {q|$q^1 \geq q$} (Deaton and Muellbauer, 1980).
transitivity	-	For any three bundles, *q1, q2* and *q3*, if $q1 \geq q2$ and $q2 \geq q3$, then $q1 = q3$. Transitivity also known as consistency because it tests whether consumers behave in a consistent manner or not.

All of the axioms discussed above are now sufficient to allow a representation of consumer's preferences ordering by the derivation of the utility function (Deaton and Muellbauer, 1980). The behaviour of the consumer can then be expressed as an optimisation problem where the consumer chooses the consumption bundle of goods that maximises their utility subject to their budget constraint. By solving the optimisation function, the demand function can be obtained. The indirect utility function, which is the maximum achievable utility under the given prices and income, can be derived by substituting back the demand function into the utility equation (Walker, 2001).

The first extension to classic economic consumer theory that is necessary to a discrete choice experiment is the Lancastrian economic theory of value. Lancaster (1966) proposed that the attributes of the goods determine the utility derived from the good. And so, the utility can be expressed as a function of the attributes of the goods. However, according to Ben-Akiva and Lerman (1985), respondents in the choice experiment have been observed not to choose the same alternative in repetitions of the similar choice situations. Consequently, a probabilistic choice mechanism, which is the RUT has been introduced to explain the behavioural inconsistencies of the respondent.

Originally proposed by Thurstone (1927) and further developed by Luce (1959) and Marschak (1960), the fundamental idea behind RUT is that the respondent, as a decision maker, is assumed to select the alternative that gives the highest utility to them. Any observed deficiencies in choice behaviour are taken to be a result of the researcher's observational deficiencies. Nevertheless, the utilities are unidentified to the researcher with certainty and are therefore treated by the researcher as random variable consisting of an observable component and an unobservable component. Manski (1977) recognised four sources of randomness, i.e. unobserved attributes, unobserved taste variations, instrumental variables and measurement errors.

Finally, in classical economic consumer theory, the continuous (e.g. each of the goods is offered in perfectly divisible quantities) space of goods is assumed, whereas, in the discrete choice theory, the goods are discontinuous and discrete. However, in the discrete choice procedure, the choice set must exhibit three characteristics (Train, 2003). Firstly, the alternatives must be mutually exclusive, that means the respondents choice of one alternative necessarily suggests not choosing any of the other alternatives. In other words, there is only one alternative chosen by the respondent from each choice sets. Secondly, the choice set must be exhaustive in that all potential alternatives are included. Lastly, the number of alternatives must be finite. In conclusion, the use of a discrete sign of alternatives requires a different analytical method which includes the direct use of utility functions instead of deriving demand functions as applied in consumer theory[4].

3.3.1 The Derivation of Discrete Choice Modelling

A discrete choice model can be derived by referring to McFadden (1974) and Train (2003). This discrete choice model has a theoretical foundation in the characteristic theory of value by Lancaster (1966) and RUT developed by Manski (1977).

In a discrete choice model, a respondent or decision maker n faces a choice amongst a set of alternatives J in the choice set. Each alternative gives a certain level of utility to the respondents. The utility which the respondent n obtains from alternative j is U_{nj}, $j = 1,..., J$. This utility is known to the respondent but not to the researcher. As a decision maker, the respondent chooses the alternative that offers the greatest utility. Therefore, the behavioural model when the respondent n chooses alternative i if and only if:

$$U_{ni} > U_{nj}, \forall j \neq i$$

[4] See Ben-Akiva and Lerman (1985) for an explanation of this analytical approach

The researcher does not observe the respondent's utility but observes some attributes of the alternatives x_{nj} as faced by the respondent, and some attributes of the respondents s_n. Now the researcher can specify a function that relates these observed factors to the respondent's utility. This function is denoted as:

$$V_{nj} = V\,(x_{nj}, s_n) \tag{3.3}$$

and is known as the representative utility (Train, 2003). Utility depends on V_{nj} which includes aspects specifically related to the respondent s_n as well as to the choice attribute x_{nj}. The attribute x_{nj} varies across choices and probably amongst the respondents too. The components of s_n comprise the characteristics of the decision maker *n* and are therefore identical for all choices carried out by the decision maker *n* (Green, 2002). Consequently, these individual-specific terms s_n will fall out of the probability equation (Equation 3.14 in Section 3.4) because they do not vary across the alternatives. If the model is to allow individual-specific influence, then the model must be modified as described in Section 3.3.2.

Since there are parts of utility that the researcher does not observe, $V_{nj} \neq U_{nj}$. The utility is therefore decomposed into two components. The first component of the utility V_{nj} is called the deterministic or observable component which represents the part of utility observed by the researcher. The second component is the difference between true utility U_{nj} and the portion of utility which is captured by the researcher in V_{nj}. In particular, it captures the elements that affect utility but are not counted in V_{nj}. It is called the random component or error term, denoted as ε_{nj}. This error term ε_{nj} is not defined for a choice situation *per se*. Rather, it is described relative to the researcher's illustration of the choice situation. Thus, both components can be written as:

$$U_{nj} = V_{nj} + \varepsilon_{nj} \tag{3.4}$$

where:

U_{nj} is the true utility of alternative *j* for respondent *n*,

V_{nj} is the deterministic or observable component of the utility estimated by the researcher, and

ε_{nj} is the error term of the utility and is unknown to the researcher.

The researcher does not have any information about the error term, and ε_{nj} is therefore treated as the random vector. The joint probability density of random vectors, $\varepsilon_n = (\varepsilon_{n1}, \varepsilon_{n2}, \varepsilon_{n3}, \ldots \varepsilon_{nJ})$ is denoted by $f\,(\varepsilon_n)$. Using this density, probabilistic statements about the respondent's choice can be made by the researcher. Therefore, the probability that a respondent *n* chooses alternative *i* over alternative *j*, given the set of alternatives *J* is stated as:

$$
\begin{aligned}
P_{ni} &= \text{Prob}(U_{ni} > U_{nj}, \forall j \neq i) \qquad (3.5)\\
&= \text{Prob}(V_{ni} + \varepsilon_{ni} > V_{nj} + \varepsilon_{nj}, \forall j \neq i)\\
&= \text{Prob}(\varepsilon_{nj} - \varepsilon_{ni} < V_{ni} - V_{nj}, \forall j \neq i)
\end{aligned}
$$

Equation 3.5 shows that the probability of respondent *n* choosing alternative *i* is equal to the probability of the difference in the observed component of utility associated with *i* compared to alternative *j*, i.e. $V_{ni} - V_{nj}$, being larger than the difference in the unobserved component of utility of alternative *i* compared to alternative *j*, i.e. $\varepsilon_{nj} - \varepsilon_{ni}$, after evaluating all alternatives in the choice set *J*.

This probability is a cumulative distribution, that is, the probability that each random term $\varepsilon_{nj} - \varepsilon_{ni}$ is lower than the observed quantity $V_{ni} - V_{nj}$. Thus, using the density $f(\varepsilon_n)$, the cumulative probability can be modified as:

$$
\begin{aligned}
P_{ni} &= \text{Prob}\,(\varepsilon_{nj} - \varepsilon_{ni} < V_{ni} - V_{nj}, \forall\, j \neq i) \qquad (3.6)\\
&= \int_{\varepsilon} I\,(\varepsilon_{nj} - \varepsilon_{ni} < V_{ni} - V_{nj}, \forall\, j \neq i)\, f(\varepsilon_n) d\varepsilon_n
\end{aligned}
$$

where $I(\cdot)$ is the indicator function that is equivalent to 1 when the term in parentheses is true and 0 otherwise. This function is a multidimensional integral over the density of the unobserved component of utility, $f(\varepsilon_n)$. Thus, the probability that a respondent selects an alternative is the estimated value of the indicator function, where the expectations are the possible values of the unobserved part of the utility. Simplifying assumptions on the distributions of the random error terms are made in the discrete CE, with the purpose of maintaining a parsimonious structure. This action leads to the construction of a different discrete choice model.

3.3.2 Common Properties of the Discrete Choice Model and their Implications

There are some common properties which affect the estimation and specification of the discrete choice model (Train, 2003). One property is related to the irrelevant absolute level of utility of both the decision maker's behaviour and the researcher's model. If the utility of all of the alternatives is added with constant, then the alternative with the highest utility does not change. Referring to Equation 3.5, the choice probability depends only on the difference in utility and not on its absolute level. There are some implications for the identification and specification of the discrete choice model due to the fact that only differences in utility matter. To be concise, it means that the estimable parameters are only those that capture differences across alternatives. Thus, for the parameters such as alternative specific constant and socio-demographic variables to be identified and estimated, these parameters need to be specified in such a way that they capture differences across alternatives. Another property is the irrelevant scale of utility as described further in this section.

Alternative Specific Constants

The alternative specific constants (ASC) are usually specified in a discrete choice model. The observed part of utility is often specified to be linear in parameter with the below constant:

$$V_{nj} = x_{nj}ß + k_j \tag{3.7}$$

where x_{nj} is a vector of variables which relate to alternative j as encountered by a respondent n, $ß$ are the coefficients or parameters of that variables, and k_j is a constant that is specific to alternative j. The ASC for an alternative captures the average impact on the utility of all the excluded factors in the model (Train, 2003). In general, the ASC functioning like the constant in a regression model, which similarly captures the average impact of all the factors that are not included in the model.

When the ASC's are included in the discrete choice model, the unobserved component of utility ε_{nj} has zero mean by construction. If ε_{nj} shows a nonzero mean when the constants are not added in, then adding the constants produces zero mean for the remaining error, that is: if $U_{nj} = x'_{nj}ß + \varepsilon^*_{nj}$ with $E(\varepsilon_{nj})^* = kj \neq 0$, then $U_{nj} = x'_{nj}ß + kj + \varepsilon_{nj}$ with $E(\varepsilon_{nj}) = 0$. Hence, it is rational to include a constant for each alternative. Nevertheless, since only differences in utility matter, only differences in the ASC are relevant, not their absolute levels. Regarding the estimation with J alternative, J - 1 alternative specific constants can enter the model at the most, with one of the constants being normalised to zero.

There are two main reasons for the inclusion of ASC's in the discrete choice model. Firstly, they are included when the alternatives are in the labelled format and not in the generic format. If the alternatives are in generic format, then the ASC is assumed to be zero for that alternative since the utility differences between the alternatives is caused by the attributes which have already been integrated into the model (Kjaer, 2005). Secondly, the inclusion of ASC's is to explicitly account for the status quo effect in the discrete CE analysis (Hensher et al., 2015;

Scarpa, Ferrini and Willis, 2005a), as done in Chapters 8, 9 and 10. Since the ASC represents the utility of selecting the status quo option, the negative coefficient indicates that choosing the status quo decreases utility. On the other hand, the positive coefficient indicates that respondents attach some positive utility to the status quo situation.

Socio-demographic Variables

Socio-demographic variables of the respondents can be introduced in the discrete choice model if they are specified in a particular way that produces a difference in utility over alternatives. As mentioned in Section 3.3.1, the characteristics of the decision maker (respondent) do not vary over the alternatives. For that reason, socio-demographic variables can only be added to the model if they are specified in such a way that generates differences in utility over the alternatives. This can be done by creating a set of dummy variables for the choices and multiplying each of them by the characteristics of the decision maker (Train, 2003).

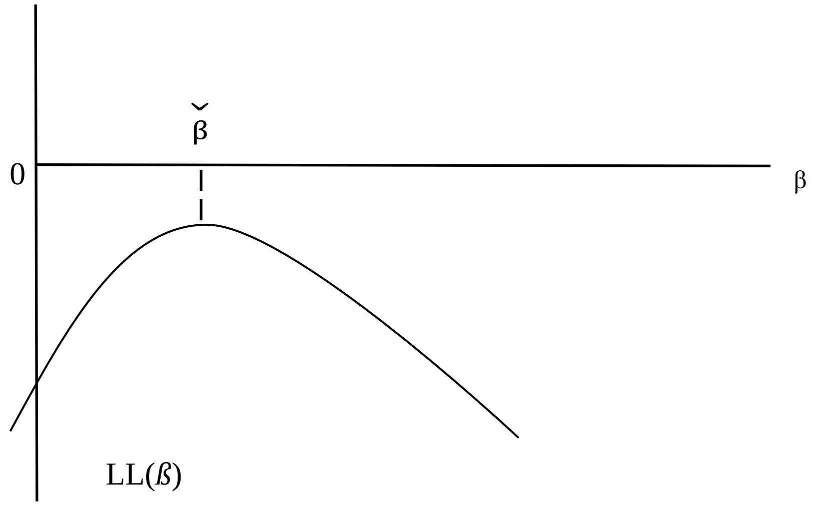
The Overall Scale of Utility is Irrelevant

In a similar situation like adding a constant to the utility of all alternatives does not change the choice of the respondent, neither does multiplying each alternative's utility by a constant. Regardless of how the utility is scaled, the alternative which possesses the highest utility is the same. For example, the model with $U_{nj}^{0} = V_{nj} + \varepsilon_{nj} \; \forall j$ is equivalent to $U_{nj}^{1} = \lambda V_{nj} + \lambda \varepsilon_{nj} \; \forall j$ for all $\lambda > 0$. To take this fact into account, the researcher usually normalises the scale of utility. This is done by normalising the variance of error terms since the error term is linked by definition to the scale of utility (Train, 2003). Hence, normalising the variance of the error terms is equivalent to normalising the scale of utility (Train, 2003).

3.3.3 Discrete Choice Model Estimation

The aim of model estimation is to make interpretations of the unknown utility parameter values in Equation 3.5. The maximum likelihood estimation is the most common and straightforward statistical approach to estimating the coefficients of the discrete choice experiment (Ben-Akiva and Lerman, 1985). The fundamental idea underpinning the maximum likelihood estimation is that a particular sample could be generated by different populations, and is more likely to come from one population than another (Louviere et al., 2000). Hence, the maximum likelihood approximations are based on a set of population parameters that generate the observed sample most often. As shown in Figure 3.1, the goal is to find the coefficient values $\check{\beta}$ that maximise the log-likelihood function LL(ß) = $\sum_{n=1}^{N} \ln P_n(ß)/N$, where $P_n(ß)$ is the probability of the observed outcome for respondent n, N is the sample size, and ß is a vector of coefficients. The log-likelihood value is always negative, as the likelihood is a probability between 0 and 1 and therefore, the log of any number within this range is negative.

Figure 3.1: Maximum Likelihood Estimate



Source: Adapted from Train (2003)

3.3.4 Statistical Significance of the Model Estimates

The statistical significance of individual coefficient ß in the model is determined using the Wald test statistic which is equivalent to the simple *t*-test (Hensher et al., 2015). The Wald test statistic can be written as:

$$\text{Wald} = ß_i/s_i \tag{3.8}$$

where $ß_i$ is the coefficient estimate, and s_i is the standard error for each attribute. If a 99 percent confidence level is assumed, then the critical Wald value is 2.576. Hence, if the absolute value of the Wald statistic is larger or equal to 2.576, then the researcher can conclude that the coefficient estimate is statistically significant. On the contrary, if the absolute value of the Wald statistic is less than the critical Wald value of 2.576, then the coefficient is not statistically significant. The reasons why some attributes in the study may not be statistically significant include; (1) the attribute is not an important influence on the choice under study, (2) the presence of outlier on some observations, and (3) the presence of non-normality in the distribution of the attributes which limits the effectiveness of *t*-test (equivalent to Wald tests) in establishing levels of statistical significance of the parameter (Louviere et al., 2000).

3.3.5 Overall Model Significance, Goodness-of-Fit and Model Comparison

The likelihood ratio test is used in the discrete choice model analysis in order to test a set of restrictions on models parameters evaluated by the maximum likelihood procedure (Ben-Akiva and Lerman, 1985). The measure of goodness of fit, or how well the model with the estimated parameter performs compared with the model when all parameters are zero, is made on the basis of the log-likelihood function (Train, 2003). The likelihood ratio index which is analogous to R^2 in a linear regression (Cameron and Windmeijer, 1997) is expressed as:

$$\rho^2 = 1 - \mathrm{LL}(\beta_b) / \mathrm{LL}(\beta_0) \tag{3.9}$$

where ρ^2 (also called as pseudo R^2) is equal to one minus the log-likelihood value at the estimated parameters (β_b) and LL(β_0) is its value when all the parameters are set to zero. The smaller the LL(β_b) / LL(β_0) ratio, the better the statistical fit of the model and thus the larger the value of ρ^2 would be. The ρ^2 values between 0.2 and 0.4 are considered to be indicative of extremely good model fits (Louviere et al., 2000).

Another statistical test used to measure the overall model performance is the log-likelihood ratio test (LLR test). The LLR test statistic is specified as:

$$\text{LLR test} = -2[\mathrm{LL}(\beta_0) - \mathrm{LL}(\beta_b)] \tag{3.10}$$

where LL(β_0) is the constrained maximum value of the LL function for null model (i.e. when all the parameters are restricted to zero) and (β_b) is the unconstrained maximum value of the LL function.

The statistic is distributed chi-squared with degrees of freedom equivalent to the difference in the number of estimated parameters between the full and reduced models (K_b – K_0), where K = the number of estimated parameters (Fitzmaurice, Laird and Ware, 2004). If the calculated chi-square value surpasses the critical value for the specified level of confidence (e.g. alpha value of 0.05), then the null hypothesis that the parameters of β_S are equal to zero will be rejected (Louviere et al., 2000).

The likelihood ratio test can also be used to compare two different discrete choice model specifications, provided that one of the models is nested under the other. The test statistic is defined as:

$$\text{LLR test} = -2[\mathrm{LL}(\beta_{simplemodel}) - \mathrm{LL}(\beta_{complexmodel})] \tag{3.11}$$

where the calculation used is similar to the Equation 3.10. If the calculated chi-square value exceeds the critical value for a certain confidence level, then the null hypothesis that the new model does not statistically improve the LL of the prior model can be rejected.

3.4 The Conditional Logit Model

The model commonly used to estimate the choice experiment exercise is the Conditional Logit[5] (CL) Model. This model can be developed with the assumption that all of the error terms are independently and identically distributed (IID) in the choice set with a Weibull distribution[6]. Therefore, the probability of respondent *n* choosing alternative *i* can be expressed as:

$$P_{ni} = \frac{exp\ (\mu V_{ni})}{\sum_j^i exp\ (\mu V_{nj})} \qquad (3.12)$$

where μ is the scale parameter. The scale parameter cannot be identified in any single sample and hence is expected to be μ=1. By assuming that V_{ni} is linear in parameters, the functional form of the respondent systematic component of the utility function can be written as:

$$V_{ni} = \beta_1 X_{ni} + \beta_2 X_{2ni} + \beta_3 X_{3ni} \ \ldots.\ B_k X_{kni} \qquad (3.13)$$

where X_s are the variables in the utility function and the β_s are the coefficients to be estimated. If a single vector of coefficients β_s that applies to all the utility functions related to all of the alternatives is defined, the equation (3.12) can be rewritten as:

$$P_{ni} = \frac{exp\ (\beta'\ V_{ni})}{\sum_j^i exp\ (\beta'\ V_{nj})} \qquad (3.14)$$

where:

P_{ni} = Respondent *n* choice probability of alternative *i,*
V_{ni} and V_{nj} = vectors describing the attribute of *i* and *j*, and
β = vectors of coefficients

[5] Conditional Logit Model (CL) is also known as McFadden's logit because it is a Multinomial Logit (MNL) Model extended by McFadden (1974). The central differentiation between these two models is straightforward: MNL model focuses on the respondent as the unit of analysis and uses the respondent's characteristics as explanatory variables; in contrast, CL model focuses on the set of alternatives for each respondent and the explanatory variables are characteristics of those alternative (Hoffman and Duncan, 1988)
[6] Weibull distribution is also known as the Type I extreme value or Gumbel distribution which implies that the error terms are logistically distributed (Freeman et al., 2014).

The following step is used to estimate the choice probability and to calculate the welfare measure by estimating the coefficient value of β in equation 3.13. The standard approach to determining the value of β can be done through maximum likelihood (ML) procedure as stated in equation 3.15 (Hanley et al., 2001):

$$LL = \sum_{n=1}^{N} \sum_{j=1}^{J} y_{ni} \log P_{ni} \quad (3.15)$$

where:

LL = Log likelihood function

y_{ni} = indicator variable defines as y_{ni} = 1 if respondent *n* chooses alternative *i* and zero otherwise

3.4.1 The Limitations of the Conditional Logit Model

Regardless of the widespread use of the CL model, there are limitations of this model concerning representing choice behaviour. Train (2003) lists the weaknesses of CL model as follows:

1) CL model can represent systematic taste variation that relates to observed characteristics of the respondent but not for a random taste variation.
2) CL model implies proportional substitution between alternatives. A different model is needed to capture more flexible forms of substitution.
3) CL model can capture the dynamics of repeated choice if unobserved factors are independent over time but cannot handle situations where unobserved factors are correlated over time.

Taste Variation

Different people put a different value on each attribute of the alternatives. For example, the size of a car or a house is probably more important to households with many members or a higher income, compared to smaller households or poorer households. Decision makers' tastes also vary for reasons unrelated to observed demographic characteristics. For instance, two people who have the same level of education will make different choices, reflecting their individual preferences. The CL model can only capture taste variations that vary systematically on observed variables. In other words, the CL model assumes homogeneity in preferences.

Meanwhile, tastes that vary with unobserved variables or that are purely random cannot be captured by the CL model (Train, 2003).

The Independence from Irrelevant Alternatives (IIA) Property and Substitution

Independence from Irrelevant Alternatives property implies that logit models permit a certain pattern of substitution. In more detail, this property states that for an individual respondent, the ratio of the logit probabilities for any two alternatives, say, *i* and *k*, is:

$$\frac{Pni}{Pnk} = \frac{e^{v_{ni}}/\sum_j e^{V_{nj}}}{e^{v_{nk}}/\sum_j e^{V_{nj}}} \tag{3.16}$$

$$= \frac{e^{v_{ni}}}{e^{v_{nk}}} = e^{v_{ni}} - e^{v_{nk}}$$

whereby this ratio is totally unaffected by the presence of other attributes from another alternative. In other words, the relative odds of choosing *i* over *k* is similar irrespective of the availability of any other alternatives or what the attributes of the other alternatives are (Train, 2003). One key advantage of IIA is the ability to estimate a choice model using a sample of alternatives, developed by McFadden (1978). However, as pointed out by Chipman (1960) and Debreu (1960), IIA is inappropriate and implausible when there are some alternatives containing choices that are close substitutes.

To illustrate the IIA property, consider the famous red bus/blue bus example. A traveller has a choice of going to work by car or taking a blue bus. For simplicity, it is assumed that the representative utility for the both modes are the same, such that the choice probabilities are equivalent to one:

$$P_{car} = 1/2 \tag{3.17}$$

$$P_{bus} = 1/2$$

$$P_{car} + P_{bus} = 1$$

Now suppose that another bus service which is the red bus is introduced. The traveller considers the new bus service has equal attributes to the existing bus service, except that the buses are different in colours. For the logit model under the IIA property, the ratio of the choice probabilities is the same whether or not the red bus exists, and the ratio is equal to one. Hence, the new choice probabilities can be written as:

$$P_{car} = 1/3 \tag{3.18}$$

$$P_{redbus} = 1/3$$
$$P_{bluebus} = 1/3$$
$$P_{car} + P_{redbus} + P_{bluebus} = 1$$

In real life, this is unrealistic because the traveller will be most likely to treat the two bus modes as a single alternative and the choice probabilities represent this behaviour can be written as follows:

$$P_{car} = 1/2 \quad (3.19)$$
$$P_{redbus} = 1/4$$
$$P_{bluebus} = 1/4$$
$$P_{car} + P_{redbus} + P_{bluebus} = 1$$

This example shows that using the CL model with the IIA property would lead to an overestimation of the probability of selecting the buses and an underestimation of the probability of selecting a car. The ratio of choice probabilities for the car and the blue bus actually changes with the introduction of the red bus, instead of remaining constant as required by the logit model.

Panel Nature of Data

Respondents in stated discrete CE surveys are asked a series of hypothetical choice questions, with varying attribute products which the researcher can observe. Data that represents the sequence of choices made by each respondent is called panel data (Train, 2003). The CL model can capture dynamics related to observed factors that enter the decision process. Nevertheless, dynamics associated with unobserved factors cannot be handled by the CL model since these factors are assumed to be unrelated over choices.

3.4.2 Taste (Preference) Heterogeneity

As describe in the section 3.4.1, the CL model assumes preferences (taste) to be homogenous and thus, it does not account for taste heterogeneity. Taste heterogeneity indicates that individuals do not have the same preferences when choosing alternatives in the choice cards. Therefore, assuming homogenous preferences when in fact preferences do vary across individuals will result in biased parameter estimates. For example, it has been found that restricting the preferences of individuals to being homogeneous often leads the mean consumer surplus to be significantly different (Breffle and Morey, 2000). Thus, including taste heterogeneity in the discrete choice model could increase the accuracy and reliability of parameter estimates.

There are two parts of taste heterogeneity; systematic (observed taste heterogeneity) and random (unobserved taste heterogeneity). Systematic heterogeneity means that the taste variation of respondents can be associated with some observed characteristic of the respondents (e.g. age, gender, income). In a random heterogeneity situation, choices and tastes of two respondents can be different although they have the similarly observed variables.

The CL model can capture the systematic heterogeneity by allowing the interaction between the socio-demographic characteristics of the respondent with the attribute alternative (e.g. Yang, Burton, Cai and Zhang, 2016) or with the alternative specific constant. This model is called a CL model with interactions. As describe in Section 3.3.2, this model specification allows ASC, or socio-economic demographic variables, to enter the utility function in a way that they build differences in utility over alternatives. However, the CL model does not account for random heterogeneity among decision makers.

As a response to the weaknesses of the CL model in order to account for the preference heterogeneity among decision makers, a number of models have been suggested as an alternative to the standard CL model. In this sense, two main approaches to modelling random heterogeneity have emerged, namely the mixed logit model and the latent class model. The following sections examine these two modelling methods.

3.5 The Mixed Logit Model

The mixed logit model (MXL) is a highly flexible model that can estimate any random utility model (McFadden and Train, 2000). The term 'mixed logit' reflects the mixture of logit for the choice probabilities comprised in the model (Hensher and Greene, 2003). MXL is also known as random parameter logit (RPL) or random coefficient logit (Train, 2003). Other terms that relate to MXL and are used to define various error specifications in the discrete choice model, such as error component, taste variation, random effect and unobserved heterogeneity.

MXL obviates three limitations of the conditional logit model by allowing for random taste variation, unrestricted substitution patterns, and correlations in unobserved factors over time. MXL can be derived from several different behavioural specifications where each derivation provides a particular interpretation (Train, 2003).

The derivation and estimation of the MXL in this study are based on Train (2003). Mixed logit models are based on mixed logit probabilities which are integral of standard logit probabilities over a density of parameters. Thus, choice probabilities in MXL can be expressed in the form:

$$P_{ni} = L_{ni}(\beta) f(\beta)\, d\beta \tag{3.20}$$

where $L_{ni}(\beta)$ is the logit probability estimated at parameter β:

$$L_{ni}(\beta) = \frac{e^{v_{ni(\beta)}}}{\sum_{j=1}^{J} e^{v_{nj(\beta)}}} \tag{3.21}$$

and $f(\beta)$ is the density function. $V_{ni(\beta)}$ presenting the portion of utility which depends on parameters β. When the utility is linear in β, thus, $V_{ni(\beta)} = \beta' x_{ni}$. In this circumstance, the mixed logit probability takes its usual form:

$$P_{ni} = \int \left(\frac{e^{\beta' x_{ni}}}{\sum_j e^{\beta' x_{nj}}} \right) f(\beta)\, d\beta \tag{3.22}$$

The mixed logit probability is a weighted average of the logit formulation estimated at different values β, with the weights given by density $f(\beta)$. In particular, from the statistics literature, a mixed function is the weighted average of several functions. Meanwhile, the density that provides the weights is called the mixing distribution. Thus, the mixed logit is the combination of the logit function estimated at different β with $f(\beta)$ as the mixing distribution. The mixing distribution $f(\beta)$ can be specified to be continuous, or discrete (Bhat, 1996). The continuous distribution is called the random parameter logit model while the discrete distribution is known as the latent class model, as further described in Section 3.6.

The mixed logit formulation can be explored in two formally equivalent specifications, yet conceptually different ways (Train, 2003; Koppleman and Bhat, 2006). To be specific, the mixed logit formulation can be generated from two specifications; (1) the error component which allows the flexible substitution patterns across alternatives (involves the relaxation of the IIA property), and (2) the random coefficient which accommodates unobserved taste heterogeneity of the respondents (Koppleman and Bhat, 2006). Nevertheless, the random coefficients are the most widely used and have a straightforward derivation. Therefore, the random coefficient specification is chosen for the data analysis in this study.

Random Parameter Logit

The random parameter logit (RPL) model allows the taste parameters for attributes to be varied continuously through the sample. Under the random parameter specification, the decision maker *n* faces a choice among *j* alternatives. The utility can be specified as:

$$U_{nj} = \beta'_n x_{nj} + \varepsilon_{nj} \tag{3.23}$$

where x_{nj} is a vector of observed variables that relate to alternatives *j* and the decision maker *n*, β_n is an unobserved vector of the coefficients for each *n* and represents the decision maker's tastes which vary in the population with density $f(\beta)$. This density is a function of parameters θ that denote, for instance, the mean and covariance of the β in the population. Thus, the density can be denoted as $f(\beta_n|\theta)$. Meanwhile, ε_{nj} is an unobserved random term, assumed to be IID extreme value, independent of β_n and x_{nj}.

The aim is to estimate the population parameter (θ) *w*hich describes the distribution. As explained in details in Section 4.3, the estimation of θ can be made based on different assumptions about its distribution. Examples of distributions are normal, lognormal, uniform and triangular. In most applications, the distribution is specified to be normal or lognormal.

The respondent, as a decision maker, knows the value of his β_n and ε_{nj}'s for all *j* and selects alternative *i* if and only if $U_{ni} > U_{nj}$ for all $j \neq i$. The researcher observes x_{nj} but not β_n or the ε_{nj}'s. If the researcher observed β_n, then the choice probability that respondent *n* chooses alternative *j* would be standard logit in which the probability conditional on β_n and can be written as:

$$L_{ni}(\beta_n) = \frac{e^{\beta' x_{ni}}}{\sum_j e^{\beta' x_{nj}}} \tag{3.24}$$

However, the researcher does not know the actual tastes β_n, thus, cannot condition the probabilities values on β. Thus, to estimate β_n, the assumption that the decision maker's tastes follow a particular distribution is made with density $f(\beta|\theta)$. Therefore, the unconditional choice probabilities is the integral of $L_{ni}(\beta_n)$ over all possible values of β_n, which represents the mixed logit probability:

$$P_{ni} = \int \left(\frac{e^{\beta' x_{ni}}}{\sum_j e^{\beta' x_{nj}}}\right) f(\beta)\, d\beta \tag{3.25}$$

The values of unknown preference parameter β differ in the population based on the assumed distribution, as opposed to being fixed as in the conditional logit model. The variance in β induces correlation in utility over attributes. In particular, the coefficient vector for every decision maker n can be stated as the sum of the population mean b and standard deviation s. As stated by Hensher and Green (2003), the standard deviation of the parameter β indicates the individual's tastes relative to the average tastes of the population, thus accommodating the presence of unobserved heterogeneity in the sampled population.

Once the type of distribution is specified, the estimation of the parameter to describe density f can be completed. The estimation can be done by maximizing the log-likelihood function as expressed in equation 3.26 (Revelt and Train, 1998).

$$LL(\theta) = \sum_{n} \ln P_{ni}(\theta) \tag{3.26}$$

However, the choice probability in equation 3.25 cannot be estimated exactly because the integral does not have a closed form. Therefore, the integral is estimated through simulation in order to maximise the log-likelihood function (Train, 2003).

Referring to Train (2003), the simulation of the log likelihood function can be done through a simulation procedure for any given value of θ, the procedure being as follows. First, a value of β is drawn from $f(\beta|\theta)$ and this is denoted as β_r. Subscript r =1 refers to the first draw. Secondly, the logit formula $L_{ni}(\beta_r)$ is calculated for this draw. Lastly, the first and second steps are calculated many times, and the results are averaged. The average results are the simulated probability as presented in equation 3.27:

$$\check{P}_{ni} = \frac{1}{R} \sum_{r=1}^{R} L_{ni}(\beta_r) \tag{3.27}$$

where R is the total number of draws, $\check{P}_{ni}$ is an unbiased estimator of P_{ni} by construction. The simulated log-likelihood (SLL) can be derived by inserting the simulated probabilities into the log-likelihood function:

$$\text{SLL} \sum_{n=1}^{N} \sum_{j=1}^{J} d_{\text{nj}} \ln \check{P}_{nj} \tag{3.28}$$

where $d_{nj} = 1$ if decision maker n chooses alternative j and zero otherwise.

One of the issues in the RPL model is to select the number of draws r in the analysis. The best step is to estimate models with a number of draws such as 25, 50, 100, 250, 500 and 1000 for confirmation of model stability and precision of model estimations (Hensher and Greene, 2003). Commonly, the complex model, with a large number of random parameters, requires a large number of draws to stabilise the estimates (Greene, 2002). The chosen number of draws also depends on the simulation method applied.

Pseudo-random draw sequences have been used extensively for the estimation of random parameters (Revelt and Train, 1998). The method requires a fairly large number of draws for a good performance of model estimation, thus leading to a very time-consuming analysis. The Standard Halton Sequences (SHS) method, which uses more uniformly distributed sequence within the domain of integration, has significantly improved accuracy of results, with fewer draws and less computational time. Bhat (2001) and Train (2003) found that 100 Halton draws produced a better accuracy of model than using 1000 pseudo-random draws.

Another issue is the assumption of the distribution of the random parameters. Section 4.3 specifically addressed the research question related to this issue and presents a small review of the related literature.

3.6 The Latent Class Model

As discussed in Section 3.5, the mixing distribution $f(\beta)$ in equation 3.22 can also be discrete, with β taking a finite set of values. In this situation, the MXL model becomes the latent class model (LCM) (Train, 2003). In contrast to the standard MNL model or CL model, the latent class model enables the researcher to observe preference heterogeneity through identifying and characterising various preference groups (Boxall and Adamowicz, 2002; Greene and Hensher, 2003; Garrod, Ruto, Willis and Powe, 2012). In this approach, the respondent's heterogeneity of preference is taken into account by a discrete distribution over unobservable endogenous or latent classes of respondents (Wedel and Kamakura, 2000).

The LCM has been used to estimate preference heterogeneity in various fields which include public preferences for landscapes (e.g. Sevenant and Antrop, 2010; Garrod et al., 2012), recreation choice (e.g. Boxall and Adamowicz, 2002; Scarpa and Thiene, 2005; Baerenklau, 2010), wetland management (e.g. Birol et al, 2006; Birol, Hanley, Koundouri and Kountouris, 2009), road environment preferences (e.g. Greene and Hensher, 2003) and water supply (Scarpa et al., 2005b).

3.6.1 Derivation of the Latent Class Model

The LCM assumes the population consists of *S* (unknown) latent class, (s = 1,….., *S*) and the respondent belongs to a particular class. Thus, the population is represented as comprising a finite number of classes, or segments. Within each class, preferences are assumed to be homogeneous. However, each segment differs in their preference structure. Respondents are assigned to different segments simultaneously with the analysis of choices. The total of the segments is endogenously determined by the data whereas the membership to a segment is influenced by the respondent's socioeconomic and attitudinal characteristics.

According to Swait (2006), the respondent's choices are observed, but their class membership is not observed, i.e., it is latent. Consequently, LCM is developed from a two-stage model, namely a choice model that is conditional on class membership and a class membership model. The derivation of LCM in this study is based on Swait (1994, 2006).

The utility function for respondent *n'*s choice, among *J* alternatives, assumes that the respondent belongs to segment *s* and can be written as:

$$U_{nj|s} = \beta_s x_{nj} + \varepsilon_{nj|s} \tag{3.29}$$

where β_s is the segment specific coefficients vector, x_{nj} is the attributes vector of each alternative, and $\varepsilon_{nj|s}$ denotes the random component of utility for respondent *n*. By assuming that respondents are utility maximisers and conditional on membership of a particular segment, respondent *n* will select alternative *j* if and only if $U_{nj|s} \geq U_{ni|s} = j \neq s$. Under assumption that the random error terms ε_{nj} are independently and identically distributed and follow a Type 1 extreme value distribution, thus, the probability alternative *j* is chosen by a respondent *i* who belongs to segment *s* is given by:

$$P_{nj|s} = \frac{e^{\beta s x_{nj}}}{\sum_J e^{\beta s x_{nj}}} \tag{3.30}$$

This provides the first choice model, and it is conditional on class membership. Within class membership, the choice is characterised by the IIA property inherent to the CL model.

Secondly, the class membership model is developed. The prediction of an individual's membership being in particular segment is made using an unobservable latent segment membership likelihood function (Y_{ns}^*) as follows:

$$Y^*_{ns} = \Gamma'_s Z_n + V_{ns},\ s = 1,\ldots, S \tag{3.31}$$

where Z_n is the vector of individual respondent variables, for instance, socioeconomics, attitudes or perception that affect classification probabilities; Γ'_s is a segment-specific parameter vector; and V_{ns}, is the stochastic error term. A conceptual explanation of Y^*_{ns} is that it is a latent factor score that determines the likelihood of respondent *n* being in segment *s*. The rule for the class membership assignment is to put respondent *n* in segment *s* if Y^*_{ns} is greater than the factor scores for all other classes:

$$Y^*_{ns} \geq \max \{Y^*_{ns'}\},\ s' \neq s,\ s' = 1,\ldots, \mathrm{S} \tag{3.32}$$

Assuming that the stochastic error terms V_{ns} are IID, the class assignment probabilities for segment membership Q_{ns} turn into:

$$Q_{ns} = \frac{e^{\Gamma's\, Zn}}{\sum_s e^{\Gamma's\, Zn}} \tag{3.33}$$

where Z_n is the above mentioned set of the respondent's observable characteristics, for example, psychometric (i.e. attitudes and perceptions) as well as socio-demographic variables. These variables are observable to the researcher. They become the indicators of latent factors (unobservable) that can enter the membership likelihood function Y_{ns} and be employed to categorise respondents into segments (Ben-Akiva et al., 2002).

To develop a model that accounts for choice and class membership, the products of the probabilities in Equation 3.30 and Equation 3.33 are estimated concurrently through the latent class model:

$$P_{njs} = P_{nj|s}.Q_{ns} \tag{3.34}$$

which gives the joint probabilities P_{njs} that respondent *n* chooses alternative *j* and belongs to segment *s* is:

$$P_{njs} = \left[\frac{e^{\beta s x_{nj}}}{\sum_J e^{\beta s x_{nj}}}\right]\left[\frac{e^{\Gamma's\, Zn}}{\sum_s e^{\Gamma's\, Zn}}\right] \tag{3.35}$$

The marginal probability of observing respondent *n* in segment *s* selecting alternative *j* is therefore:

$$P_{nj} = \sum_{s=1}^{S}\left[\frac{e^{\beta s x_{nj}}}{\sum_J e^{\beta s x_{nj}}}\right]\left[\frac{e^{\Gamma's\, Zn}}{\sum_s e^{\Gamma's\, Zn}}\right] \tag{3.36}$$

The equation above describes the probability of choosing alternative *j* which is equal to the sum over all latent classes *s* of the class-specific membership model conditional on class $P_{nj|s}$, multiplied with the probability of being in the Q_{ns} class. The β values for every segment and the probability of membership are estimated by simulation as described by Swait (1994).

The pseudo-R^2 value can be used to determine whether heterogeneity exists in the choice data. If the pseudo-R^2 value increases when the number of segments is increased in the model, it indicates that heterogeneity exists in the choice data (Ruto, Garrod and Scarpa, 2008).

3.6.2 Determining the Number of Segments

In a latent class model, the number of segments can be determined using various statistical tests including Akaike Information Criterion (AIC), Akaike Information Criterion three (AIC-3), Bayesian Information Criterion (BIC), etc. where the model with the minimum information criteria value is preferred. The number of the segments can also be determined by reflecting the aim of the study, the past research experience and researcher's own judgement. The calculation formula for the AIC, BIC and AIC-3 Criteria are as follows:

$$AIC = -2(LL - K) \qquad (3.37)$$
$$BIC = -2LL + K * \ln(N)$$
$$AIC - 3 = -3(LL - K)$$

where *LL* is the log-likelihood of the model, *K* is the number of estimated parameters and *N* is the number of observations in the sample. All these tests (AIC, BIC, AIC-3) are a useful guide, but often recommend different values for the segment for each of the estimated models (Desarbo et al., 1997).

3.7 Welfare Measures in Discrete Choice Model

A number of welfare measures can be estimated using choice model data. In Chapter 8 to 10, the welfare measures calculated are the marginal WTP values. This measure helps us to understand the impact of attributes changes to the economics and also the implications to the associated policy.

Marginal WTP

Marginal WTP value, sometimes called the implicit price, is calculated by dividing the coefficient value of any attribute by the coefficient value of cost attribute (Hoyos, 2010). The implicit price value indicates the amount of money that respondents are willing to pay in order to have the benefit of the attribute improvement (Bennett and Adamowicz, 2001). Thus, the WTP for a unit change in attribute *i*, for example, can be calculated as the negative of the ratio of *i's* β coefficient divided by the parameter of cost attribute β_{cost}.

$$WTP = - \beta_i / \beta_{cost} \quad (3.38)$$

where:

β_i = the coefficient of any of the attributes in the model

β_{cost} = the price coefficient

3.8 Conclusion

This chapter presented an overview of the discrete choice model used in this study. This included a review of literature from previous non-valuation studies and the design process of discrete choice experiments. The design process includes the issues of selecting the attributes and their levels followed by choice of experimental design. The remainder of the chapter involved the design of choice experiment question, the sampling process and the data collection procedures.

This chapter also discussed the theoretical background of the discrete choice model and the derivation of the logit family of choice modelling. This includes the CL, MXL and LCM models. Several important aspects were discussed for each logit model, including their advantages and limitations. Finally, the economic measure of welfare (WTP) used in this study was derived and explained.

Chapter 4: Literature Review of the Status Quo Issue, Attribute non-attendance and the Different Distributional Assumptions of Random Parameters in the Mixed Logit Model

4.0 Introduction

The objective of this chapter is to serve as a point of reference for the analysis in Chapters 8, 9 and 10. This chapter discusses some methodological issues related to the choice experiment technique. It begins with Section 4.1 where the section presents a review of the inclusion and exclusion of a status quo alternative in choice experiment questions by previous researchers. The explanation of the contribution of this study towards the status quo issue is also discussed in this section. Section 4.2 discusses the effect of attribute non-attendance and the distinction between the stated non-attendance and inferred non-attendance. This section also addresses the issues in dealing with the attribute non-attendance. In Section 4.3, the influence of the different distributional assumptions of random parameters is explained and discussed. Finally, concluding remarks are presented in Section 4.4.

4.1 Status Quo

The implementation of choice experiment requires some important decisions to be made and one such decision is whether to present the forced or unforced choice card to the respondents, by excluding or including a constant alternative, which often called in the literature as ‘status quo’, ‘opt-out’, ‘no option’, ‘no-choice’ or ‘choose none’. In brief, this refers to the extent to which the respondents are given a chance to not select an option (not being forced to choose), or to choose to stay with their status quo (current preference). However, status quo is not always the current preference of the respondent, but may be the only practical alternative available for some households in the presence of a budget constraint. The inclusion or exclusion of the constant alternative in a discrete choice experiment is determined by the objective of the study (Carson et al., 1994; Dhar and Simonson, 2003; Veldwijk et al., 2014). For example, when the objective of the research is to measure market penetration (Carson et al., 1994) or to determine the potential participation in a health program (Veldwijk et al., 2014), a constant alternative should always be included; if in real life making no purchase or ‘not participating’ is an option too. However, in certain situations, constant alternatives make no sense and should not be offered on the choice card. For instance mode choice for work trips, whereby the workers certainly have to make work trips, and they have to choose which mode they prefer.

4.1.1 Inclusion and Exclusion of the Status Quo: Why is it Important?

Status quo, or a ‘do nothing’ situation, is an alternative which describes the current scenario. The inclusion of the status quo alternative in choice tasks is standard practice in CE applications and is used in many studies (see Table 3.1). The SQ alternative allows analysts to calculate welfare estimates for changes from current situations to other situations (Boyle and Ozdemir, 2009). Most importantly, the inclusion of the status quo option is a way to mimic the real market transaction where the consumer cannot be forced to purchase a product (Carson et al., 1994) and to follow the Hicksian welfare measurement argument (Hanley et al., 2001).

There are several factors driving respondents to choose the constant alternative. For example, SQ is chosen by the respondents when they feel unwilling to pay or reluctant to respond to the changes presented. This might be due to particular reasons such as to dispute the attributes trade-off (von Haefen, Massey and Adamowicz, 2005), to avoid making difficult decisions (Carson et al., 1994), and also having no preference for improvement. These situations encourage the decision makers to stick with the status quo option.

Another factor is the complexity of the CE question that encourages the respondents to choose the SQ option (Boxall et al., 2009), i.e. the SQ option is being used as ‘an easy way out’ from the complex choice task. The respondents also tend to select the constant alternative when they find the proposed scenario to be unrealistic (Kataria et al., 2012), the alternatives are unattractive (Brazell et al., 2006) or the options do not meet their minimum acceptable level (Carlsson et al., 2007). Finally, the constant alternative is chosen when there is no compelling rationale for choice, either because the selection of the best alternative is difficult or because neither alternative stands out in comparison (Dhar and Simonson, 2003).

The inclusion of the SQ option comes with a ‘price’. According to Samuelson and Zeckhauser (1988), status quo effects account for various economic phenomena, and one of them is the difficulty of changing public policies. The constant alternative does not vary across the alternatives. Thus, when the respondents stick with the SQ alternative, no information is gained on the relative attractiveness of the available hypothetical alternatives (Brazell et al., 2006; Kallas and Gil, 2012). This suggests that the coefficients of the available alternatives, other than the constant alternative are estimated from fewer observations as the number of times the constant alternative is chosen over the sample increases. Therefore, not presenting the SQ option encourages decision makers to choose between the other available hypothetical alternatives. Furthermore, from a welfare-theoretical point of view it is not important to incorporate unrelated option such as the status quo, if the goal is to make a comparison between different clearly defined choice options (Carlsson et al., 2007).

The issue of whether to incorporate the status quo alternative in CE question, so far, remains unsolved. Many previous CE studies typically chose to include a status quo option as one of the alternatives in their choice sets, since it is believed that the addition of the status quo is one way of ensuring the unforced situation; where the respondents have the option to reject all alternatives, and therefore its inclusion could provide more accurate welfare measures. Based on a review of published studies, a number of researchers have also excluded the SQ option (e.g. Breffle and Rowe, 2002; Carlsson et al., 2007; Boyle and Ozdemir, 2009; Rigby, Alcon and Burton, 2010).

4.1.2 Related Literature and Contribution

A number of studies have been undertaken in transport, marketing and environmental economics, all of which have examined the effect of inclusion and exclusion of the status quo in CE choice. Although many important results have been obtained, the most interesting finding is whether the inclusion or exclusion of the status quo option gives a significant impact on the welfare estimations. An interesting point pertaining to this finding is whether it is necessary to offer the constant alternative in the CE choice card, if the inclusion of this alternative does not have a significant impact on the welfare estimations.

Studies that examined the effect of forced and unforced choice format of CE questions have led to the application of a split sample design and a dual response choice experiment design. Table 4.1 presents an overview of both of the designs and the impact of inclusion or exclusion of the status quo option towards the welfare estimate. In the split sample design, the first format presents the unforced situation with the inclusion of the status quo or other constant alternatives, whilst the second format offers the forced choice situation without the constant alternative. Alternatively, in the dual response choice experiment design respondents are presented with a forced choice situation at the beginning of the task, prior to being asked to repeat their choice in the unforced situation at the end of the task, or vice-versa. Therefore, a dual response design enables the estimation of forced and unforced situations within the same sample. In the CE literature, dual response has also been employed in other ways, such as asking the respondent to choose between two hypothetical alternatives and then asking respondents whether they would pay for their selected alternative or not (Kallas and Gil, 2012).

Table 4.1: Overview of Split Sample and Dual Response Choice Experiment Designs

Design	Authors (years)	Does the inclusion or exclusion of the constant alternative has a significant influence on welfare estimates?
Split sample CE	Breffle and Rowe (2002)	n/a
	Dhar and Simonson (2003)	n/a
	Enneking (2004)	No
	Carlsson et al., (2007)	No
Dual response CE	Brazell et al., (2006)	n/a
	Boyle and Ozdemir (2009)	No
	Rose and Hess (2009)	No
	Kallas and Gil (2012)	No
	Kallas, Escobar and Gil (2013)	Yes
	Veldwijk et al., (2014)	Yes
	Penn, Hu and Cox (2014)	Yes

The inclusion or exclusion of the constant alternative has no significant effect on welfare estimates

A number of researchers have found that the inclusion or exclusion of the constant alternative does not significantly affect the welfare estimations. In the field of marketing, Enneking (2004) applied a split sample design of CE in order to examine consumers' WTP for the quality assurance scheme introduced in the German meat sector. The results revealed that the WTP value was quite similar in both forced (excluded no-choice option) and unforced (included no-choice option) binary choice models. Similarly a study by Carlsson et al., (2007), who examined consumers' preferences for non-market food process attributes in Sweden, revealed that the differences in marginal WTP for the random parameter logit models in CE were small in relation to two survey versions; with and without the opt-out option. More precisely, they concluded that the inclusion of an opt-out option has no significant effect on marginal WTP. They also found no evidence relating to biased choice occurring as a consequence of excluding the opt-out option in the choice set. However, it was found that the opt-out version resulted in greater unobserved heterogeneity; since most of the coefficient standard deviations were significant in the random parameter model with opt-out, and insignificant in the random parameter model without opt-out.

In another pioneering study, Kallas and Gil (2012) analysed consumers' willingness to pay for rabbit meat attributes in Catalonia, Spain, using the dual response CE design. In the first task, respondents were asked to make a choice between two hypothetical alternatives, simulating the forced choice of a CE question. In the second task, respondents were asked if they were willing to buy their selected alternative from the first task, simulating the unforced CE question. The results revealed that the attributes were ranked similarly in both forced and unforced tasks. The WTP values obtained from the unforced task were slightly lower than those obtained in the forced task, in almost all attributes' levels.

In the field of transport, Rose and Hess (2009) examined commuters and non-commuters' route choice behaviour in Sydney, Australia. Firstly, respondents were asked to select their preferred alternative from three alternatives; a reference alternative and two hypothetical alternatives. Then, they were asked to choose between the remaining alternatives in the second task only if the reference alternative had been their primary choice. The WTP values, in the form of values of travel time savings, did not differ across the dual response data, whether estimated as pooled or separated data sources.

Having established that the inclusion or exclusion of the constant alternative does not affect the welfare estimate, it may be deemed unnecessary to offer the constant alternative in the choice set. In addition, Boyle and Ozdemir (2009) stated that excluding the status quo option should have no effect on a respondent's choice on the basis that at least one of the alternatives presented in a choice experiment question is preferred to the status quo by a respondent. Therefore, the respondent's choice should not affect the econometric estimation and the later use of coefficient estimates for welfare evaluation. In the study of the estimation of the value Maine residents placed on a farmland conservation easement program in the U.S., it was found that the exclusion of status quo alternatives did not affect the estimates of welfare and preference parameters. Meanwhile, Rigby et al., (2010) found no evidence in their pilot survey or main survey of respondents expressing any view of a preference to reject all the hypothetical alternatives in the choice set.

The inclusion or exclusion of the constant alternative has a significant effect on welfare estimates

Several studies have discovered that the inclusion or exclusion of the constant alternative has a significant effect on welfare estimate. For example, Kallas et al., (2013) examined consumers' preferences toward a red wine for a special occasion in Catalonia, Spain. In a dual response CE design, the respondents were first asked to choose their preferred alternative from a set of available alternatives, without a no-choice option and then they were asked whether they were willing to pay the selected option within the same exercise. It was found that the score rankings of the attributes were the same in the forced and unforced choices. However, there were significant differences between the implicit prices in both choices. In addition, the utility of the most preferred levels was significantly higher in the unforced choice compared with the forced choice.

In the field of environmental economics, Penn et al., (2014) evaluated the recreational beaches attributes among tourists and residents in Oahu, Hawaii using the dual response CE design. Initially, respondents made a forced choice among three hypothetical alternatives in each choice set. After making the forced choice, respondents were asked whether they would really go to the particular beach that had been chosen by them in the forced choice. For those who answered "no", their answer represented an opt-out decision and their answer in the first step represented a real forced choice. For those who answered "yes", it meant the alternative they selected in the first step represented an unforced choice. Thus, by applying the dual response CE question, every respondent must answer two questions per situation in a way that some were making forced choices and others were making unforced choices. Joint tests for notable differences in the attributes between both forced and unforced choices were shown to be significant. Moreover, the WTP values were also significantly different for both models.

A recent study by Veldwijk et al., (2014) investigated the extent to which the respondents' choice behaviour was influenced by the inclusion of an opt-out option in DCE (unforced choice). This study involved participants in The Netherlands diagnosed with type 2 diabetes mellitus where the participants were asked to choose the lifestyle program they preferred. Veldwijk and colleagues (2014) found that the attributes estimated from both forced and unforced mixed logit models differed but there were no significant differences in the relative order of the attribute. They also found that the WTP value for one attribute differed significantly between both models.

Other general implications

Some studies have found that the inclusion or exclusion of the constant alternative affects the consistency of choice responses and the choice proportion of the available alternatives. As an example, a coherence of responses has been found in the CE choice card without the SQ option (Breffle and Rowe, 2002). In addition, Breffle and Rowe (2002) suggested that including a status quo alternative does not ensure the formation of a more realistic choice set nor, does it improve value estimates. With the objective to evaluate the public's preferences for resource enhancement projects, in and around the waters of Green Bay, United States, Breffle and Rowe (2002) had split the choice question format into three. The first format was the simple resource-to-resource question that excluded the status quo option and created a forced choice situation between two alternatives that do not currently exist. The second format was the referendum format which included the status quo option to be compared with resource enhancement at a higher cost, and the third format was the composite choice format (multiple changes in attributes and levels, no status quo).

Their justifications are based on several points; (1) the status quo is not a realistic policy alternative when the removal or enhancement, or both, of the resources, might be undertaken in future, (2) the respondents are already mindful that the choice they are going to make is associated with the alternative resource improvement, therefore offering the status quo option seems to be unfeasible or unimportant to policy makers, and (3) status quo is not a preferred alternative for many respondents. Using the binary-choice probit model, the final result provided empirical evidence that the resource-to-resource question which excluded the status quo option appeared superior the other formats in term of response coherence.

The effect of the constant alternative on the choice proportion of the hypothetical alternatives can be found in Dhar and Simonson (2003) and Brazell et al., (2006). Dhar and Simonson (2003) applied a split sample design of CE in order to examine the effect of a no-choice option towards the choice share of hypothetical alternatives. The hypothetical alternatives consisted of an "all-average" (or impoverished) option and a "mixed" (enriched) option. The respondents consisted of visitors to a science museum who were asked to make (hypothetical) purchase decisions in several product categories (e.g. camcorder, calculator, portable computer). The respondents were randomly assigned the forced choice option (only two hypothetical options) or free choice option (two hypothetical options + no-choice option). There were approximately 70 respondents in each group. The findings revealed that the all-average option (hypothetical option) lost a significantly higher share to the no-choice option. In other words, the choice share of the all average option was lower when the no-choice option was available.

The addition of a constant alternative has resulted in an increase in the share of the most popular hypothetical alternative (Brazell et al., (2006). In a study conducted by Brazell et al., (2006), the respondents were asked to evaluate MP3 players defined in terms of nine attributes (e.g. brand name, size, voice recorder, rechargeable battery, the amount of memory). Respondents evaluated a forced-choice task, followed by the unforced choice task, in a dual response CE design. The results revealed that there were significant differences in the choice proportion of three available alternatives in twelve choice tasks from the first and second stages of dual response tasks. When the no choice option was added, the most popular available alternatives gained in share size, but the choice proportion increased significantly in one case only. However, in study two where the respondents were asked to evaluate laptop computers described in terms of six attributes (brand, memory, microprocessor, pointing device, size and price), there were no significant differences found in the choice proportion of the alternatives. In addition, there was no tendency for the most popular alternative to gain in share size when the no choice option was included.

4.1.3 Conclusion

The necessity for offering the SQ alternative in CE question is still being debated due to the possible affect on the attribute level estimates and calculated trade-offs. Nevertheless, the existing empirical evidences relating to this issue is still limited. It is therefore of interest to investigate the implication of the status quo option towards welfare estimates. Although the inclusion of the SQ option is thought to follow a fairly standard application of CE (e.g. presenting rational choice task), there are arguments raised in relation to it. For example, if individual preferences are assessed to find out which elements define the most preferred program or treatment, the inclusion of the constant alternative might not be a necessity but rather a threat to efficiency (Veldwijk et al., 2014). In contrast, there is an argument that the exclusion of the SQ option will result in biased estimates of the preference parameter (Haaijer, Kamakura and Wedel, 2001). Thus, whether the constant alternative is preferable in a CE survey design is not always clear-cut, however the impacts of its inclusion and exclusion can be examined empirically.

Therefore, this study aims to bring a fresh perspective to some of the on-going debates about the SQ issue through an examination of the inclusion and exclusion of the SQ alternative in the choice set. Previous studies have applied two different versions of CE questions in order to examine the effect of constant alternatives towards the valuation estimates, namely a split sample design and a dual response choice experiment design. However, the dual response format imposes a higher cognitive burden on the respondents as they have to evaluate a large number of choice cards and the choice complexity increases. Thus, a split sample design of CE is considered as suitable for use in this study to examine the SQ issue. In addition, the application of a split sample design of a CE questionnaire in order to explore the effect of constant alternative has not received a great deal of attention compared to the dual response CE design.

4.2 Attribute Non-Attendance (ANA)

An underlying assumption regarding the choice experiment technique is the continuity axiom of consumer behaviour. It assumes that respondents have fully considered each and every presented attribute in a choice set during the decision-making process. When respondents have thoroughly evaluated all the presented attributes in a choice set simultaneously, making trade-offs between them, and have selected the most preferred attribute bundle with the highest utility, they have applied compensatory decision-making to the task.

Evidently, the completion of the choice tasks in CE requires a significant cognitive effort (Campbell and Lorimer, 2009) and unlimited processing capacity from the respondents (Shah and Oppenheimer, 2008) in evaluating all the suggested attributes. However, in experimental practices, these two expectations may well be unfounded and difficult to sustain. This is because the complexity of the task in CE, can be deemed as challenging to the respondents, for example trading off one attribute against another, since they might be unclear or unfamiliar with the attributes presented.

The passive bounded rationality model assumes that respondents attempt to assess all information provided in the choice set, but they simply make mistakes when processing that information (DeShazo and Fermo, 2004). In reality, human capacity is limited to process information with varying degrees of magnitude in order to achieve a utility-maximising choice (Hensher, Rose and Greene, 2005a). As a result, a combination of the complex choice task and a limited respondent cognitive ability may lead to inconsistencies of choices that affect the valuation of the goods (Sælensminde, 2001). Such presented choices may be daunting for some respondents, who may choose to focus only on a subset of choice attributes. Recent studies have shown that individuals lack both the ability and the cognitive resources to provide accurate judgments and optimise their decision based on all presented attributes (Cameron and DeShazo, 2010).

Therefore, to simplify the complex task in CE, respondents tend to impose constraints when making the trade-offs between attributes (Campbell and Lorimer, 2009). When the respondents impose confines, it means that they have applied some attribute processing strategies with the aim of choosing among the competing alternatives presented. As explained by Hensher et al., (2005a), these strategies include respondents (i) ignoring specific attributes as a strategy to cope with the task complexity of CE, (ii) deciding that the costs of assessing such particular attribute are greater than the benefits, and (iii) not attending to an irrelevant attribute because it does not influence the choice made. In a nutshell, attribute processing strategies can be regarded as an indicator that there are some irrelevant attributes in the choice set for certain respondents (Sælensminde, 2006) and one of these strategies is referred to as the attribute non-attendance.

Generally, respondents in CE might ignore the attribute for different reasons. Interestingly, Scarpa, Thiene and Hensher (2010), and Carlsson, Kataria and Lampi (2010), point out the importance of more studies to discover the primary reasons why respondents ignore attributes. Hence, in order to differentiate between different strategies applied by the respondents, e.g. (i) and (iii) as mention above by Hensher et al., (2005a), or in order to identify the reasons why the respondents ignored a certain attribute, follow-up questions regarding their reasons for ignoring certain attributes can be provided in the questionnaire (e.g. Alemu et al., 2013). The interesting finding revealed by Alemu et al., (2013) was that the behavioural reasons underlying statements of ANA had significant bearings on the suitability of the standard stated ANA method. They finally concluded that using the standard approach of identifying ANA, in combination with a recoding scheme of ANA statements conditional on stated reasons, might be a more suitable method.

4.2.1 The Implication of ANA

ANA is a specific category of processing strategies, or heuristics where respondents ignore certain attributes and their accompanying levels when evaluating choice tasks (Campbell, Hutchinson and Scarpa, 2008; Scarpa et al., 2009). This behaviour implies that respondents have a tendency to focus solely on a subset of attributes, ignoring all other differences between the alternatives. This leads to the violation of the continuity axiom and the assumption of compensatory decision-making. Ignoring attributes in the choice task implies non-compensatory behaviour because when the particular attribute is ignored by the respondent, no matter how much the level of a given attribute is improved, the improvement will fail to compensate for degrading in the levels of other attributes (Scarpa et al., 2009). Discontinuous preference ordering such as lexicographic (attending to one attribute) implies non-compensatory behaviour, which limits the ability to compute marginal rates of substitution between attributes, and it, therefore, cannot be representative of a conventional utility function (Lancsar and Louviere, 2006).

ANA in the CE application has become an issue which has received much academic attention recently. Regardless of the reason why the respondent ignores attributes, it is important for the researcher to consider this behaviour when estimating a stated preference model. Based on the CE literature, it is believed that a failure to account for ANA may give biased welfare estimates and thus result in potential wrong policy implications (e.g. Campbell et al., 2008; Hensher and Rose, 2009; Carlsson et al., 2010; Caputo, Loo, Scarpa, Nayga and Verbeke, 2014). Two approaches have been suggested to identify ANA in CE, namely, stated non-attendance (SNA) and inferred non-attendance (INA). While the stated ANA involves asking respondents directly whether or not they have ignored some attributes during the completion of the choice tasks, the inferred ANA uses an analytical model which interprets ANA from the observed pattern of choice. However, there is no clear “winner” between these two approaches as revealed by Scarpa, Zanoli, Bruschi and Naspetti (2013).

4.2.2 Stated Non-Attendance (SNA)

SNA approach fundamentally uses complementary information gained from respondents who state the ANA rules they employed. There are two ways that can be applied to monitor SNA in CE: at the serial level or the choice task level (see Table 4.2). In the serial SNA approach, the question is asked at the end of the whole choice task regarding which attributes respondents have systematically ignored. In contrast to the serial SNA approach, the choice task level approach asks respondents to report which attributes they ignored after each single choice task. This may reveal whether ANA differs from choice task to choice task as respondents go through each of the choice situations (Scarpa et al., 2010). Evidence on attribute processing strategies can be integrated into the estimation of choice data in two ways; (1) by modifying the model for an unexplained variance, or (2) by eliminating discontinuous responses from the data analysis (Campbell et al., 2008; Kosenius, 2013).

Table 4.2: Overview of Serial and Choice Task SNA Approaches

Researcher	Follow-up Stated ANA question	Model	Serial Level	Choice Task Level
Hensher et al., (2005a)	Respondents were asked to state which attribute they ignored or not-attended to	MXL	√	
Campbell et al., (2008)	Respondents were asked whether or not they considered each of the attributes during decision making process	ECL	√	
Puckett and Hensher, (2008, 2009)	‘‘Is any of the information shown not relevant when you make your choice? If an attribute did not matter to your decision, please click on the label of the attribute below. If any particular attributes for a given alternative did not matter to your decision, please click on the specific attribute. You may click on a selected item to de-select it”.	MXL, ECL		√
Campbell and Lorimer, 2009	For each attribute, respondents were asked to state whether they considered the attribute or ignored it.	RPL	√	
Meyerhoff and Liebe (2009b)	“Were all attributes of wind power generation on the preceding choice card decisive for you?”	ECL		√
Hensher and Rose (2009)	“Please indicate which of the following attributes you ignored when considering the choices you made in the 10 games”.	Multinomial Logit Model	√	

Table 4.2 (continued): Overview of Serial and Choice Task SNA Approaches

Researcher	Follow-up Stated ANA question	Model	Serial Level	Choice Task Level
Carlsson et al., (2010)	"Was (were) there any attribute(s) that you did not consider when you made your choices? (Several alternatives are possible)".	RPL	√	
Hess and Hensher (2010)	''Please indicate which of the following attributes you ignored when considering the choices you made in the 16 games".	Mixed Multinomial Logit Model	√	
Scarpa et al., (2010)	"Which of the following attributes have you ignored?"	Random Utility Model		√
Kosenius (2013)	"When choosing the preferred alternative, did you consider every part of each alternative" "Were some characteristics more important than others; if yes, which one(s)"	ECL	√	
Hole, Kolstad and Gyrd-Hansen (2013)	"When you made your choices, were there any factors/attributes you chose not to take account of?"	Endogenous Attribute Attendance Model	√	
Scarpa et al., (2013)	Based on an ordinal scale; 'never', 'rarely', 'sometimes', 'often', 'always', respondents were asked to specify how much they felt they attended to each attribute	MXL	√	

Table 4.2 (continued): Overview of Serial and Choice Task SNA Approaches

Researcher	Follow-up Stated ANA question	Model	Serial Level	Choice Task Level
Alemu et al., (2013)	Asked respondents follow-up questions regarding their reasons for ignoring attributes. 1. It is not important to me 2. It made it easier to choose between alternatives 3. The levels for the attribute were unrealistically high/low 4. I don't think that this attribute should be weighed against the others 5. Do not know	ECL	√	
Caputo et al., (2014)	"Have you ignored any of the attributes? If yes, which of the following attributes did you ignore?"	RPL-Error Component	√	√
Nguyen, Robinson, Whitty, Kaneko and Chinh (2015)	Respondents answered 'yes' or 'no' to their attribute ignoring for every attribute	MXL	√	

The most important finding when ANA is accounted for is related to the impact on welfare estimates. Table 4.3 summarises the effect of ANA towards welfare estimate.

Table 4.3: The Impact of ANA towards Welfare Estimate

Researcher	Welfare estimate decreased when accounting for ANA	Welfare estimate increased when accounting for ANA	No significant different found on welfare estimate when accounting for ANA
Hensher et al., (2005a)	√		
Hensher, Rose and Bertoia (2007)		√	
Campbell et al., (2008)	√		
Puckett and Hensher (2008, 2009)	√		
Campbell and Lorimer (2009)	√		
Carlsson et al., (2010)			√
Kosenius (2013)		√	
Nguyen et al., (2015)			√

Accounting for ANA decreased the welfare estimates

Evidence of attribute non-attendance leading to a decrease in the welfare estimates has been found in various fields where the CE is used, including transportation and environmental economics. For example, in the field of transportation, Hensher et al., (2005a) investigated the influence of individuals not attending to specific attributes on the WTP for travel time savings, based on additional information provided by respondents. In literature relating to the discrete CE, Hensher et al., (2005a) were among the earliest contributors to attribute non-attendance issue. In a study of car commuters in Sydney, Australia, two designs of MXL were estimated where model 1 assumed that all attributes were attended to and model 2 excluded attributes not attended to by respondents in the analysis. They found that the goodness-of-fit of both models was impressive. When attribute non-attendance was accounted by restricting ignored parameters to zero, the estimated WTP value for travel time savings was found to decrease. Hensher et al., (2005a) also noticed that the recognition of attribute processing strategy was important and should be taken into account in CE studies that have WTP as their objective.

WTP estimates have also been found to decrease for each attribute when ANA was accounted for (see Campbell et al., 2008). In a survey on the general public's attitude and preferences regarding improvements in rural environmental landscape attributes in the Republic of Ireland, Campbell et al., (2008) discovered that 36% of respondents were considered to have discontinuous preferences (ignoring attributes). To account for ANA behaviour, the parameter of the ignored attributes was restricted to zero and this resulted in significant improvements in model performance. The respondents who had discontinuous preference behaviour were believed to ignore some particular attributes because they felt those attributes were not relevant in determining their choices. Moreover, Campbell et al., (2008) found that the magnitude of the WTP estimates decreased for each attribute, namely the conservation of wildlife habitat, preservation of water quality in rivers and lakes, preservation of hedgerows and safeguarding of pastures from erosion and overgrazing. The result implied that ignoring discontinuous preferences in CE could potentially create inflated WTP estimates. The evidence from this study suggests that CE studies should include a procedure for identifying and dealing with ANA.

Similar to that of Hensher et al., (2005a) and Campbell et al., (2008), Campbell and Lorimer (2009) found that the WTP estimates showed lower WTP values when attribute non-attendance was incorporated into the model. In addition, 75% of the respondents did not consider all the attributes when making their choices and were likely to adopt an attribute processing strategy in order to simplify their decision making. In relation to the model fit, an improvement in model performance was noticed when ANA was taken into account. Another study by Puckett and Hensher (2008) examined the attribute processing strategies of respondents within an empirical analysis of freight transport providers and their clients in Sydney, Australia. The results revealed that the WTP value for the component of travel time was higher in the model that assumed all attributes were attended across all respondents, as well as across alternatives and choice sets, compared to the model that was restricted based on the available attribute processing strategy information. Similar results were obtained by Puckett and Hensher (2009), demonstrating that over-estimation occurred when ignoring processing heterogeneity.

Accounting for ANA increased the welfare estimates

In contrast to the studies mentioned earlier, several studies found that accounting for attribute non-attendance increased the welfare estimates. For example, in the field of transportation, Hensher et al., (2007) found that the mean and standard deviation WTP were higher in the model that removed the ignored attribute, although the goodness of fit of this model was slightly lower compared to the model that did not account for the ANA.

A similar result was found by Kosenius (2013) who introduced a scale parameter in the model and eliminated less important attributes perceived by the respondents, in order to investigate the preference discontinuity. Following Campbell et al., (2008), a scale parameter was introduced in the error component logit (ECL) model in order to reveal changes in variance, specifically; heterogeneity in the error term of respondents who ignored a subset of attributes and respondents who considered all attributes. They found that the model performance improved when the information on preference discontinuity was accounted for, either by introducing the scale parameter in the error component logit model or by eliminating the less important attributes. Furthermore, the Scale Model suggested equal variances of choices between respondents who had continuous and discontinuous preferences. The efficiency of the WTP values was increased in the elimination approach. They finally concluded that the effect of more informed analysis on magnitudes of willingness to pay estimates was small.

Other general implications

Some studies have found that there was no significant difference in WTP between the restricted model (accounting for ANA) and unrestricted model. In a study that examined how the public living in Sweden evaluated three different environmental quality objectives, Carlsson et al., (2010) found that the majority of respondents ignored at least one attribute in the choice cards. When accounting for attribute non-attendance based on the feedbacks from the respondents, they found no significant difference in WTP with the standard model. This finding is contrary to the results of the previous study which compared models, with and without accounting for the ignored attributes (e.g. Hensher et al., 2005a, Campbell et al., 2008, Campbell and Lorimer, 2009). In addition, the model fit was lower in the restricted model. Carlsson et al., (2010) finally concluded that instead of ignoring attributes completely, respondents seem to put less weight on the attributes they claimed to have ignored, based on the fact that the most commonly ignored non-price attributes always had the lowest WTP rankings across three environmental objectives.

In another case, the WTP value was decreased for some attributes and increased for the other attributes, when accounting for non-attendance as revealed by Scarpa et al. (2010). In other words, a unidirectional change in WTP was not found. However, in a study focusing on the value of alpine park management services, Scarpa et al. (2010) found noticeable improvements in model fit especially when accounting for ANA at the choice task level.

A recent paper from Nguyen et al., (2015) who investigated the ANA issue in a developing country context, obtained similar WTP results to Carlsson et al., (2010). A households' preferences for the enhancements in cyclone warning services in Vietnam were elicited in this study. The results revealed that the preferences between the respondents who ignored the attributes and those who attended to the attributes were different. In line with previous studies by Hensher et al., (2005a) and Campbell et al., (2008), this study found that the model fit was better in models accounting for ANA. However, this study was not able to provide conclusive support for the assumption that the stated non-attendance affects WTP value estimates, since the WTP values derived from the full model and restricted model were statistically similar.

A different study by Alemu et al., (2013) applied an extension of the standard SNA approach by focusing on the behavioural reason underlying the statements of ANA. In this study, German tourists' preferences for recreational fishing site characteristics when on vacation in Denmark were assessed. Following the standard SNA approach, supplementary questions were provided to obtain information from the respondents regarding ignoring specific attributes. They also provided subsequent follow-up questions to reveal the reasons why respondents ignored such particular attributes. The follow-up was asked for each attribute listed as having been ignored. Comparing results from models that were dealing with non-attendance and models that excluded non-attendance revealed only minor differences in terms of the significance of the attributes. Similar to Hensher et al., (2007) and Carlsson et al., (2010), the model fit was found to decrease in the models that dealt with non-attendance attributes. Alemu et al., (2013) also claimed that the standard SNA approach of assigning a fixed zero contribution to the likelihood function from the ignored attributes might produce a biased result. Finally, this study suggested that using the standard SNA in combination with the recoding scheme of ANA statement conditional on stated reasons can improve the current approach.

4.2.3 Inferred Non-Attendance (INA)

Rather than asking respondents to state their attribute non-attendance, INA applied an econometric model to estimate the probability of ANA without the use of additional information. In this approach, latent class models are typically used where each class indicates a certain ANA decision rule and the parameter for the ignored attributes has been set to zero (Campbell, 2008; Scarpa et al., 2009; Campbell, Lorimer, Aravena and Hutchinson, 2010b).

Improvement in model fit and lower WTP values were found by Campbell (2008) and Campbell et al., (2010b). For example, Campbell (2008) used LCM to derive and incorporate discontinuous preferences of the general public in a survey regarding the existence value of rare and endangered fish species in Lough Melvin Catchment in Ireland. In this study, a two-stage estimation procedure was used. In the first procedure, LCM was estimated with two classes: first class, where all the attribute coefficients were estimated without restriction while in the second class attribute coefficients were restricted to zero. Then, the results were used to modify the weights of the attribute coefficients in a multinomial error component model with the aim of accounting for ANA. Comparing this model to a standard error component model that was not taking ANA into account, Campbell found a better model fit and lower WTP estimates when ANA was taken into consideration.

Similar results were also found in a study by Campbell et al., (2010b) which examined public preferences for restoration activities. In their study, they applied an equality constrained LCM. Three models were estimated: the first was standard multinomial logit model following the continuity axiom assumption, the second model was an equality constrained LCM where they assigned a class for every possible ANA, and lastly by retrieving the conditional class membership probabilities they recovered estimates of the weights for each attribute in order to avoid unnecessary weight allocated to ANA by the respondents. They found an improvement in model fits and lower WTP estimate when accounting for ANA. Meanwhile, Scarpa et al., (2009) proposed two ways of inferring attribute non-attendance in discrete CE which they argued to be applicable to data sets without supplementary questions. The first involved restricting parameters to zero in a LCM framework, whilst the second was based on stochastic attribute selection and grounded in Bayesian estimation. In all studies, the results indicated that accounting for ANA significantly improved model fit.

A study by Lagarde (2013) used a LCM in a step-wise approach in order to account for different ANA patterns by healthcare providers, based on their preferences towards the introduction of a new guiding principle to handling malaria in pregnancy in Ghana. The results revealed that only 2.6% of the respondents considered all attributes when making their choices between the two hypothetical scenarios presented; with a majority considering only one or two attributes. They also found that accounting for ANA improved the model fit and affected the magnitude of some of the parameters and WTP estimates, compare with the standard analysis.

Another study by Hess and Hensher (2010) inferred ANA through the examination of respondent-specific coefficient distributions, gained through conditioning on observed choices. The results revealed that some respondents ignored a subset of explanatory variables. They also found that the inferred attribute processing strategies were not necessarily consistent with the information obtained from the supplementary questions in the stated attribute processing strategies. Inconsistency was indicated by the differences in the percentage of respondents who ignored attributes, besides the allocation of particular respondents to the not ignoring and ignoring groups. In addition, the inferred strategies did produce a consistent result in the ignoring part of the population, i.e. zero valuations and a slightly better model fit. There was also some evidence that respondents who indicated that they ignored or not-attend to a particular attribute may simply have assigned it lesser importance.

4.2.4 Issues in Dealing with ANA

The growing literature in the choice experiment has identified situations where respondents apply different information processing strategies when assessing a choice task including ANA. The majority of research focusing on ANA issues in CE applications proposed that by taking ANA into account is possible to improve model fit. Potentially ANA can be seen to affect WTP estimates, although the results are not unambiguous. In fact, there is no consensus on exactly how ANA should be managed (Alemu et al., 2013): more specifically, how to detect the respondents who ignored certain attributes and how to model data when ANA has been identified.

However, it is believed that studies which fail to take into account whether respondents have ignored some attributes when making their choices may give biased welfare estimates and produce misleading policy implications. Based on these arguments, therefore, this study aims to explore whether or not ANA is being applied by the respondents when making their choices among the provision of important tourism facilities attributes. Before going further, it is essential to address several issues raised from the literature regarding the application of ANA.

The previous studies that examined stated ANA mostly asked respondents whether they ignored certain attributes or not when making their decision (e.g. Alemu et al., 2013; Caputo et al., 2014). The parameter of the ignored attributes was restricted to zero in the analysis[7]. However, there is evidence that respondents who claimed to have ignored some attributes may simply have assigned them lesser or lower importance (e.g. Hess and Hensher, 2010; Hess, 2014) based on the fact that the most ignored attribute receives the lowest preference ranking in the estimated utility model. Besides, there is evidence that not all of the respondents who claimed to have ignored an attribute really did (Carlsson et al., 2010). In other words, there is a discrepancy between what respondents declare and what they actually do. Thus, restricting the parameter of the ignored attributes to zero may be inappropriate and lead to misspecification of models (e.g. Campbell and Lorimer, 2009; Alemu et al., 2013). Taking everything into account, it seems inadequate to simply ask respondents whether they have ignored some attributes or not. Following this direction is the work of Scarpa et al., (2013) and Colombo, Christie and Hanley (2013), who asked respondents to indicate their frequency of attendance to each attribute (e.g. never, sometimes, always), whereas Alemu et al., (2013) asked respondents to indicate the reasons why an attribute has been ignored.

Thus, the gap observed in previous studies indicates a need for further research to identify how respondents pay attention to the attributes. This includes whether they ignored certain attributes or just assigned the attribute as being of lesser importance when making their choice. The supplementary question to identify their different perceptions towards each attribute can be asked at the end of the choice task as a method of dealing with ANA. This is in line with what has been suggested by previous researchers; whereby they suggested future studies should include methods for detecting and dealing with attribute processing strategies. Therefore, the effect on the model fit and the estimation of welfare can be further evaluated.

Given the significant implication of not accounting for ANA in terms of welfare estimates and also the implication of mistakenly assigning the respondent's perception towards attributes presented in the discrete choice experiment, this study makes a unique and novel contribution to research on ANA issue regarding the stated ANA supplementary questionnaire design. A different strategy was used whereby the respondents in this study were given four statements to choose for each attribute; (1) Did you ignore this attribute because it is not important to you?, (2) Did you put less emphasis on this attribute because there were more important attributes in the choice set?, (3) Did you gave the same weight as all the other attributes in reaching your

[7] If a respondent *n* states that she/he ignored an attribute *i* in a choice situation, the attribute coefficient β_{ni} will be constrained to zero in the utility function.

choice?, and (4) Did you put more emphasis on this attribute because it is more important than other attributes?. These options were provided at the end of the choice tasks.

Even though it may be beneficial to identify ANA at the choice task level rather than at the serial level as suggested by Hensher (2006b), there is no conclusive evidence which supports the notion that applying a stated ANA question at the choice task level would always produce a better result, compared to the serial level. For example, in a survey that employs CE to examine the externalities of onshore wind power generation in Germany, Meyerhoff and Liebe (2009b) found that the choice task ANA produces a better model fit compared to the so-called reconstructed serial non-attendance. However, they cannot find any significant differences in marginal WTP values for both of the techniques. Meanwhile, Scarpa et al., (2010) found that the choice tasks ANA have a tendency to imply smaller WTP values than in the model that accounts for ANA at the serial level (reconstructed from ANA at the choice task level), although the choice tasks ANA provides a better model fit. In contrast, Caputo et al., (2014) find that most of the WTP values in the choice task ANA are higher compared to the serial task ANA.

Providing the ANA supplementary question at the serial choice task is considered to be the best method to apply in this study since asking respondents to state their attribute non-attendance after every choice task could affect their behaviour in subsequent choice questions (e.g. Carlsson et al., 2010; Nguyen et al., 2015). In particular, answering the ANA question after the first choice task could make the respondents think that they are expected to ignore some attributes in the choice cards or put more focus on all the attributes. As a consequence, respondents' behaviour towards the following choice tasks may change and their choices may not reflect their true preferences. Moreover, asking the ANA questions after each choice task may increase the burden of the choice task (Colombo et al., 2013) and takes more respondent effort to complete the task (Caputo et al., 2014).

4.3 The Influence of Different Distributional Assumptions of Random Parameters

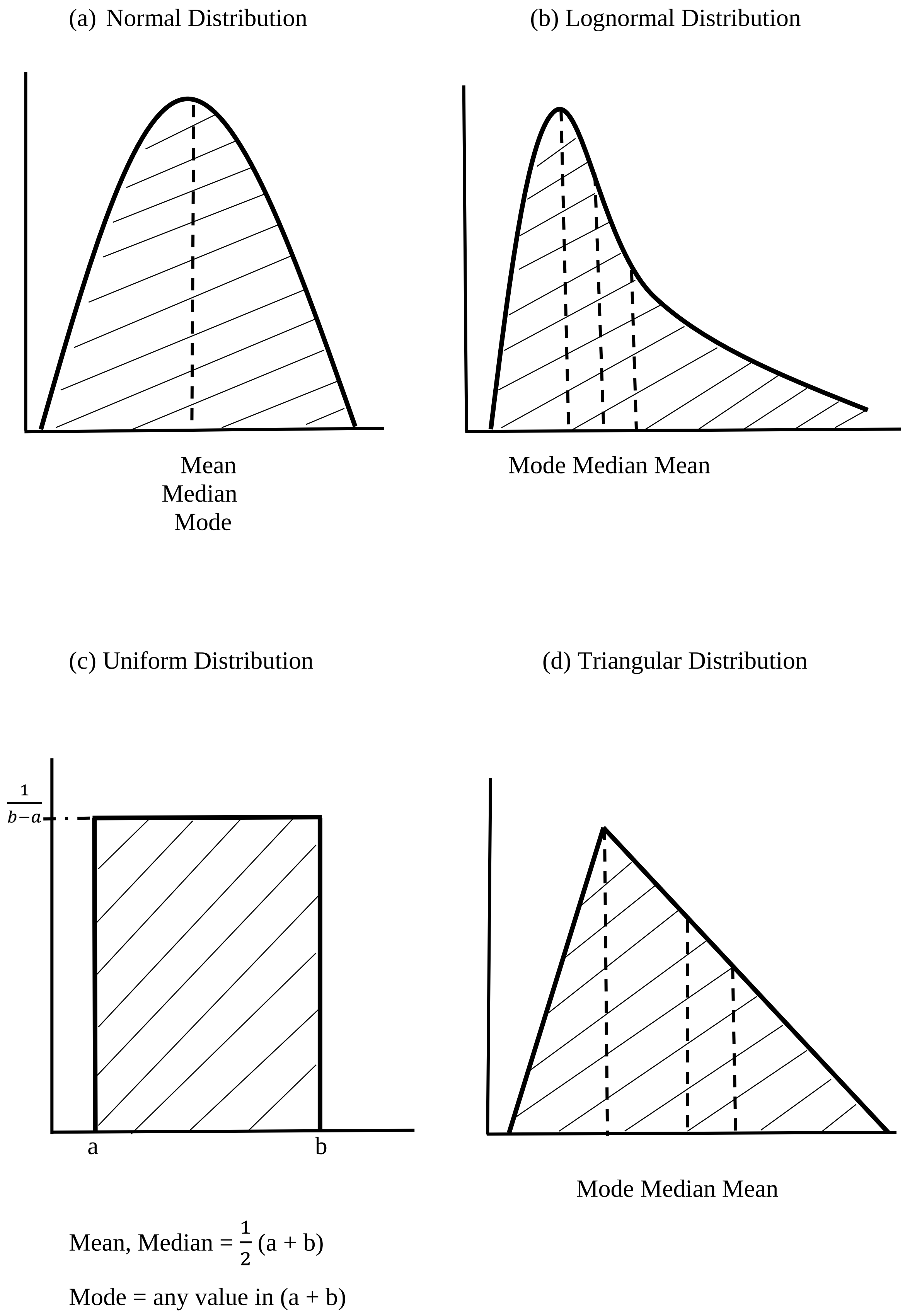
The use of the mixed logit model offers an effective way of extending the standard conditional logit model by permitting one or several parameters of the model to be randomly distributed. The most interesting element of the MXL application is the assumption regarding the distribution of each of the random parameters. There are four most popular predefined functional forms; normal, lognormal, triangular and uniform (see Figure 4.1). As clarified by Hensher and Green (2003), distributions are fundamentally arbitrary approximations to the real behavioural profile. Specific distributions are selected with a sense that the "empirical truth" is somewhere in their domain.

The earlier applications of MXL used a normal distribution which is equivalent to making an *a* priori assumption (coefficient values could be both positive and negative in the population) for random parameters, together with a fixed term for the price attribute. The use of a fixed price coefficient aids the computation of WTP values and the interpretation of the model, since the WTP (the ratio between the attributes and price coefficients) for each attribute is distributed similarly as the attribute's coefficient (Revelt and Train, 1998). Also, models with all random coefficients did not converge in any reasonable number of iterations, leading to a specification of an unidentified model (Ruud, 1996).

Basically, any form of distribution could be used, however in previous applications researchers mostly specified the random parameters as normal or lognormal distributed (Revelt and Train, 1998; Train, 1998; Layton and Brown, 2000; Train and Weeks, 2005; Garrod et al., 2014, Grisolia and Willis, 2016) where $f(\beta)$: $\beta \sim N(b, W)$ or $ln(\beta) \sim N(b, W)$ with the parameters b (mean) and W (covariance) are valued (Train, 2003). The normal distribution is unbounded where there is no strict sign for the coefficient estimate. Thus, the coefficient values can be both positive and negative. The normal distribution is relatively easy to apply, however, in a certain situation it is inappropriate for any attribute whose coefficient should be bound. To evade these difficulties, the adoption of bounded distributions, known as simple transformations of normal, have been proposed.

For example, the lognormal distribution (distribution skewed to the right) is suitable to be used when the coefficient needs to have a specific non-negative sign, or in another words, restricting the sign of the parameter. This property has made the lognormal distribution easily exploited in order to achieve the required restriction. However, it has a very long right-hand tail that makes the WTP calculations difficult (Hensher and Green, 2003). The long right-hand tail characteristic makes it unsuitable to be used for the price coefficient because it can produce a small coefficient for the price, thus leading to a high WTP value for one unit change in an attribute.

Figure 4.1: The Example of Different Types of Distributions



As explained by Scarpa et al., (2008), models with conveniently tractable distributions for taste coefficients, for instance, the normal and the lognormal, often yield estimates that imply counter-intuitive distributions of WTP. This is because the estimation of WTP values involves a ratio between attributes and price coefficients, where the price becomes the denominator. This highlights the reason why the fixed price coefficient is often chosen to be used in the MXL, even though different distributions are assumed for other attributes.

In contrast, the normal and triangular distributions are suitable to be used when there is no assurance of the sign of the coefficient. One of the weaknesses related to the use of normal distribution is its infinity tails ($-\infty$, ∞) which may lead to a very extreme coefficient. The triangular distribution may solve this problem because it possesses shorter tails compare to the normal distribution. Furthermore, it also allows for a peak in the density function and asymmetrical shapes (Hess, Bierlaire and Polack, 2005).

The uniform distribution with a (0, 1) bound is suitable for dummy variables. The advantage of uniform and triangular distribution is associated with their values being limited to '$b - s$' and '$b + s$' (where b = mean and the s = spread; b and s are the parameters to be estimated) (Hensher and Green, 2003). Densities have been bound on both sides in order to avoid the risk of estimating extreme values for the coefficients which relate to the application of normal and lognormal distributions (Train, 2003).

A glaring deficiency which all distributions have is related to the sign and length of the tail. As argued by Hensher (2001), none of the random distributions have all the appropriate properties, and the selection of the best random distribution is still an area of current research. Even though the standard assumption for the random parameters is a normal distribution, in principle any of the random distributions expected to fit the estimated coefficients can be used (Nahuelhual, Loureiro and Loomis, 2004).

Related Literature and Contribution

Some researchers have explored the sensitivity of coefficient and welfare estimates based on the choice of random distributions specification. The mutual conclusion is that distribution specification matters. In some studies, the attribute coefficient and welfare estimates were found to be identical for all distributions used. As an example, Hensher and Green (2003) examined the welfare effect of the MXL with normal, lognormal, triangular and uniform distributions. The results revealed that the mean welfare estimates were very similar across the normal, uniform and triangular distributions, whilst the lognormal distribution produced results which contrasted by about triple. The standard deviation of the lognormal distribution was also large. Moreover, even though the mean welfare estimates were similar across the normal, uniform and triangular distributions, the standard deviation values varied by as much as 17%.

Meanwhile, the similar attribute coefficients estimates were found by Colombino and Nese (2009) who investigated the used of normal, uniform and triangular distribution to assess visitors preferences towards cultural heritage management policies of an archaeological site at Paestum, Italy. Since 1998, Paestum has been listed as a UNESCO World Heritage Site. The selected attributes were opening times, audio guides, café, cultural events, exhibitions, laboratory, audio-visuals, documentation centre and price of admission. They found that all the estimates of the mean of β (attribute coefficients) were similar whether a normal, uniform or triangular distribution was implemented. Their findings also revealed a negative WTP of the visitors for the development of a café bar inside the archaeological area, but the MXL estimates indicated that 46% of visitors stated a positive utility for a café.

In contrast to the above studies, the WTP values were found to be different across distributions as revealed by Ghosh et al., (2013). In order to examine the effect of different distributional assumptions of random parameters in MXL, Ghosh et al., (2013) used a case study regarding a feeder service to bus stops in rural India. The estimations of MXL and corresponding WTP were compared using normal, lognormal, uniform, triangular and Johnson's S_B distributions. They also applied a constrained distribution where the standard distribution was made equal to the mean. However, model convergence could not be achieved for lognormal and Johnson's S_B distributions. The results of this study demonstrated that the goodness-of-fit of the models and WTP values were varied based on different distributional assumptions of random parameters. Interestingly, constrained distributions produced a better model fit compared to the unconstrained distributions. They also found that MXL with constrained triangular distribution (mean = spread) was superior to other models. Finally, they mentioned the importance for researchers to use different distributional assumptions when developing MXL. The best one can be selected based on the goodness-of-fit statistics.

A study that found WTP estimates were affected by different assumptions of distributions was carried out by Regier, Ryan, Phimister and Marra (2009) who elicited public preferences for a novel genetic technology in order to identify genetic causes of mental retardation/developmental delay. A parallel objective of this study was to specify heterogeneity distributions and to examine the distribution of preferences for the attributes. WTP measures were derived from the coefficients in the two estimated models: model 1 was an all parameters random specification and model 2 specified coefficients that were both fixed and random. The results demonstrated that different distributional assumptions (normal and lognormal) affect the WTP estimates. It was also noted that when the cost parameter was assumed to be log-normally distributed, WTP calculations were complicated to perform.

Another interesting finding is that particular distributions provide the best model fit in comparison to the others. For example, Milton, Shankar and Mannering (2008) examined the injury-severity distributions of accidents on highway segments in Washington, and the effects that weather, traffic and highway characteristics have on these distributions. The normal, lognormal, uniform and triangular distributions were considered for the random distributions. It was found that the normal distribution provided the best statistical fit compared to other distributions. Similar results were reported by Revelt and Train (1998) and Hensher, Shore and Train (2005b), who estimated the normal and lognormal distribution, finding that the model with normal distribution produced a higher log-likelihood value. Another study by Gkritza and Mannering (2008) also revealed the same result where normal distribution provided the best statistical fit compared to lognormal, triangular and uniform distributions.

Meanwhile, in another pioneering study by Hess and Rose (2006), the Johnson's S_B distribution was found to produce a better model fit. Hess and Rose (2006) estimated four mixed multinomial logit models with different random distribution assumptions; normal, uniform, symmetrical triangular, and one of the distributions in the Johnson's[8] system of distributions, namely Johnson's S_B[9]. It was found that the model using the Johnson's S_B produced the best model performance. Meanwhile, the differences in model fit between the other three models were very small.

Train and Weeks (2005) compared and estimated two different models with convenient distributions (normal and lognormal); 'model in preference space' (parameterized in terms of coefficients) and 'models in WTP space' (parameterized in terms of willingness to pay). In particular, the distributional assumptions and restrictions were placed on the coefficients or on the WTP's. They found that models using normal and lognormal distributions for coefficients (models in preference space) fit the data better than the models in WTP space but provide less reasonable distribution for the willingness to pay. Finally, they concluded that there is a need

[8] Johnson's system comprises of three distributions which are related to the normal distribution and described by the transformations to normality; 1) the Jonson's S_B distribution (which is bounded), 2) the Jonson's S_U distribution (which is unbounded), and 3) the Jonson's S_L distribution (which is the lognormal distribution) (Wicklin, 2013).

[9] According to Flynn (2006), the Johnson's S_B distribution transforms a bounded random variable by deducting the minimum and dividing by the range. Then, the result of this transformation is distributed as a standard normal variable.

for future research to identify the suitable distribution to be used, and the best distribution-fit is dependent on the situation.

The selection of the suitable distribution of random parameter and its major impact on the final WTP estimates is continuously being discussed. Based on current findings, the effect of distributional assumptions of MXL models on goodness-of-fit and WTP values has not been investigated adequately. Therefore, taking into account the effect of different random parameters distributions towards the WTP, this study aims to examine and compare the MXL estimations with different types of random parameter distributions in different CE data sets (forced and unforced).

4.4 Conclusion

This chapter presented a review of literature regarding some of the methodological issues in choice experiments, namely; (1) the status quo issue, (2) the attribute non-attendance issue, and (3) the issue of different distributional assumptions of random parameters. The effect of each of the methodological issues in CE towards the welfare estimation was also discussed. This chapter also explained the novel contribution of this study to this growing area of research in choice experiment literature.

Specifically, there are three main contributions of this study to the CE literature. Firstly, this study used a split sample design to examine the effect of inclusion or exclusion of the SQ option on welfare estimation in the context of tourism research. This study also introduced a new supplementary question at the end of the choice card, to identify if any bias in choice occurred as a result of presenting two different versions of the discrete CE questions to respondents. Secondly, this study introduced a new stated attribute non-attendance question to elicit non-attendance information from the respondents; and compared three different MXL models that account for ANA information with the benchmark model that did not account for ANA. Lastly, this study tested and compared the MXL model with different types of random parameter distributions, namely the normal, the lognormal, the triangular and the uniform distributions, for both forced and unforced samples.

Chapter 5: Study Area Description

5.0 Introduction

This chapter begins with some key information about the location of Malaysia in Section 5.1. Information about lakes in Malaysia is provided in Section 5.2, whilst details of the chosen lake area of study such as location, history, climate, and flora and fauna are presented in Section 5.3. Section 5.4 presents the establishment and history of Kenyir Lake. Section 5.5 documents the available attractions, outlining activities which are commonly undertaken at the lake. Information on accommodation and available facilities are also presented in this section. Section 5.6 discusses the management and the responsible bodies, and their roles in managing the lake. The chapter ends with some general conclusions.

5.1 An Overview of Malaysia

Malaysia is located in South East Asia and has two different parts; The Peninsular of Malaysia to the west and East Malaysia to the east. The Peninsular of Malaysia consists of 12 states whilst East Malaysia consists of Sabah and Sarawak with the South China Sea separating them. Malaysia is bordered by Thailand and Brunei to the north and Singapore and Indonesia to the south. Located in the equatorial zone, Malaysia has a warm and humid climate throughout the year. This country experiences a dry season from June to September and a rainy season from December to March during the monsoon. Malaysia records an average rainfall between 2,000 and 2,500 millimetres (mm) per year. The total land area of Malaysia is 330,433 square kilometres (km^2). Sabah and Sarawak recorded 73,620 km^2 and 123,985 km^2 of land areas, respectively.

Figure 5.1: Map of Malaysia

Source: http://images.nationmaster.com/nm/motw/middle_east_and_asia/malaysia_adm98.jpg

5.2 Lakes in Malaysia

In Malaysia, there are two types of lakes: natural lakes and man-made lakes. Natural lakes include wetlands, swamp areas and other ponds or lakes that were formed naturally while man-made lakes and reservoirs were formed through mining, drainage systems and dams and those created for recreational use. These lakes have many functions for the people and the country. The primary uses of lakes and reservoirs in Malaysia are: domestic water supply, industrial production, agricultural irrigation, hydroelectric power generation, urban storm water control, navigation and recreational benefits. Most importantly, lakes support the ecosystem and biodiversity of many habitats across the world.

Examples of natural lakes include Tasik Bera (the biggest natural lake in Malaysia) and Tasik Chini in Pahang, and Tasik Dayang Bunting in Langkawi, Kedah. Famous man-made lakes in Malaysia are like Tasik Kenyir in Terengganu and Tasik Chendoroh in Perak, where both are important for the generation of hydroelectric. Many lakes have become popular tourist sites and their economic development has created a source of income for the country. Amongst the popular tourism and recreation lakes are Tasik Perdana and Tasik Titiwangsa in Selangor and Tasik Kenyir in Terengganu.

There are ninety lakes and reservoirs, in thirteen states and two federal territories, in Malaysia (see Table 5.1). The overall size of these ninety lakes encompasses an area of approximately 1000 square kilometres with a total volume of 30 billion cubic metres of water, which is equivalent to two-and-a-half times the annual consumption of water for all industrial, agriculture and domestic purposes in Peninsula Malaysia (Academy of Sciences Malaysia [ASM], 2009).

Table 5.1: Inventory of Malaysian Lakes and Reservoirs

State	Number	Area (km^2)	Volume (mm^2)
Perlis	2	13.33	40
Kedah	7	95.03	1,637.76
Perak	11	284.68	6,766.50
Selangor	15	11.38	511.32
Pahang	10	94.69	355.71
Kelantan	4	11.34	76.80
Johor	13	84.22	940.02
Melaka	4	8.75	81.30
N Sembilan	5	2.25	182.33
P. Pinang	4	0.94	47.20
Terengganu	2	370.80	13,600
Sarawak	4	97.08	6,080
Sabah	5	1.81	29.61
Labuan	3	0.50	5.40
Putrajaya	1	7.50	45
Total	90	1,094.89	30,398.95

Source: ASM (2009)

5.3 Kenyir Lake Ecotourism Area

Kenyir Lake is one of the famous ecotourism sites in Malaysia. It offers a broad range of environmental goods and services to the visitors. The lake contributes significant economic benefits to the country. The uniqueness of this lake is that it was formed by the construction of the hydroelectric dam used for the generation of electricity.

5.3.1 Geography

Kenyir Lake is located in the west-central of Terengganu, Malaysia. Specifically, it is located at 5012.902' North latitude and 102038.306' East longitude. The surface area of this lake is 260 km^2 and it is one of the two major lakes in the Peninsula of Malaysia (Gin, 2009). Containing 340 small islands, Kenyir Lake is surrounded by the world's oldest rainforest. Kenyir Lake also includes part of Taman Negara or the Malaysia National Park, and it serves as one of the access points for visitors. This National Park is bordered by Pahang in the south and Kelantan in the west.

5.3.2 History

Before the formation of the lake, the area was a centre of early civilisation in the Neolithic era. Caves are located around the lake. Batu Tok Bidan and Bewah Caves have produced important archaeological discoveries for instance axes and stone tools from the Neolithic era (about 10,000 years ago). In 1956 and 1970, a group of archaeologists discovered some artefacts such as kitchen utensils, axes and tools. This finding revealed a thriving economic activity here during that era. When the area was flooded between 1978 and 1985, most of the tops of the caves remained above the water level, creating 340 man-made islands.

5.3.3 Climate

Kenyir Lake experiences a strongly stratified tropical climate with daily temperatures ranging from 24.2^{0}C to 32.0^{0}C for surface water and temperatures ranging from 20.8^{0}C to 24.0^{0}C for water at the bottom of the lake (Fatimah and Lock, 1994). The annual rainy season is from November to February and during this time all outdoor activities are reduced for the safety of visitors. However, November is also the best time for anglers to fish as it is early monsoon season. Plenty of fish during this season makes this place particularly attractive for eager anglers.

5.3.4 Flora and Fauna

Surrounded by some of the world's oldest tropical rainforest in Malaysia, Kenyir Lake is a home for nature lovers and eco-tourists. Hundreds of species of wildlife, fish, exotic birds, and flora and fauna have been identified as living here for thousands of years. The area of Kenyir is habitat to over three hundred species of orchids, eight thousand species of flowers, more than two thousand species of trees and plants, three hundred species of fungus and much more. Valuable species of forest timber such as Keruing, Meranti and Kapur have been identified as growing here. Kenyir Lake is also known as an angler's heaven due to the numerous freshwater fish living here. There are about three hundred species of freshwater fish dwelling in the lake such as Kelah, Toman, Kelisa, Lampan and Baung. Fishing has been a major attraction of Kenyir Lake for the past few years.

5.4 The Establishment of Kenyir Lake

Well-known as one of the man-made lakes built in Malaysia due to water retention from the Kenyir Lake Hydroelectric Dam that was completely built in 1985, it is the largest man-made lake ever built to generate electricity in Southeast Asia. Figure 5.2 presents the location of the main dam in the lake.

Sultan Mahmud Power Station or the Kenyir dam, which led to the creation of Kenyir Lake, was mainly constructed for national hydroelectric power generation and flood mitigation purposes and maintained by Tenaga Nasional Berhad (see Figure 5.3). This hydroelectric power station generates electricity of up to 400MegaWatt (MW) per day in order to fulfil the needs of the people in the country. Sungai Terengganu or Terengganu River was impounded, from 15 km west of Kuala Berang and 55 km upstream of Kuala Terengganu, with the purpose of completing the construction of Kenyir reservoir (Ros, Sidek, Razak and Ahmad, 2009). An important function of the reservoir is its role in reducing the flood levels of the lower Terengganu River basin.

The surrounding area has become famous to the public since the existence of the Kenyir Dam. Visiting tourists have created an increased awareness of the city Kuala Berang, located in Hulu Terengganu. This region was formerly known as a 'dead city' before it became acclaimed by visitors. The construction of Kenyir Lake drowned several villages and forests in the process. Many wild animals were saved during the construction of the dam. The construction of this dam has created new economic returns for the nearby population of which the majority were previously farmers. In 1993, KETENGAH a government agency, was authorised to develop Kenyir Lake as a major tourist destination in the country.

Figure 5.2: Map of Kenyir Lake Main Dam

Source: Go2TravelMalaysia.com
(http://go2travelmalaysia.com/tour_malaysia/kenyir_intro.htm)

Figure 5.3: Sultan Mahmud Hydroelectric Power Station

Source: PSI Incontrol Sdn. Bhd.
(http://www.psi-incontrol.com/v2/index.php/news/local-happenings/91-governor-refurbishment-successfully-completed)

5.5 Ecotourism Attractions and Recreational Activities in Kenyir Lake

There are various attractions that can be found at Kenyir Lake. The area offers natural resources such as waterfalls, caves, hills and freshwater fish to be enjoyed by the visitors. Recreational activities that are encouraged include camping, jungle tracking and canoeing. Table 5.2 presents some of these attractions.

Table 5.2: The Attractions of Kenyir Lake

Attraction	Details of Attraction
1) Resources Waterfalls	• Lasir Waterfall Lasir Waterfall is situated 16 km to the south of Gawi Jetty and is among the famous picnic spots at Kenyir Lake. • Saok Waterfall Around 20-minute boat ride from Gawi Jetty, Saok Waterfall is situated at the east of Pulau Besar. This waterfall has become popular with the visitors. • Tembat Waterfall This waterfall has a big camping space and it is the most famous destination for campers. It takes nearly an hour by boat ride from Gawi Jetty.
Caves	• Bewah Cave Situated in Bewah Hill, this cave offers a fantastic view of the towering limestone hills. • Taat Cave This cave has fascinating stalactites and stalagmites which come in different forms, sizes and shapes. The wall is lined with naturally engraved white limestone.
Hill regions	• The hill regions of Kenyir Lake are a world of untouched virgin tropical forest expected to be millions of years old. The highest peak is Mount Chergau whilst the second highest peak is Mount Gagau.
National Park	• The water part of Kenyir Lake is a part of the Malaysian National Park. This National Park covers part of three states, namely, Pahang, Kelantan and Terengganu.

Table 5.2 (continued): The Attractions of Kenyir Lake

Attraction	Details of Attraction
Parks & Gardens	• Butterfly Park • Bird Park • Herbal Park • Orchid Garden
2) Activities Fishing	• The lake is well-known as an angler's heaven for freshwater fishing. Hundreds of species of fish such as Lampam, Baung, Kelah**,** Toman, Seberau and Kelisa and are easily found. Good fishing spots are at Petuang, Cacing, Saok, Leban, Terengganu River, etc.
Camping/ Jungle tracking	• Well-known areas for camping are Gawi Jetty, along the rivers of Saok, Lasir, Tembat and Lawit, and Bewah in the National Park. For jungle trekking activities, the famous and interesting trails are Lawit and Mount Gagau.
Water Sports	• Canoeing, kayaking, rafting, boating and shooting rapids are among the water sports activities available at this lake. With a sprawling water catchment area of nearly 38,000 hectares, Kenyir Lake is being promoted as a water sports circuit by KETENGAH.
Stay in houseboat	• Houseboats are large boats, prepared with basic facilities for example, beds, television, living room, kitchen, bathroom, refrigerator and dining room. Most of the houseboats on Kenyir Lake offer a set price as part of the package. Tourists can sleepover in this boat and enjoy the activities that are offered in the package.

Source: Department of KETENGAH (2016)

A wide range of ecotourism attractions and recreational facilities provided here make this place a suitable choice for nature-loving visitors who love to spend their holidays doing recreational activities. At the same time, the education and awareness programmes which help to protect and conserve the natural resources surrounding this place of Mother Nature are conducted by the government agencies and involve students and residents.

Accommodation

There are seven resorts and chalets available at different prices, providing a range of affordable choice for visitors (see Table 5.3). Moreover, the simplicity of the houseboats, where the visitor can choose to sleep over, has also becomes one of the main attractions here. Houseboats are large boats which are equipped with various items such as beds, television, mattresses, kitchen and toilet. Each houseboat can accommodate 10 up to 25 visitors at one time. The visitors can rent a houseboat for as low as RM 1000 for one night. Houseboats were initially operated by the local people. The operation and management of the services are the sole responsibility of the houseboat operators. However, the KETENGAH agency is the responsible authority that monitors the operation and issues the licenses.

Table 5.3: List of Available Hotels and Resorts at Kenyir Lake

Hotel/Resort	Number of Chalet/Room	Contact details (Phone)
Petang Island Resort	26 chalets	+609-622 1276/ 822 2176
Lake Kenyir Resort & Taman Negara	150 rooms	+609-666 888/ 666 8305
Kenyir Sanctuary Resort	80 rooms	+609-824 4360
Federal Government Rest House	23 rooms	+603-88883032
Lake Land Resort	44 chalets	+609-626 2020
Musang Kenyir Resort	44 rooms	+609-623 1888
Tanjung Mentong Resort	24 rooms	+609-623 6682

Source: Kenyir Lake Tourist Information Centre (2016)

Other Facilities

Tourist Information Centre (TIC) is one of the facilities provided at Kenyir Lake. It gives information about Kenyir Lake’s background and information to tourists on how to manage their trip. Other facilities here include Pengkalan Gawi or Gawi Jetty, a parking area and toilet which visitors can currently use for free. Food stalls are also provided here.

5.6 Management and Administration of Kenyir Lake

KETENGAH has been given the mandate to promote the growth of the tourism industry at Kenyir Lake since 1993, and until now it is the main government agency responsible for managing and administering the lake. It is an agency under Ministry of Rural and Regional Development, incorporated on 12 April 1973 with permission to carry out economic and social development in an area of 443, 876 hectares. This area covers the interior of Dungun, Kemaman and Hulu Terengganu Districts, including Kenyir Lake. Some other agencies have their own particular roles in managing the lake (see Table 5.4).

Table 5.4: Government Agencies and Roles in the Management of Kenyir Lake

Agency	Role
Central Terengganu Development Authority, (KETENGAH)	• KETENGAH is the main authority responsible for managing Kenyir Lake overall. • KETENGAH aims to efficiently exploit the water and natural resource elements by focusing on development that is based on the 5A + 1C Approach (Attraction, Accessibility, Activity, Accommodation, Advertising and Promotion, Conservation and Reservation) to make Kenyir Lake an excellent tourist destination.
Tenaga National Berhad (TNB)	• TNB is the responsible body for the management of the Sultan Mahmud Power Station, which is a major hydroelectric dam in the state. TNB monitors the lake approximately 1.8km from the dam and the rest is under the supervision of KETENGAH.
The Department of Wildlife and National Parks (PERHILITAN).	• This department is responsible for maintaining the National Park, regulating and controlling all activities, including preventing illegal logging and others.
Police Marine Unit	• The Marine Police patrol the lake and are responsible for taking care of all aspects of security on Kenyir Lake.

Source: Department of KETENGAH (2016)

5.7 Conclusion

This study aims to investigate public preferences, using the Kenyir Lake recreational site as a case study area. The Kenyir Lake has been chosen because of its function in serving visitors, offering a broad range of environmental goods and services, including recreational benefits without any charges. In addition, Kenyir Lake receives a steep increase in the number of visitor every year, implying a high demand for its recreational use. Therefore, it is of interest for this study to examine the visitors' preferences relating to recreational site attributes provided at Kenyir Lake.

KETENGAH policies to develop the lake as a duty-free area also involves a development plan to improve the infrastructure and basic facilities at that lake. Having adequate facilities to accommodate visitors' needs is important since it can have an impact on visitor numbers. Thus, understanding visitors' preferences towards the tourist facilities attributes provided at the lake could provide KETENGAH agency with better policy recommendations regarding the improvement of tourist facilities which can be taken into the future.

Chapter 6: Research Methodology

6.0 Introduction

This chapter begins with an explanation of the process of generating the attributes and their levels for the choice experiment questions in Section 6.1. Included in this section is a discussion on how the final attributes and their levels were selected and a detailed explanation of two qualitative techniques used to determine the final attributes levels; namely a focus group meeting and a one-to-one interview with the policy maker. The final attributes and their levels are presented in Section 6.2. Following this, Section 6.3 describes the experimental design used to develop the choice sets.

Section 6.4 presents the description of two versions of questionnaire designs employed in this study in order to elicit information from the respondents, namely the forced and unforced CE questions. Section 6.5 explains the pilot survey conducted in this study, followed by a discussion of sampling and the implementation of the actual survey in Section 6.6. The chapter ends with some general conclusions.

6.1 Research Method Used in the Design of the Choice Experiment

The combination of qualitative and quantitative approaches, known as a mixed method, is usually considered as standard practice in the application of stated preference studies. The qualitative approach involves group interviews and individual interviews (Powe, 2007). Focus group interviews are mostly used in the qualitative approach and could be combined with any quantitative approach to improve the questionnaire survey designs (e.g. Clark, Burgess and Harrison, 2000; Willis, McMahon, Garrod and Powe, 2002; Powe, Garrod and McMahon, 2005; Greiner, Bliemer and Ballweg, 2014).

As highlighted by Clark et al., (2000), the mixed method is needed to capture the value of complex environmental goods, for example, the cultural value of nature or landscape. This view is supported by Powe et al., (2005), who explains several advantages of integrating the qualitative method in the process of valuing environmental goods. Some advantages of this method are that it allows the researchers to (1) understand how respondents discuss and conceive the goods valued, (2) understand the respondents' thought processes and motivation for their decision, (3) test the appropriateness of the valuation process, and (4) explore the acceptability level of the public on the valuation exercise.

Clark et al., (2000) and Powe et al., (2005), for example, investigated the respondents' thought processes when answering the quantitative questions at the time of the survey. In the study which valued the benefits of specific nature conservation policy in the United Kingdom, Clark et al., (2000) examined the respondents' thought processes when they were given the CVM questions. Respondents were given an opportunity to provide their thoughts about the WTP question, their understanding of the stated WTP value and any issue they might have relating to the WTP question. Meanwhile, Powe et al., (2005) used a combination of CE questions and six post-questionnaire focus group meetings in a study of water supply in the United Kingdom. The respondents were first asked to complete the questionnaire. At the end of the meetings, the respondents were given a chance to reconsider their responses and make any necessary changes.

The CE questionnaire design in this study involved the use of two qualitative research methods, namely, focus groups and interviews. One of the objectives of the qualitative research method applied in this study was to generate a list of attributes and levels which adequately described the facilities requiring improvement at the jetty area. However, at the initial start of research, it was impossible for the researcher to conduct a focus group in order to set up the suitable attributes and levels to be used, due to the distance between the researcher and the study site. Therefore, at the first stage, other alternatives were used to determine the preliminary attributes and levels related to policy and management for the Gawi Jetty. These includes a review of past studies, the availability of secondary information and online discussions with the responsible officer.

6.1.1 A Review of Literature

Before starting the CE questionnaire design, a review of previous recreational site studies was conducted to help identify the related attributes. Based on this, a CE study typically chooses attributes from the characteristic of goods to be valued. Table 6.1 demonstrates the various site attributes investigated from previous economic studies in Malaysia and other parts of the world, which can be used to classify the relevant attributes levels for this study. The attributes can be divided into six main categories.

Table 6.1: Specific Categories of Attributes Used in Economic Studies

Attribute categories	Specific Attributes	Relevant studies
Amenities	Accessibility (from jetty), changing and shower facilities, patrols, picnic shelter or resting place, quality of road access	(e.g. Boxall et al., 1996; Schroeder and Louviere, 1999; Holmes and Adamowicz, 2003; Christie et al., 2007; Bullock, 2008; Yacob et al., 2009; Juutinen et al., 2011; Hasan-Basri and Karim, 2016)
Recreational Facilities	Camping facilities, boating, playground,	(e.g. Adamowicz et al., 1994; Schroeder and Louviere, 1999; Bullock, 2008; Christie and Hanley, 2008; Kaffashi et al., 2015a; Hasan-Basri and Karim, 2016)
Fishing	Size of fish, average number of fish caught per day	(e.g. Adamowicz et al., 1994; Crabtree et al., 2004; Lawrence, 2005)
Information	Provision of information (e.g. board, sign boards)	(e.g. Chin, Moore, Wallington and Dowling, 2000; Yacob et al., 2009; Juutinen et al., 2011; Kaffashi et al., 2015a. Hasan-Basri and Karim, 2016)
Natural Attraction	Nature watching, the moose population, number of birds	(e.g. Boxall et al., 1996; Othman et al., 2004; Christie et al., 2007; Bullock, 2008)
Price	Entrance fee, conservation charge, annual contribution to fund	(e.g. Adamowicz et al., 1994; Alpizar et al., 2003; Jamal et al., 2004; Shuib et al., 2006; Kaffashi, Shamsudin, Radam, Rahim and Yacob, 2015b)

Given the review above and using the various sources of secondary information such as brochures and the government report for the future development plan at Kenyir Lake, a preliminary list of attributes was identified for this study (e.g. toilet, jetty, car park). The selection of attributes was closely related to the future development plan at Kenyir Lake, which is focused on the tourist facilities improvement. Therefore, the improvement of facilities was the main consideration in determining the preliminary list of attributes at an early stage. As being reported in Table 6.1, amenities and recreational facilities have been widely chosen as attributes in the CE study.

Acknowledging the limitations of developing attribute levels based on the previous literature, Coast et al., (2012) argue that a well-suited and appropriate method used to derive attributes levels relies on qualitative studies, as it can reveal the experience and perception of the potential beneficiaries.

6.1.2 Online Discussion with the Policy Maker

In order to further define the preliminary attributes, a number of structured discussions were held with the policy maker who is responsible for providing the tourist facilities at the lake. The first discussion was an online discussion held in the middle of June 2015 with the tourism and development manager from the KETENGAH department. The discussion was directly focused on attribute levels improvement which were relevant to the management and policy of the lake. Six attributes were determined as an outcome from the first online discussion; toilet, jetty, car park, tourist information centre, children's playground and entrance fee. The second online discussion, held in the middle of July 2015, determined the appropriateness of the levels chosen for each of the attributes. As a result, a list of attributes levels reported in Table 6.2 was selected. All attributes and levels included the current tourist facilities offered as the status quo.

Table 6.2: Attribute and Level Selected for Kenyir Lake

Attribute	Level	Current Situation/ Status Quo
Toilet	Basic Medium Superior	Basic
Jetty	One Two	One
Car Park	30 100	30
Tourist Information Centre	Basic Medium Superior	Basic

Table 6.2 (continued): Attribute and Level Selected for Kenyir Lake

Attribute	Level	Current Situation/ Status Quo
Children's Playground	Small Large	Small
Entrance Fee	RM 0 RM 1 RM 2.50 RM 5 RM 7.50 RM 10	RM 0

6.1.3 Focus Group Meetings

Focus group research, through social gathering and interaction, is useful for revealing the beliefs, experiences, feelings and reactions of participants in a way which is not practical using other methods, for instance, observation, individual interview, or questionnaire (Gibbs, 1997). Focus groups usually meet only once, and the agenda followed by participants is much more controlled by the moderator (Krueger and Casey, 2015). Interaction in the meeting can generate more ideas, thus, provide more useful information.

In this study, two focus group meetings were conducted before the pilot survey. Before determining what topics to be considered in the meeting, it is essential to decide on the degree of structure to give to the meetings. A possible structure for the meetings, as addressed by Powe (2007, p. 40), is as follows:

> **Opening:** introductory dialogue and then begin with an icebreaker. It is also important to emphasise what people have in common and state rules such as only one person to speak at a time.
>
> **Introduce the topic for discussion:** this can be in broad terms to gain an understanding of experiences, attitudes and preferences.
>
> **Key questions:** usually for or five questions that focus on the specifics of the scenario.

Ending questions: 'all things considered', the final position of the participants on the critical areas of concern, which will clarify their opinions. This may be in response to a summary by the moderator.

The structure outlined by Powe (2007) was implemented for both of the meetings conducted in this study. Generally, the focus group meetings were conducted to get feedback on the early version of the questionnaire. Each meeting involved six to eight participants. The focus group meeting used in this study had three objectives, namely; (1) to refine the list of attributes levels, (2) to explore the attribute non-attendance or simplifying strategies employed by the participant, and 3) to get the feedback on a split sample design of the CE questionnaires.

The aim of the first objective was to determine the relevance of the chosen attributes to the potential groups of respondents, as well as ensuring that the policy-relevant attributes coincide with those of the respondents (Bennet and Blamey, 2001). The aim of the second objective was to explore whether the respondents employed simplifying strategies when making their choice. The aim of the third objective was to compare the feedback from the respondents between the two versions of the CE question; with and without the status quo option. A further aim was to determine whether the participants could understand and interpret the information provided in the questionnaire as intended by the researcher. All the focus group meetings were recorded, and the approval was obtained orally from the participants beforehand. Recording the focus group meeting is crucial to ensure that any comments and suggestions are not overlooked.

At the start of the meeting, participants were informed that the results of the discussion would be beneficial to the researcher in the design of questionnaire which would elicit values on changes to tourist facilities offered at the jetty. The results obtained from the questionnaire survey would, in turn, be used to notify the responsible decision maker which would then impact upon the provision of tourist facilities. The first meeting was held in Newcastle. The meeting consisted of Malaysian postgraduate students who were studying at Newcastle University and Northumbria University as the participants. The second meeting was conducted with the visitors at Gawi Jetty, Kenyir Lake.

First focus group meeting

The first focus group discussion conducted at Newcastle in January 2016 began with a brief introduction about the purpose of the meeting, followed by an explanation of the topic to be discussed. Then, participants (6 students) were asked to answer several general questions, and one of the first discussion points involved asking the participants if they had visited the specified area for recreational purpose in the past year. Feedback from the session indicated that almost all of the participants had visited the recreational area within the past year. Participants were asked about their visit purpose to the recreational area, what are the important facilities provided at the recreational area, and were there any problems encountered during their visit.

The list of attributes and levels were shown to the participants, and they were asked to answer draft versions of CE questions which consisted of six different combinations of choice cards. Each choice card consisted of two hypothetical options. The feedbacks from the participant was varied.

For example, one participant discussed the toilet attribute when explaining the important facilities during her visit to the recreational area. She agreed that the toilet was the most important facility for a visitor for any recreational area. She explained that the toilet usually becomes the main problem due to poor provision, low level of maintenance, and toilets not being provided to address the needs of the different kinds of visitors. She added that toilets with baby changing room facilities was very important when she visited a recreational area with her family. This facility, however, was not important when she visited a recreational area with her friend. Other participants also agreed with her, and they concluded that the importance of a wide range of toilet provision, or other facilities such as a children’s playground, depended on what types of groups of visitors visited Kenyir Lake.

The car park issue surfaced when one of the participants complained about the congestion in the parking area when she went to a well-known recreational park. For her, having enough parking spaces was important in any tourist area. This was because, based on her experience, having a problem when parking the car would disrupt the activities that had been planned. Meanwhile, the tourist information centre attribute was important for some of the visitors when they visited a recreational area for the first time. However, the attribute was not important for the visitors who already had the experience of visiting the area.

Some of the participants agreed with the proposed entrance fee, and some did not. Those who disagreed believed that the government was responsible for the fee. Meanwhile, those who agreed that the participants should pay the entrance fee were more concerned with the benefits that they would get from visiting the recreational area in exchange for the charges imposed.

Some participants asked why they would have to pay a higher amount of entrance fee for fewer attributes improvement compared to another hypothetical option with more attributes improvement. At first, they were confused with the attributes offered in the choice card. The question was answered by one of the participants, who described the trade-off process in the CE questions. In the end, all the participants were happy with the attributes, and gained an understanding of the concept of trade-offs in the CE method.

To explore the attribute non-attendance or simplifying strategies that might be employed by the participants, they were asked whether they considered all attributes presented to them or whether they had ignored certain attributes. Feedback from the sessions revealed that certain attributes had been ignored by the participants when making their decision. For example, one participant explained that when she was making her choice, her primary attention was only on the toilet and car park attributes improvements. Therefore, she did not concentrate on the improvement offered for the other attributes, as the other attributes were not necessary for her.

Another participant explained that all attributes were important, however, when making her choice, she put more emphasis on certain attributes and less emphasis on the rest of the attributes. Even though there were participants who felt that the attributes to be considered were too many for them, some of them agreed that they had considered all the attributes evenly when making their choice.

To explore the effectiveness of a split sample design, each participant was asked to answer the second version of the CE questions which consisted of six different combinations of choice cards. Each choice card contained three options; two hypothetical options and the SQ option. They were asked to compare this second version of CE question with the first version they had answered at the beginning of the meeting. It is worth nothing here that the reason why the split sample design was chosen in this study had been explained earlier in the meeting to the participants before they answered the questions.

Their opinion about both versions was discussed. One of the participants became confused in making a choice in the second version of CE question. She said that the choice became difficult because there were three alternatives to be considered, compared to only two alternatives in the first version. Another participant gave a different feedback where she said that the SQ offered in the second version did not influence her choice too much. This is because the facilities improvement was more important for her rather than the SQ.

As explained in Section 4.1.2, some studies have used a dual response design of CE question to examine the status quo issue. To investigate whether the dual response design might suitable to be applied in this study, the opinions from the participants were elicited by presenting an example of dual response CE questions. Negative feedback was received, such as the participants were not willing to answer a large number of CE questions and it was very time-consuming to answer all the questions.

In the end, all the respondents agreed that a split sample design would be the best way to test for the SQ issues because a different version would provide a different feedback. Therefore, the researcher can make a comparison of the results from both versions. It could then help the researcher to determine whether the status quo is still relevant or not as one of the alternatives in the choice set.

The second focus group meeting

The second focus group meeting was carried out at Gawi Jetty in the first week of February 2016. The participants consisted of eight volunteer visitors, and the meeting was conducted at the resting hut located at the jetty. The structure of this meeting was similar to the first focus group meeting. The discussion began with some general questions, and one of the first discussion questions involved asking the participants if they had visited Kenyir Lake before this. Feedback from the session indicated that only two participants were first-time visitors to Kenyir Lake, while the rest of the participants had come to Kenyir Lake, approximately within the past five years.

The preliminary compilation of attributes and levels were shown to the participants, and they were asked to answer one example version of the CE question (without the SQ option), following the same procedure in the first focus group meeting. It is worth noting here that the participants had been informed about the proposed attributes levels which were initially based on the outcome of the discussion with the responsible policy maker and the first focus group meeting.

The feedback from the participants was varied. For example, when discussing the important facilities at Gawi Jetty, two of the participants explained that the tourist information centre was important to them mainly because they were both the first-time visitors to the lake. Although they can get the information about the lake from other sources such as the internet, it was probably not as complete as the information provided at tourist information centre. Meanwhile, the other participants explained that this attribute was not important since they are already acquainted with the features and the activities they can enjoy at the lake.

Most of the participants agreed that the toilet and jetty were the most highly important facility for them. One of the participants addressed the importance of the provision of wide range of toilet service at this lake, like the other recreational places in Malaysia. Based on his previous experience, the unavailability of a bathroom service at the Gawi Jetty made it difficult for him to shower and change clothes after enjoying the water sports activities. Other participants also agreed with him. They added that, as a recreational area surrounded by lakes and water, transportation become the main mode of travel and most of the visitors were exposed to the water. Thus, having the bathroom facilities provides convenience to visitors if they want to change their clothes at the end of activities before leaving for home. In the end, all the participants concluded that the wide range of toilet services such as the availability of bathroom and a baby changing room would benefit various types of groups of visitors.

After considering all the important points given in the meeting, it was confirmed that the participants understood the attributes and agreed with their levels. The next task was to explore whether the participants had ignored certain attributes or not when making their choice. This was done by asking them whether they had considered all the attributes in the choice card. One of the participants, who was the first time visitor said that he considered all the attributes presented in the choice cards. Another participant gave a different feedback where she said that she ignored some unimportant attributes. She gave the example that the tourist information centre was not important for her because she was a return visitor. As a return visitor, she did not use the tourist information centre since she was already well-informed about the features and activities at the lake.

To explore the effectiveness of a split sample design of the CE question used in this study, the respondents were asked to answer a second version of CE questions which consisted of the SQ option. Then, they were asked to compare this version with the first version they had answered beforehand. One of the participants explained that the second version of CE question enabled him to avoid making a difficult decision between two hypothetical options because he could choose the status quo option. He further explained that the status quo option should be offered in the choice card because not all of the visitors would agree with the introduction of the entrance fee at Kenyir Lake.

Another participant gave different feedback where she said that making a choice between two hypothetical options in every choice card was easier compared to three options with the SQ. This is because, without the SQ option, she can focus on what is being offered regarding the facilities being improved. She added that, as a return visitor, she certainly would support any effort put in improving tourist facilities at Kenyir Lake. The feedbacks received confirmed that the participants were comfortable with both of the questionnaire versions.

Similar to the first focus group meeting, the respondents were also presented with a dual response CE question and the feedbacks received did not support the use of the dual response CE questions in this study. Toward the end of the meeting, all the participants agreed with the split sample design of the CE questionnaire.

6.1.4 Consultation with the Policy Maker through One-to-One Interview

The interview was held with the objective to verify the attributes that would be used in the actual survey. Validating the attribute based on the policy maker’s perspective was important because the attributes used in the survey needed to be seen as policy-relevant (Blamey et al., 2002). The interview was held on the second week of February 2016 with the executive officer from tourism and development division of Kenyir Lake, KETENGAH. This interview was a continuation of the online discussion that occurred before.

One of the challenges in gathering the list of attributes and their levels was the limited availability of secondary information, this being more pronounced with respect to the classification of the current situation level for certain attributes. To validate the current baseline level for each attribute used in this study, a site visit was done together with the officer before a further discussion was held. After validating the current level of each attribute from the site visit, a further discussion with the related officer was conducted. The feedback from the discussion helped to reveal the potential plans for improvement of the facilities surrounding the area. Furthermore, the discussion provided information which helped to define the level of attributes representing the higher level of improvement to facilities. All the comments and feedback received from the focus group meetings were considered and combined with the suggestions from the officer in order to generate the list of the attributes levels. As a result, the officer was happy with the chosen attributes levels at the end of the consultation.

In order to evaluate the suitability of pictographs to be used in the attribute card, an interview was undertaken with the promotion officer from tourism and development division of Kenyir Lake, KETENGAH. A list of coloured pictographs representing the proposed attribute levels was shown to the officer, and he was asked about the appropriateness and clarity of the pictograph in demonstrating the attributes. Positive comments were received, and the officer was satisfied that the suggested coloured pictographs were appropriate to present the attributes levels. Figure 6.1 shows the attribute card with the description of the attributes levels and their pictographs.

Figure 6.1: The Attribute Card

Toilet

Variety in the range of provision will assist not only visitors with a disability, but also benefit elderly, those with babies or young children

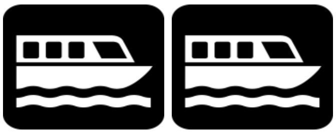
Current	*Proposal*	*Proposal*
BASIC	**MEDIUM**	**SUPERIOR**
Toilet for men, toilet for women, and toilet for disabled people	Toilet for men, toilet for women, toilet for disabled people and bathrooms	Toilet for men, toilet for women, toilet for disabled people, bathrooms and babies' changing rooms

Jetty

Jetty is a place where boat anchor to load and unload the passenger

Current	*Proposal*
ONE	**TWO**
There is only one jetty where the speed boats and houseboats load and unload the passengers	Jetty A for the speed boats passenger while Jetty B for the house boat passengers

Jetty A



Jetty A Jetty B

Car Park

There is only a small car park located at the jetty with limited number of parking slots. Adding more slots to the car park can provide more convenience for the visitors because they can simply park their car at a safe place

Current	*Proposal*
The current slots are limited and cannot accommodate the increasing numbers of visitors' car	Adding more slots can reduce the congestion problem, and visitors do not have to wait or queue to get space
	
30 slots	**100 slots**

Tourist Information Centre

The main function of the tourist information centre is to ensure that the tourists get the latest information on the tourism offer and hence, aid them to optimize their knowledge and experiences while enjoying their trip.

Current	*Proposal*	*Proposal*
BASIC	**MEDIUM**	**SUPERIOR**
Brochures, pamphlets and information boards	Brochures, pamphlets, information boards and video presentation	Brochures, pamphlets, information boards, video presentation and the availability of tourist information counsellor
		

Children's Playground

Providing a safe and stimulating children's playgrounds could add more attraction for the visitors to come

Curent	*Proposal*
SMALL	**BIG**
The current playground is small, old and limited in equipment	A big playground with a new equipment can provide a plenty of space for children to play.
	

Entrance Fee

Entrance fee is the money that each visitor would have to pay when they enter this lake. This fee would be used for the provision and maintenance of the facilities provided at the jetty

RM 0	**RM 1**	**RM 2.50**	**RM 5**	**RM 7.50**	**RM 10**

6.2 Choice of Attributes and Levels

Improvements to tourist facilities were described in terms of five attributes with varying levels, exclusive of the entrance fee attribute (Table 6.3). The different levels were selected to be realistic and indicate possible future values if policy measures were to be implemented (Bennett and Blamey 2001). In this study, two attributes were assigned with three levels, three attributes were assigned with two levels and one attribute with six levels. The current condition represented the situation as it is currently on the lake. The entrance fee attribute was included to determine the WTP values for the attribute levels.

A reason for using the entrance fee as a payment vehicle in this study is the fact that this type of payment system is commonly used in most of the recreational places in Malaysia (e.g. Redang Island, Perhentian Island, Malaysian Agriculture Park, Taman Negara National Park). Moreover, participants in the focus group meetings had no objection with the use of an entrance fee as a payment option.

Other possible payment mechanisms, such as income taxes, are very difficult to implement since many individuals in Malaysia do not pay income taxes. Income tax as a mechanism is likely to decrease the perceived payment consequentiality in a CE questionnaire survey (Hassan, Olsen and Thorsen, 2017). Therefore, this type of payment system was not considered in this study. In addition, with the use of entrance fee system, people already have information about this existing system and this is easier than introducing and explaining a new payment vehicle in detail.

The other possible payment vehicles that could be applied in this study, include parking charges, and a contribution to a trust fund, and these could be less controversial from a property rights perspective. This is because imposing entrance fees to a public area is not a common practice in some places. For example, according to Campos, Caparros and Oviedo (2007), establishing entrance fees to threatened forests in Spain is not a common practice; and individuals are aware of free access as a right, though this is not always legally the case. Parking charges are commonly applied by the National Trust in England, as an access charge for walking on land it owns. In addition, Hanley and Ruffell (1993) revealed that the price paid for parking at more than sixty recreational areas studied was a good predictor of stated WTP. An advantage of parking charges, as a payment vehicle, is that a permanent person is not necessarily required to collect the fee at the entry point: a ticket machine can be installed. This payment vehicle might be more economically efficient where visitor numbers are low.

A description of six attributes used in the two discrete choice experiment surveys follows.

Table 6.3: Attribute Description, Levels and Variable Names

Attribute	Description	Variable Names and Levels	
Toilet	Toilets are an important facility. Toilet services should address the needs of visitors, both in terms of availability and accessibility. Furthermore, variety in the range of provision will assist not only visitors with a disability but also benefit elderly, those with babies or young children.	***Basic***	***10 toilets + 2 disabled toilets***
		Medium	Basic + bathrooms
		Superior	Medium + Babies' changing rooms
Jetty	The current size of the jetty is too small and creates a crowded situation where visitors need to join a long queue while waiting for the boats, especially during peak season. The small size of the jetty makes it quite dangerous, especially for those who bring small children. Another jetty would separate visitors into small groups.	***One***	***The current small jetty where the speed boats and houseboats load and unload passengers.***
		Two	One jetty for a speedboats and another one jetty for the houseboats to load and unload passengers.
Car Park	Parking may be severely inadequate at any tourism site, an especially a site that receives an increasing number of visitors every year. There is only a small car park located at the jetty with a limited number of the parking slots. Adding more slots to the car park can provide more convenience for the visitors because they can simply park their car in a safe place.	***30 slots***	***The current slots are limited and cannot accommodate the increasing numbers of visitors' car.***
		100 slots	Adding more slots can reduce the congestion problem, and visitors do not have to wait or queue to get space.

Table 6.3 (continued): Attribute Description, Levels and Variable Names

Attribute	Description	Variable Names and Levels	
TIC	The main function of the tourist information centre is to ensure that the tourists get the latest information on the tourism offers and hence are able to optimize their knowledge and experiences whilst enjoying their trip. This can be achieved by offering attractive information such as video presentation and a knowledgeable tourist guide.	***Basic***	***Brochures, pamphlets and information boards.***
		Medium	Basic + video presentation.
		Superior	Medium + tourist information counsellor
Children's Playground	Providing a safe and stimulating children's playground could add more attraction for the visitors to come.	***Small***	***The playground is small, old and limited in equipment.***
		Large	A large playground with a new equipment can provide a plenty of space for children to play.
Entrance Fee	Entrance fee is the money that visitors need to pay (per person) when they enter this lake. This fee is going to be used for the provision and maintenance of the facilities provided at the jetty.	***RM 0***	***Currently there is no charge for entrance fee.***
		RM 1	Entrance fee amount is RM1.
		RM 2.5	Entrance fee amount is RM2.50.
		RM 5	Entrance fee amount is RM5.
		RM 7.50	Entrance fee amount is RM7.50.
		RM10	Entrance fee amount is RM10.

Note: The bold italic statement is the current situation of each attribute.

6.3 Experimental Design

Having identified the appropriate attributes and levels to be used in this study, an experimental design was constructed to develop the choice sets. The D-efficient experimental design was generated from the SAS programme. It produced 36 different choice cards suitable to be used in this study.

The D-efficient experimental design was used as opposed to orthogonal design for several reasons. According to Bliemer and Rose (2006), at a given sample size, D-efficient designs are expected to produce smaller standard errors, or on the contrary, require smaller sample sizes to produce bigger t-ratios as compared to the orthogonal designs. Moreover, the number of choice situations in D-efficient designs can be kept small. This contrasts with orthogonal designs where the number of choice situations cannot be decreased without losing orthogonality (Bliemer and Rose, 2006).

Overall, D-efficient designs are favoured since they increase the efficiency of sampling, allow estimation of unbiased coefficients, and possibly facilitate the reduction in the costs of the survey (Huber and Zwerina, 1996). This view was supported by Campbell (2007) where the author revealed that the survey cost declined by 30%, and the sampling efficiency increased by 44%, when a D-efficient design was applied.

Asking a respondent to answer all thirty-six choice cards is cognitively too demanding for them. Taking into consideration the complexity of a CE question and to avoid tedium, the choice cards were blocked into six versions of six choice cards each. In the unforced question, the status quo option, which represents the current situation in the study site, was included as one of the alternatives in the choice card. Thus, there were three alternatives for each choice set in the unforced question. Many researchers in CE studies have employed the combination of two options and one current situation option (e.g. Hanley et al., 1998b; Willis, 2009). See Table 3.1 for previous studies that have used the combination of three options. All thirty-six choice sets are shown in Appendix A.

To examine whether the status quo is relevant as one of the alternatives in the choice set, the status quo option was excluded in the forced questionnaire. Thus, there were only two alternatives presented in each choice set for the forced questionnaire. In total, there were twelve sets of forced and unforced questionnaires. Each respondent was randomly assigned one of these twelve sets and hence answered six choice cards.

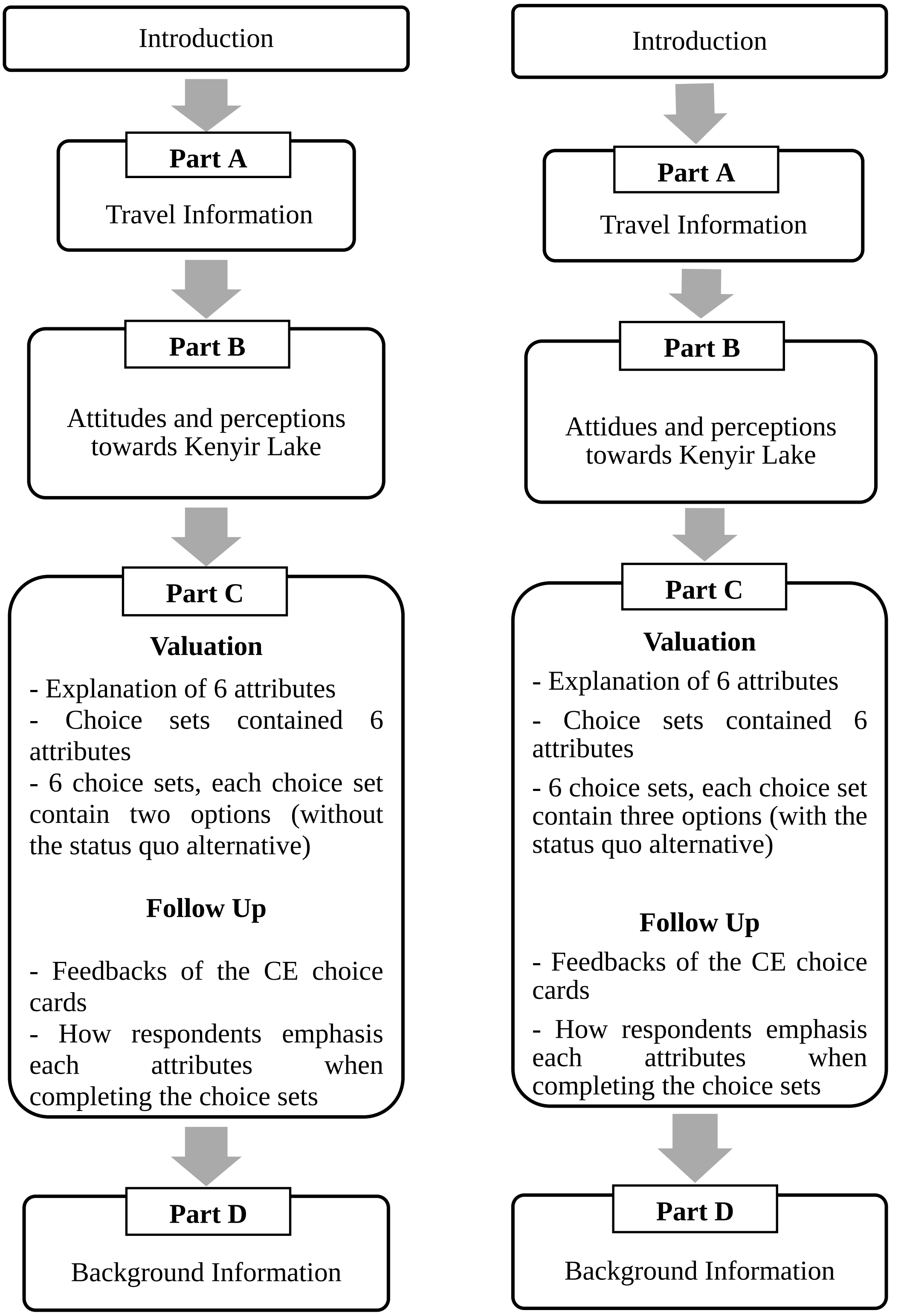
6.4 Questionnaire Design for Choice Experiment

Two versions of the CE questionnaire survey, one with the status quo alternative and one without the status quo alternative, were administered to examine the effect of including and excluding the status quo option in welfare estimates. Both versions of the questionnaire were administered in-person face-to-face interviews by the enumerator at the Gawi Jetty, Kenyir Lake, between the period of March to May 2016.

In this section, a description of two questionnaires (with and without the status quo option) will be presented together in order to identify the differences between both versions. Each questionnaire consisted of four main parts. The questions in Part A, B, and D of all two questionnaires were the same while the questions in Part C varied based on the combination of six choice cards and whether the status quo option was included or excluded in the choice set (see Figure 6.2). Overall, in all other respects, for example, the design and wording of the questionnaire, both of the versions were identical.

All the questions were translated into Bahasa Malaysia which is the national language of Malaysia. The approximate time taken to complete each questionnaire was 20 minutes to 25 minutes. Both versions of the questionnaires were tested in the pilot survey before applying the questionnaires in the actual survey, in line with the recommendation in the discrete CE literature (e.g. Morrison, Bennett, Blamey and Louviere, 2002; Greiner et al., 2014). The final questionnaire for both versions was developed after taking into consideration the comments given in the pilot survey.

Figure 6.2: Two Discrete Choice Experiments Survey



Choice Experiment without the SQ

Choice Experiment with the SQ

6.4.1 Introduction

The enumerator approached respondents by introducing herself and then informed them that she was a Ph.D. student at Newcastle University carrying out research on the tourist facilities at Gawi Jetty, Kenyir Lake. Preliminary information was provided to determine whether the respondent would be willing to take part in the survey. The enumerator further explained that the information gathered from the respondents would be used to help improve the quality of tourist facilities surrounding the Gawi Jetty. Respondents were also informed that the surveys were voluntary and all the responses given would be kept confidential.

6.4.2 Part A: Travel Information

This part of the questionnaire solicited information on, among others: the purpose of their visit, if their visit was the first time or a repeat visit and the type of group they were travelling with. For the repeat visitor, they were asked how many times they have visited Kenyir Lake in the last five years including the current trip. Other questions such as the distance between their residence and the lake, whether they are staying overnight or not, and would they be likely to re-visit Kenyir Lake in the next five years. For the visitors who were staying overnight, they were asked the number of days they stayed or intended to stay at Kenyir Lake. They were also asked about the place or accommodation they chose to stay in.

6.4.3 Part B: Attitudes and Perceptions towards Kenyir Lake

This part of the questionnaire was used to gather information about respondents' attitudes and perceptions towards Kenyir Lake. In this section, respondents were asked about their opinion towards natural amenities provided at the lake. They were also asked about the quality of their experience based on the interesting activities enjoyed at the lake. All the questions were asked using a 1 to 5 Likert scale format. At the end of this part, respondents were asked about the level of quality they attach to the five main facilities provided at the Gawi Jetty, namely, toilet, jetty, car park, tourist information centre, and children's playground, using a 1 to 5 Likert scale format. These questions were asked with the aim of focusing the respondents' attention on the topic of study, as well as being used as warm-up questions (Krupnick and Adamowicz, 2006).

6.4.4 Part C: Choice Experiment

To introduce the valuation scenario for both choice experiment surveys, this part began with a statement explaining the importance of the provision of facilities based on visitors' requirements. Respondents were also informed that their preferences for facilities would be used to notify authorities about the facilities that could be improved. The explanation of attributes and levels used in the study was also given in this part and it also contained information about the status quo or current situation of facilities provided at the jetty. The explanation of attributes used in the discrete choice experiment study was assisted by the attribute card which presented a description of the attributes levels and their pictographs. An example of a choice card was shown to the respondents before they were presented with six different combinations of choice cards. This was to help the respondent to understand the choice card process and choose their most preferred option for all choice sets with different combinations of attributes and levels. The price or entrance fee is also included as one of the attributes, for example as shown below in Figure 6.3.

Figure 6.3: Example of Choice Experiment Choice Card

An example of a choice card is presented below. Two possible development options for the tourism facilities at Gawi Jetty are presented. If you would like to see an additional jetty, more car parking slots, and superior toilets; but you are happy with the basic tourist information centre and a small children's play area, and are willing to pay an entrance fee of RM 10 per person you should choose Option 1.

If you would like to see a large children's play area, superior information centre, an additional jetty, more car parking slots; but you are happy with the existing toilet conditions, and are willing to pay an entrance fee of RM 7.50 per person, then you should choose Option 2.

Alternatively, if you are happy with the current situation at Gawi Jetty or you do not want to pay an entrance fee then you should choose the Current Situation option.

Please tick √ which option you prefer.

Facilities	**Option 1**	**Option 2**	**Current Situation**
Toilet	Superior	Basic	Basic
Jetty	Two	Two	One
Car Park	100 slots	100 slots	30 slots
Tourist Information Centre	Basic	Superior	Basic
Children's Playground	Small	Large	Small
Entrance Fee	RM 10	RM 7.50	RM 0
YOUR OPTION	√		

Following the completion of the choice cards, respondents in both discrete choice experiments were asked about their feedback regarding the choice card design. This was done to determine whether the choice card bias occurred within the two versions of the questionnaire; with and without the status quo. Furthermore, a supplementary question which asked respondents how they considered each attribute during the choice process was also provided at the end of this part. This was done in order to investigate the issue of whether the respondents had ignored certain attributes or may, in fact, have just found the attribute of lesser importance.

6.4.5 Part D: Background Information

This part is the final part of the questionnaire that contained questions which helped to provide background information, including the socioeconomic characteristics of each individual respondent. It includes questions on gender, age, nationality, the level of education, occupation, the number of persons in their household and monthly gross household income (in Ringgit Malaysia). As noted by Mitchell and Carson (1989), the questions about the personal characteristics of the respondents, such as the background question are best left at the last part of the questionnaire, when the respondents are more comfortable about being interviewed and less likely to take offense at having the interviewer probing into their private life.

6.5 Pilot Survey

A pilot survey was conducted at the Gawi Jetty for the first week of March 2016, and the targeted respondents were the visitors who came to the lake. Face-to-face interviews using the questionnaires were employed. This method was comfortable and worked very well, particularly for the CE question. Participants have a chance of assistance from the interviewers for the questions they did not understand. In order to avoid disruption which can irritate some visitors who want to enjoy their activities at the lake, the survey was done in the evening between 3.00 pm and 6.00 pm. During this period of times, the visitors were expected to have completed their activities.

In the first day of the survey, the number of voluntary participants was small. Furthermore, before the interview was completed, some voluntary participants got bored and asked to excuse themselves. The complexity of the questionnaire and length of time taken to complete the interview session was the main reason why they did not complete the interview. To overcome this challenge, the visitors who were willing to participate in the survey and gave their full cooperation until the interview was completed were offered an incentive of ten Ringgit Malaysia. The number of voluntary participations was dramatically increased after the incentive was offered.

One of the objectives of the pilot survey was to estimate the average time taken by each participant to complete the questionnaire. On average, 20 to 25 minutes was taken by most of the participants to complete the task. Other objectives were to test the suitability of the translated questionnaire, checking the choice of wording and the clarity of questions. Designing effective questionnaires in which the respondents understand the scenarios and questions is not an easy task (Mitchell and Carson, 1989). Thus, the suitability of the questionnaire design with the targeted respondents could be identified in the pilot survey.

The translated questionnaires were well-understood by the participants, except for the 'status quo' term used in the CE question with the SQ option. Most of the participants were not familiar with the SQ term and they suggested changing it. Taking into consideration the recommendation made by the participants, the 'status quo' term was changed to 'current situation' which has the same meaning and was employed in the actual survey.

Overall, twenty four pilot surveys were conducted for the CE question without the SQ option. For the CE with the SQ option, there were also 24 pilot surveys carried out to balance the data. In total, 48 questionnaires were completed in the pilot survey. The choice responses from both versions of questionnaires were analysed using the simple CL model specification. This was done to examine if the choice responses were producing results in line with *a priori* expectations.

Before starting to report the pilot test results of the simple CL models for the forced and unforced groups of the respondents, let us briefly present the *a priori* expectation about the sign on the attributes presented in Table 6.4.

Table 6.4: The Theoretical Expectation of the Explanatory Variable

Variables	Expected Sign	Explanation
Toilet	+	A variability in the provision of toilet facilities (e.g. additional bathroom and baby changing room) is expected to have a positive impact on respondents' utility.
Jetty	+	Additional jetty could reduce the crowded situation and increases convenience. Thus, respondents' utility will increase and the expected sign will be positive.
Car Park	+	An increase in the number of car park slots is expected to have a positive impact on utility.
Tourist Information Centre	+	An increase in the information provided such as offering attractive video presentation will increase the respondents' utility. Thus, the expected sign will be positive.
Playground	+	Having a bigger, safe and stimulating playground could enhance visitor experience for those with children. Thus, the utility is expected to increase and the sign will be positive.
Entrance Fee	-	An increase in the entrance fee is expected to have a negative impact on respondents' utility and willingness to pay as it decreases disposable income.

Table 6.5 presents the pilot test results of the simple CL models for the forced and unforced groups of respondents. For the forced sample, the simple CL model was statistically significant with a χ^2 statistic of 68.678, against a critical value 15.507 (with 8 degrees of freedom at alpha level 0.05). For the unforced sample, the simple CL model was statistically significant with a χ^2 statistic of 42.266, against a critical value 15.507 (with 8 degrees of freedom at alpha level 0.05). The results from both of the samples show that all the attributes have a correct sign according to the expectations. In the forced model, all the attributes were significant at least at the 10% level. Meanwhile, in the unforced model, all the attributes were significant at least at the 5% level.

Table 6.5: Pilot Survey Results

Attribute	Simple Conditional Logit Model			
	Forced		Unforced	
	Coeff.	t-stat	Coeff.	t-stat
Toilet2	0.885	2.789***	1.176	4.047***
Toilet3	1.735	4.376***	2.198	6.325***
Jetty2	0.410	1.745*	0.752	3.421***
CarP100	0.470	1.968**	0.597	2.706**
TIC2	0.576	1.687*	0.851	2.866**
TIC3	0.832	2.504**	1.176	3.851***
PlayG2	0.469	1.943*	0.469	2.150**
Fee	-0.256	-5.326***	-0.133	-3.068***
Summary Statistics				
Log-likelihood function: $LL(\beta_b)$	-63.114		-85.795	
Log-likelihood: $LL(\beta_0)$	-97.453		-106.928	
Pseudo-R^2	0.352		0.197	
Adjusted Pseudo-R^2	0.314		0.174	
Number of observations	144		144	

Notes: ***significant at 1%, **significant at 5% and *significant at 10%

6.6 Sampling and Implementation

The target population for this study involved visitors to Kenyir Lake, aged eighteen years and above. More specifically, the targeted visitors were those who showed up at the Gawi Jetty; or in other words, this study focused on the on-site survey. The justification for the on-site survey focus was based on Bateman et al., (2002). There were four factors suggested by Bateman et al., (2002, p. 91) to be considered when deciding on user and non-user populations, namely:

1) Uniqueness or substitutability of the good or service in question
2) Familiarity of respondents with the good or service
3) Scale of the change in question; and
4) Context in which the valuation results will be used (related to the payment vehicle)

This research adopted two of the factors suggested by Bateman et al., (2002). The two factors were the familiarity of respondents with the good or service, and the factor related to the payment vehicle. This decision was made due to the fact that this study focuses on the satisfaction of visitors with the tourist facilities services at Gawi Jetty, as well as the effect of introducing the entrance fee system at Kenyir Lake.

The surveys were carried out in the afternoon, between 1.00 p.m. and 6.00 p.m. on each weekday. This was the best time to approach the visitors because during this time, most of them had finished enjoying their activities. During the weekend and public holidays, the surveys were carried out earlier and over a longer period, which was between 11.00 a.m. and 7.00 p.m., because the number of visitors was higher compared to normal days. As explained in Section 3.2.4, this study is a type of intercept survey case. For the intercept survey case, the most efficient way to sample visitors is when they are about to leave the lake.

The visitors were randomly sampled. Face-to-face interviews were employed in this study, following the recommendation by the NOAA panel, for gathering information from the respondents. This technique is the most popular technique applied by researchers in the discrete CE applications (e.g. Hanley et al., 1998b; Hensher and Greene, 2003; Christie et al., 2006; Willis, 2009; Koundouri, Scarpa and Stithou, 2014).

Overall, the visitors with no children were more likely to participate in the survey. This is because the visitors who had commitments with the children were busy and they were more hesitant about taking part in the survey due to their time constraints. This situation meant interviewers approached more visitors with no children. Consequently, there is a potential of sample selection bias in the survey. According to Heckman (1979), sample selection bias may arise for two reasons, namely: (1) self-selection by the individuals or data units being examined, and (2) sample selection decisions by researchers. Therefore, the interpretation of the results derived from the interviewer-administered survey might be biased because of the sample selection decisions by researchers.

Three interviewers were employed, including postgraduate and undergraduate students from local universities. Before conducting the interviews, the interviewers were given one-day training on several issues including how to approach the respondents, introducing themselves and the research project, how to explain the questions especially the choice experiment question, and how to conduct the interview. The research risk was also discussed and explained in training. During the actual survey, the interviewers were provided with the research risk assessment document which contained emergency contact numbers that could be dialled for any emergency cases.

Collecting information from the respondents involved several procedures. Firstly, respondents were approached at the Gawi Jetty area, and they were given a brief introduction about the purpose of the study. Then, the respondents were asked for their permission to conduct the interview. If they agreed, the interview continued. If not, interviewers approached another respondent in the place.

Overall, 385 respondents were interviewed by the researcher. Nevertheless, only 360 respondents have been used in the final analysis. Table 6.6 shows the sample size and the non-response rate used in the study. The discarded sample was 6.5% or 25 respondents from total sampling. These respondents were omitted from the analysis due to the following reasons:

(a) Failed to complete Part C - the CE questions.

(b) Failed to complete Part D - the background information questions.

Since non-responders (i.e. respondents who were chosen to be included in the sample but did not complete the questionnaire survey) often differ in meaningful ways from responders who complete the questionnaire, samples that have big proportions of non-responses are not likely to be representative of the population (Hartman, Fuqua, and Jenkins, 1986). Incorrect inferences can result in misleading and distorted, or volatile, conclusions (Jones, 1996).

According to Jones (1996), the goal of the 80% to 90% useful response rate is very difficult to achieve in a real situation. However, in this study, the total useful response rate was more than 90%. Thus, the proportion of non-response was very small and it was expected not to influence results substantially.

Table 6.6: Total Number of Samples

Description	Forced Questionnaire	Unforced Questionnaire
Number of respondents interview	194 (100%)	191 (100%)
Number of samples discarded		
a. Failed to complete Part C – the CE questions	7 (3.6%)	8 (4.2%)
b. Failed to complete Part D – the background information questions	7 (3.6%)	3 (1.6%)
Number of samples used	180 (92.8%)	180 (94.2%)
Total Sample	360	

Based on the guidelines to determine the adequate sample size as suggested by Johnson et al., (2006) in Section 3.2.4, the minimum sample size for the forced and unforced sample was 250 respectively. Therefore, the target number of respondents for both samples was set at 500 in total. Due to time constraints and the high research cost incurred, this guideline could not be applied in this study. Thus, another guideline was used to determine the appropriate sample size. Based on Pearmain et al.,'s rule of thumb (as cited in de Bekker-Grob, Donkers, Jonker and Stolk, 2015), a sample size more than 100 can provide a basis for modelling preference data for discrete CE designs, whereas Bennett and Blamey (2001) proposed the minimum sample size of 50 respondents for the sub-sample in the CE design. Thus, both recommendations were referred to in order to determine the appropriate sample size for this study.

6.7 Conclusion

This chapter described the research methodology that was implemented in this study. This included the process of determining the suitable attributes and levels, the final choice of attributes and levels, the experimental design process, a brief outline of the four main parts of the questionnaire, the pilot survey and finally sampling and implementation.

Moreover, this study used a combination of qualitative approaches with the CE technique for valuing recreational site attributes. The most popular group-based qualitative method, that is, the focus group meeting, was conducted to aid determining whether the proposed attributes and levels were suitable to be used in this study. The focus group meetings were also helpful in providing the feedback for two survey versions used in this study.

There were six final attributes (toilet, jetty, car park, tourist information centre, children's playground and entrance fee); two attributes (toilet and tourist information centre) with three levels, three attributes (jetty, car park, children's playground) with two levels and one attribute (entrance fee) with six levels. These attributes produced 36 choice tasks, and these choice tasks were blocked into six different sets of questionnaires. Each set of the questionnaire contained six different choice cards with alternative combinations. In total, two hypothetical alternatives and a current situation option on the choice card, were shown to the respondents in the unforced CE question. Meanwhile, in the forced CE question, there were only two hypothetical alternatives presented to the respondents. Usable responses were analysed, and the results of this analysis are presented and discussed in the following chapter.

Chapter 7: Descriptive Analysis

7.0 Introduction

This chapter is divided into three sections which present the empirical results of the study. It begins with Section 7.1 which describes the respondents' socio-demographic characteristics, such as, gender, age, nationality, etc. The results also present some characteristics of socio-demographics of the overall Malaysian population for the comparison purposes. The comparison was undertaken to identify whether or not the sample was fully representative of the overall Malaysian population. This is indicative only. It may not necessarily represent the socio-demographic profile of outdoor recreationalists. Section 7.2 describes the respondents' travel information such as the number of visits, types of travelling group, the purposes of visit, etc. Section 7.3 presents the respondents' attitudes and perceptions towards Kenyir Lake. Finally, Section 7.4 provides the summary of the chapter and a conclusion.

7.1 Socio-demographic Profile of the Respondents

The socio-demographic profile of the respondents selected for discussion includes gender, age, nationality, level of education, the number in the household, occupation and monthly gross household income. In total, the number of respondents interviewed was 385. Of these, 25 respondents failed to complete all sections of the questionnaire. Questionnaires were discarded when the respondents did not complete one or more of the four main sections. Time constraint was the main factor which caused some respondents to fail in completing all the sections of the questionnaire. Some respondents were unwilling to proceed with the survey because they had another activity to do with their family or friends. Therefore, they have to leave quickly from the jetty.

There were also respondents who suddenly lost interest in continuing the interview because they were tired or busy with the family. In all, 360 surveys were collected with usable responses. Of these, 180 were completed for the CE forced sample while 180 were completed for the CE unforced sample. The percentage distributions for both samples for the corresponding socio-demographic profiles are summarised in Table 7.1. For comparison purpose, the results also include the census data of the overall Malaysian population.

The forced sample was made up of 55% males and 45% females, while the unforced sample consisted of 61.7% male and 38.3% female. The proportion of males for both samples is higher than that of the Malaysian population (51%). It may have been due to a sampling error of non-response, for instance, women may have been absent when the interviewers approached the respondents at the study site, or it may be due to outdoor recreationalists having a higher proportion of men than women.

The majority of the respondents in the forced and unforced samples belong to the 25-34 age group. This is similar to the majority of the Malaysian population who also belong to that age group. Almost hundred percent of respondents from both of the samples were local visitors. Factors which might explain why the number of local visitors is much higher than the international visitor include distance and travel cost.

More than half of the respondents (63.9%) in the forced sample were highly educated, with at least a diploma (28.9%) or an undergraduate and postgraduate degree (35%). Only a small fraction of them (3.9%) had a minimum of primary education. Similarly, respondents in the unforced sample (71.6%) mostly had attained a higher education, with at least a diploma (37.2%) or an undergraduate and postgraduate degree (34.4%). Only 3.4% of them had a minimum primary education. By referring to the results, it can be seen that the majority of the visitors that come to Kenyir Lake have a high level of education.

Of the 180 respondents in the forced sample, 57.1% had a household number of three to five persons, and the percentages of households with six to eight persons and two persons or fewer were 30. 6% and 6.6% respectively. Meanwhile, the percentage of households with more than eight persons was 5.7%. Of the 180 respondents in the unforced sample, 66.2% had a household number of three to five persons, and the percentages of households with six to eight persons and two persons or fewer were 28.8% and 4.4%. The percentage of households with more than eight persons was 0.6%.

In terms of occupation, 25.6% respondents in the forced sample reported working in the administration and management sector, followed by sales (20%), professional and technician (18.9%), service industry (11.6%) and students (10.6%). Business, housewives and retired composed of 8.3%, 3.3% and 1.7% respectively. In the unforced sample, 24.4% of the respondents reported working in the administration and management sector, followed by sales (21.7%), professional and technician (18.3%), service industry (16.7%) and housewife (7.8%). Business, students and retired composed of 5%, 3.9% and 2.2% respectively.

The monthly gross household income for both samples is also presented in Table 7.1. The gross monthly income was regrouped within three income levels: high (more than RM 4001), medium (RM 2001-RM 4000), and low (less than RM 2000). The results show that the majority of the respondents in the forced and unforced sample fell into the medium income category with 71.1% and 68.9% respectively. Only 13.3% and 10.5% earned less than RM 2000 in forced and unforced samples. Respondents who earn a higher income typically are willing to pay a higher price for the entrance fee. The study found that 15.6% and 20.6% respondents in the forced and unforced sample were in the high income category (more than RM 4001).

Table 7.1: Socio-demographic Characteristics of the Forced and Unforced Samples

Demographic variables		**Forced Sample (%) (n=180)**	**Unforced Sample (%) (n=180)**	**Combined Sample (%) (n=360)**	**Census[a] (%)**
Gender	Male	55	61.7	58.34	51
	Female	45	38.3	41.66	49
Age Group	18-24 years old	21.1	14.4	17.75	21.2
	25-34 years old	36.1	40.6	38.35	25.8
	35-44 years old	26.7	28.3	27.5	19.6
	45-54 years old	12.2	10.6	11.4	15.8
	55 years old and above	3.9	6.1	5	17.6
Nationality	Local	98.9	98.3	99.44	91.6
	Foreign	1.1	1.7	0.56	8.4
Education	Primary school	3.9	3.4	3.65	-
	Secondary school	26.1	14.4	20.25	-
	Pre-University	6.1	10.6	8.35	-
	Diploma	28.9	37.2	33.05	-
	Undergraduate & Postgraduate	35	34.4	34.7	-
Household number	2 persons or fewer	6.6	4.4	5.52	-
	3-5 persons	57.1	66.2	61.65	-
	6-8 persons	30.6	28.8	29.7	-
	More than 8	5.7	0.6	3.13	-
Economic Variables					
Occupation	Professional & technician	18.9	18.3	18.6	-
	Administration & management	25.6	24.4	25	-
	Service industry	11.6	16.7	14.15	-
	Business	8.3	5	6.65	-
	Sales	20	21.7	20.85	-
	Student	10.6	3.9	7.25	-

Table 7.1 (continued): Socio-demographic Characteristics of the Forced and Unforced Samples

		Forced Sample (%) (n=180)	Unforced Sample (%) (n=180)	Combined Sample (%) (n=360)	Census[a] (%)
Occupation	Housewife	3.3	7.8	5.55	-
	Retired	1.7	2.2	1.95	-
Monthly Gross Household Income	Low (less than RM 2000)	13.3	10.5	11.9	-
	Medium (RM 2001 – RM 4000)	71.1	68.9	70	-
	High (more than RM 4001)	15.6	20.6	18.1	-

a – Department of Statistics Malaysia (2014).

7.2 Travel Information of the Respondents

Table 7.2 presents the frequency analysis results of the travel information of the respondents for both samples. In this survey, the visitors were asked about how many times they had visited Kenyir Lake in the last five years including the current trip. In the forced sample, 32.2% of the respondents said this was their first trip to the lake. Over the past five years, 50% of the respondents visited the lake between 2-5 times and 17.8% visited between 6-10 times.

Meanwhile, in the unforced sample, the percentage of the first-time visitors (32.2%) was similar to that observed in the forced sample. Over the past five years, 48.3% of the respondents visited the lake between 2-5 times and 19.5% visited between 6-10 times. The results from both of the samples indicate that majority of the respondents were repeat visitors to the lake.

There were four types of the groups of visitors that came to the lake, namely, family, friends, group or club, and those who came alone. In the forced sample, the percentage of the respondents who came with their family (42.8%) was quite similar to the percentage of the respondents who came with their friend (42.3%). Meanwhile, the percentages of respondents who came alone and with a group were 4.4% and 10.5% respectively.

The percentage of the respondents who came with their family (48.9%) was slightly higher compared to the respondents who came with their friend (46.1%) in the unforced sample. Only 5% of the total respondents in the unforced sample made a single trip to the lake, and none of them made a trip with the group or club.

The results showed that the most important reason for visiting Kenyir Lake in the forced and unforced samples was dominated by vacation or recreation purposes, with 83.3% and 82.2% of the respondents respectively. Respondents were asked about the distance between their residence and Kenyir Lake. The mean distance was 300.98 kilometres in the forced sample. Meanwhile, in the unforced sample, the mean distance was 301.41 kilometres. The mean distance values suggest that the average visitor that came to the lake comprises of respondents who lived in Terengganu and who lived nearby Terengganu.

More than half of the respondents (58.3%) in the forced sample did not stay overnight. Meanwhile, for the respondents who stayed overnight, most of them (25.6%) stayed or intend to stay for 3 days at the lake. Similar results were observed in the unforced sample whereby the majority of the respondents (58.9%) did not stay overnight, and for those who stayed overnight, most of them (19.4%) stayed or intend to stay for 3 days at the lake. The most popular staying place in the forced sample was the resort, hotel and chalet (21%). Meanwhile, for the unforced sample, the most popular staying place was the house boat (24.4%). All the respondents in both samples (100%) stated that they would like to re-visit Kenyir Lake in the next five years.

Table 7.2: Travel Information of the Respondent in the Forced and Unforced Samples

	Forced		**Unforced**	
	Frequency	**Percent**	**Frequency**	**Percent**
Number of Visits				
First time visit	58	32.2	58	32.2
2-5 times	90	50	87	48.3
6-10 times	32	17.8	35	19.5
Total	180	100	130	100
Type of groups that come together				
Alone	8	4.4	9	5
Family				
2-5 people	20	11.1	19	10.5
6-10 people	53	29.5	53	29.4
11-20 people	4	2.2	16	9
Friends				
2-5 people	29	16.1	35	19.4
6-10 people	24	13.4	31	17.2
11-20 people	23	12.8	17	9.5
Group/Club				
2-20 people	2	1.1		
21-40 people	17	9.4		
Total	180	100	180	100
Purposes for visiting Kenyir Lake				
Vacation/recreation	150	83.3	148	82.2
Work/ Business trip	23	12.8	21	11.7
Educational visit	7	3.9	11	6.1
Total	180	100	180	100

Table 7.2 (continued): Travel Information of the Respondent in the Forced and Unforced Samples

	Forced		Unforced	
	Frequency	Percent	Frequency	Percent
Distance of Kenyir Lake from residence (Mean in KM)	300.98		301.41	
Staying overnight	75	41.7	74	41.1
Days stayed/intend to stay				
2 days	27	15	33	18.3
3 days	46	25.6	35	19.4
4 days	2	1.1	6	3.3
Not staying overnight	105	58.3	106	58.9
Total	180	100	180	100
Staying Place				
Camping site	9	5	6	3.3
House boat	29	16	44	24.4
Resort, Hotel and Chalet	37	21	24	13.3
Likely to re-visit Kenyir Lake in the next 5 years				
Yes	180	100	180	100

7.3 Perception towards Kenyir Lake

Respondents from both groups were asked a number of supplementary questions to determine their perception about natural resources, interesting activities and the facilities provided at the study site. The five-level Likert Scale was used to allow the respondents to express their opinion, for example, how much they disagree or agree with the given statement.

7.3.1 Perception of Natural Resource

This section is based on question 9 in the questionnaire (Appendix B and C). Each respondent is required to state their perception rating from 1 (strongly disagree) to 5 (strongly agree) to the four statements regarding the natural resources in Kenyir Lake.

Table 7.3 and 7.4 present the respondents' opinion towards natural resources at Kenyir Lake for the forced and unforced samples. The overall result shows that the majority of the respondents strongly agree with all of the statements provided and none of them expressed strongly disagree.

The statement regarding the protection of species of fish to ensure it will not become extinct in the future received a mean of 4.82 and 4.88 in the forced and unforced samples, which indicates the highest ranking in determining the attitude of the respondents relating to the resources aspect at Kenyir Lake. The mean recorded for "Kenyir Lake serves as an important water catchment area" was 4.73 in the forced sample and 4.84 in the unforced sample which indicates the second highest ranking for resource statement.

Table 7.3: Perception of the Natural Resource – Forced Sample

Statements	Mean	Answer %				
		5	4	3	2	1
1. Kenyir Lake provides an attractive natural environment for recreation	4.71	71.1	28.3	0.6	0	0
2. Kenyir Lake serves as an important water catchment area	4.73	75	22.8	2.2	0	0
3. Kenyir Lake serves as a home for wildlife habitats	4.61	69.4	22.8	7.2	0.6	0
4. The species of fish should be protected so they will not become extinct in the future	4.82	83.9	14.4	1.7	0	0

Note: 1 = Strongly disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly agree

Table 7.4: Perception of the Natural Resource – Unforced Sample

Statements	Mean	Answer %				
		5	4	3	2	1
1. Kenyir Lake provides an attractive natural environment for recreation	4.78	78.9	20	1.1	0	0
2. Kenyir Lake serves as an important water catchment area	4.84	85.6	13.3	1.1	0	0
3. Kenyir Lake serves as a home for wildlife habitats	4.76	80	16.1	3.9	0	0
4. The species of fish should be protected so they will not become extinct in the future	4.88	88.9	10	1.1	0	0

Note: 1 = Strongly disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly agree

7.3.2 Perception on the Quality of Experience towards the Interesting Activities

Based on the report from Department of KETENGAH (2016), there were eight most popular activities enjoyed by the visitor at Kenyir Lake as presented in Table 7.5 (forced sample) and 7.6 (unforced sample). Respondents from both samples were asked to express the quality of their experiences towards interesting activities at the lake, based on 1 (very dissatisfied) to 5 (very satisfied) response scale, or to state "not taken" for those activities they did not experience.

The overall result shows that the respondents in the forced and unforced samples were very satisfied with all of the activities they had experienced. By referring to the mean, the results showed that the respondents enjoyed visiting the waterfall area with a mean value of 4.82 and 4.85 for the forced and unforced samples, demonstrating the highest ranking in determining the respondents' quality of experience towards the interesting activities enjoyed at Kenyir Lake. The statistics also showed that the activity least undertaken by the respondents was camping and jungle trekking. This is because there was more than 60% of the respondents from both of the samples stated that they did not engage in this activity.

Table 7.5: The Quality of Experience of the Forced Sample towards Interesting Activities

Interesting activities	Mean	Answer %					
		5	4	3	2	1	Not taken
Fishing	4.73	47.2	16.2	0.6	0	0	36
Visiting waterfall area	4.82	80	16.7	0.6	0	0	2.8
Staying in House boat	4.53	42.2	18.3	5.6	0	0.6	33.3
Watersport activities	4.31	43.9	25.6	11.1	3.3	0	16.1
Camping and jungle trekking	4.29	15.5	13.3	5.6	0	0	65.6
Visiting Kelah Sanctuary	4.62	48.3	16.1	5	0	0	30.6
Visiting parks and gardens	4.5	40	33.9	1.1	0.6	0	24.4
Visiting caves	4.1	16.6	11.1	7.8	1.7	0.6	62.2

Note: 1 = Very dissatisfied, 2 = Dissatisfied, 3 = Neither, 4 = Satisfied, 5 = Very satisfied

Table 7.6: The Quality of Experience of the Unforced Sample towards Interesting Activities

Interesting activities	Mean	Answer %					
		5	4	3	2	1	Not taken
Fishing	4.78	51	12.8	0.6	0	0	35.6
Visiting waterfall area	4.85	86.1	12.2	1.1	0	0	0.6
Staying in House boat	4.79	55.6	11.1	1.7	0	0	31.7
Watersport activities	4.59	52.8	18.9	6.7	0	0	21.7
Camping and jungle trekking	4.45	21.7	8.9	5.6	0	0	63.9
Visiting Kelah Sanctuary	4.79	64.4	10.6	2.8	0	0	22.2
Visiting parks and gardens	4.37	46	25	12.8	0	0.6	15.6
Visiting caves	4.45	22.8	6.7	6.7	0	0	63.9

Note: 1 = Very dissatisfied, 2 = Dissatisfied, 3 = Neither, 4 = Satisfied, 5 = Very satisfied

7.3.3 Perception of the Quality of the Facilities Provided

In order to understand visitors' perceptions towards various facilities provided at Kenyir Lake, respondents were asked to rate the quality of several facilities available based on a 1 (very poor) to 5 (excellent) responses scale. Table 7.7 below reveals the respondents' rating of five main facilities at the lake.

Judging by the mean values, in the forced sample, the quality of all of the facilities provided was just average from the perception of respondents. Amongst five of the main facilities, the quality of toilet, jetty and car park were rated as 'average' by most of the respondents with 37.8%, 41.7% and 50% respectively. About 51% of the respondents rated the tourist information centre and children's playground as 'good' for quality.

Meanwhile, in the unforced sample, the toilet, jetty and car park facilities were also rated as 'average' by most of the respondents with 38.9%, 42.2% and 45.6% respectively. On the other hand, the tourist information centre and children's playground were rated as 'good' by most of the respondents with 50.6% and 48.3% respectively.

Table 7.7: The Quality of the Facilities Provided for the Forced Sample

Facilities	Mean	Answer %				
		5	4	3	2	1
Toilet	3.1	8.3	26.7	37.8	21.1	6.1
Jetty	3.13	7.2	27.3	41.7	19.4	4.4
Car park	3.28	6.1	31.1	50	10	2.8
Tourist information centre	3.80	16	50.6	31.1	1.7	0.6
Children's playground	3.79	15.6	50.6	31.1	2.7	0

Note: 1 = Very poor, 2 = Poor, 3 = Average, 4 = Good, 5 = Excellent

Table 7.8: The Quality of the Facilities Provided for the Unforced Sample

Facilities	Mean	Answer %				
		5	4	3	2	1
Toilet	2.87	2.8	28.3	38.9	13.3	16.7
Jetty	2.67	1.1	19.4	42.2	20	17.2
Car park	3.15	5	30	45.6	13.9	5.6
Tourist information centre	3.81	16.7	50.6	29.4	3.3	0
Children's playground	3.87	1.1	48.3	27.2	3.3	0

Note: 1 = Very poor, 2 = Poor, 3 = Average, 4 = Good, 5 = Excellent

7.4 Conclusion

The objective of this chapter was to present the descriptive analysis of the respondents to Kenyir Lake. The presentation of results in this chapter was divided into three sections. The first section, Section 7.1 began with the presentation of the respondents' socio-demographic profile. The second section (Section 7.2) presented the travel information of the respondents, and the third section (Section 7.3) presented the perception of the respondents toward the aspect of Kenyir Lake. In this study, data was collected by face-to-face interview, with 360 representative respondents completing interviews. The percentage results showed that majority of the respondents in the forced (67.8%) and unforced (67.8%) samples were returning visitors and all of them (100%) likely to re-visit Kenyir Lake in the next five years. Therefore, this information is very important and useful to Kenyir Lake managers as a guide to improve the management of Kenyir Lake area in the future.Visitors' perceptions toward the aspects of Kenyir Lake are very important and useful for the Department of KETENGAH for their guide in management and maintenance. In this study, the respondents' perception concentrated on the natural resources, the quality of experience towards the interesting activities, and the quality of the facilities provided at the lake.

Chapter 8: Status Quo Analysis

8.0 Introduction

The inclusion of the status quo as one of the alternatives in the choice card is still being debated in choice experiment literature (Section 4.1). This chapter aims to examine this methodological issue and contribute some knowledge to the current literature, by using two versions of a CE questionnaire with forced and unforced CE questions. To determine whether the status quo is relevant or not, as one of the alternatives in the choice set, the results from both questionnaires are then compared. The main focus of the results is on the visitors' trade-offs and WTP values for attributes.

In the CE forced choice question, there were only two hypothetical options presented to the respondents in each choice card. In contrast, in the CE unforced choice question, there were the same two hypothetical options and a status quo option presented in the choice card. Both versions of the questionnaires were distributed randomly to the respondents. Respondents were also asked a supplementary question regarding their responses towards the choice card they answered. The information gathered from the supplementary question reveals the respondents' opinions towards both sets of CE questionnaire designs in Section 8.1. This included their opinion towards the status quo option and the complexity of the choice card in terms of the number of the attributes used. Section 8.2 presents the effect of the status quo option on the share of hypothetical alternatives.

The basic model of discrete choice modelling, the conditional logit model, is used to analyse the preferences for the choice responses from the forced and unforced samples, followed by the CE interactions models in Section 8.3. Following this, in Section 8.4 and Section 8.5, the mixed logit model and the latent class model are used to account for the presence of any unobserved taste heterogeneity. Section 8.6 presents the WTP estimates for all of the models. Finally, Section 8.7 provides the summary and discussion of the implication of the findings for future research in the CE method.

8.1 Choice Card Responses

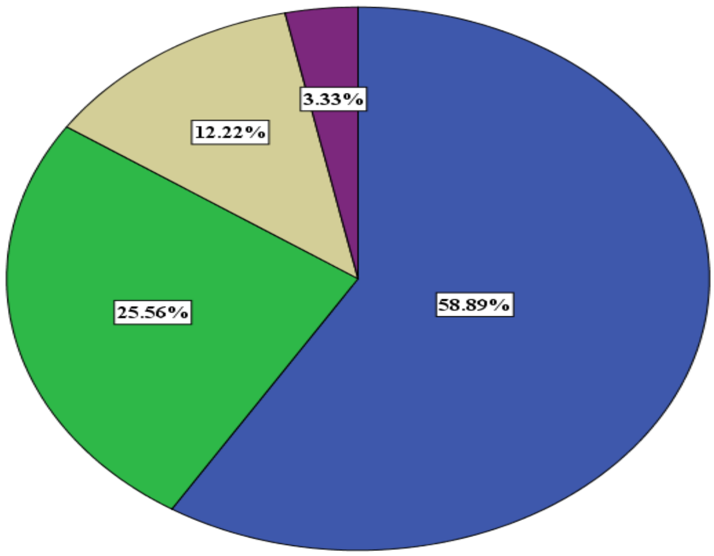
A summary of the respondents' opinions towards choice card in both versions of the CE questionnaire is presented in Figure 8.1 and Figure 8.2.

The majority of the respondents (58.89%) in the forced sample found that making a choice was easy as there were only two alternatives in the choice card. Meanwhile, in the unforced model, more than half of the respondents (53.89%) found difficulties in making their decision because there were three alternatives to be considered. By comparing both of the results, it can be suggested that the choice card with two alternatives gives convenience to the respondents compared to the choice card with three alternatives. The choice card with three alternatives seems to burden respondents when making a choice.

In the forced sample, 25.56% of respondents chose the lowest price increase option since the current situation option was not available to be selected. Only 12.22% of the respondents found that the choice was difficult with six attributes to be considered. Lastly, about 3.33% of respondents felt forced to make a choice between two hypothetical options because they could not vote for "no change". Therefore, it can be concluded that there was a small percentage of the respondents in the forced sample who might choose the current situation option, or status quo, if it was offered in the choice card. This finding suggests that the percentage of bias selection occurring due to presenting the forced choice situation to the respondents is small.

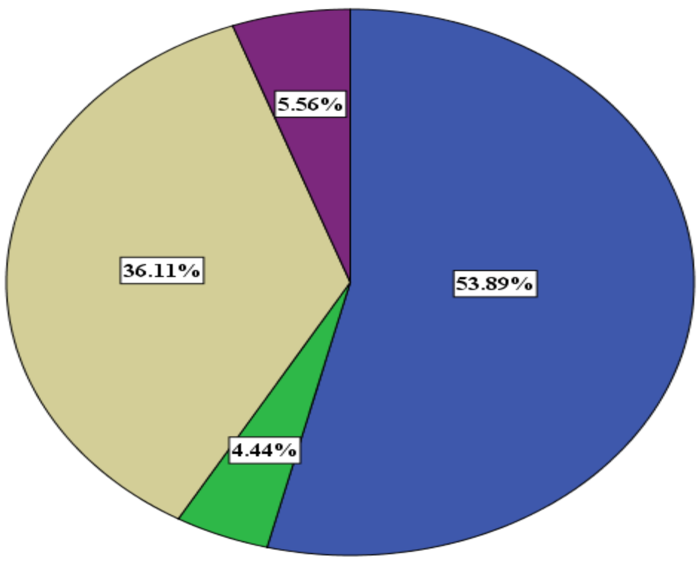
In the unforced sample, around 36% of the respondents found the choice was difficult because they had to consider six attributes. Meanwhile, 5.56% concluded that choosing the status quo was easy because they did not have to weigh up the benefits of the two hypothetical options. This finding suggests that the SQ option is selected as a way out of making a difficult decision between two hypothetical options. Only 4.44% said that they wanted the status quo because they did not want to pay an entrance fee. The findings show that only a small percentage of respondents in the unforced sample are influenced by the status quo option.

Figure 8.1: Choice Card Responses for the Forced Sample



- It was easy to make a choice because there were only two alternatives
- I tended to choose the option with the lowest price increase because there was no option to choose the current situation where there is no entrance fee
- Choice was difficult because there were 6 attributes to consider
- I felt forced to make a choice between Option 1 and Option 2 because I could not vote for "no change"

Figure 8.2: Choice Card Responses for the Unforced Sample



- It was difficult to make a choice because there were three alternatives.
- I chose the current situation because I do not want to pay an entrance fee.
- Choice was difficult because there were 6 attributes to consider.
- Choosing the current situation was easy and it meant I did not have to weigh up the benefits of the other two alternative options.

8.2 The Effect of Status Quo Option on the Share of Hypothetical Alternatives

The effect of having the status quo option on the preference between the forced and unforced CE questions was explored in six different sets of choice sets (see Appendix A). As shown in Table 8.1, the hypothetical options in all choice sets lost some share with the introduction of the status quo, with the exception of Option 2 and Option 1 in choice set E and F. The share of the Option 2 and Option 1 in choice set E and F was slightly increased when the status quo option was available.

Overall, the comparison between the choice shares of the hypothetical options in the forced and unforced choice cards revealed that the choice shares were not significantly different for both questionnaires. In total, the choice share of the status quo option was far lower (only 8.1%) compared to the Option 1 (52.3%) and Option 2 (39.5%). These findings reveal that the constant alternative does not take away a greater share from the hypothetical alternatives which respondents tend to select under a forced choice. As stated by Dhar and Simonson (2003), the choice share of the constant alternative is small in a situation where the choice set comprises an asymmetrically dominating alternative.

Thus, it is expected that the utility associated with certain attributes in real profiles tends to be unaffected in the presence of the constant alternative. As a consequence, the implicit price or willingness to pay of the attribute would remain unchanged. This consequence is therefore investigated and presented in more detail in the next section using the logit family of CE models.

Table 8.1: The Effect of the Status Quo Option on the Relative Preferences for the Hypothetical Alternatives (N=180 for each set)

Share of Option	Forced Choice	Unforced Choice
SET A		
Option 1	33.9 %	25.6%
Option 2	66.1%	63.9%
Status Quo		10.6%
SET B		
Option 1	68.3%	62.2%
Option 2	31.7%	31.1%
Status Quo		6.7%
SET C		
Option 1	54.4%	47.2%
Option 2	45.6%	42.8%
Status Quo		10.0%

Table 8.1 (continued): The Effect of the Status Quo Option on the Relative Preferences for the Hypothetical Alternatives (N=180 for each set)

Share of Option	Forced Choice	Unforced Choice
SET D		
Option 1	67.2%	62.2%
Option 2	32.8%	32.2%
Status Quo		5.6%
SET E		
Option 1	73.9%	58.9%
Option 2	26.1%	28.9%
Status Quo		12.2%
SET F		
Option 1	50.6%	57.8%
Option 2	49.4%	38.3%
Status Quo		3.9%
Total		
Option 1	58.1%	52.3%
Option 2	41.9%	39.5%
Status Quo		8.1%

8.3 Conditional Logit Model Estimation for the Status Quo Issue

The easiest and most commonly used discrete choice model is the conditional logit (CL) model. In this study, the basic CL model and the CL model with interactions were estimated to examine and analyse the preferences for choice responses from forced and unforced samples of respondents. The results are presented in the following sections.

8.3.1 Results for the Simple Conditional Logit Model

Table 8.2 reports the results of the simple CL models for the forced and unforced groups of respondents respectively. The simple CL - forced model (CL-F) is specified to account for the respondents' choice between the two hypothetical alternatives of tourist facilities. The unforced model contains two hypothetical options and the status quo option, and this model was divided into two: (1) the simple CL - unforced model with no specification of the status quo (CL-NSQ), and (2) the simple CL - unforced model with the specification of the status quo (CL-SQ). The CL-NSQ model is specified to account for the respondents' choice between tourist facilities options solely as a function of the attributes. Meanwhile, the CL-SQ model is specified to account for the status quo effects.

The alternative specific constant was used to specify the status quo, as explained in Section 3.3.2. It signifies the utility of choosing the status quo alternative. In this study, the status quo, or current situation alternative, represented the choice to maintain the existing tourist facilities services. It is worth noting here that the CL-NSQ model was included so that the coefficient estimates between the forced and unforced samples could be directly compared without the additional complication of the alternative specific constant.

The simple CL-F model was statistically significant with a χ^2 statistic of 391.722, against a critical value 15.507 (with 8 degrees of freedom at alpha level 0.05). For the unforced sample, the simple CL-NSQ model was statistically significant with a χ^2 statistic of 509.91, against a critical value 15.507 (with 8 degrees of freedom at alpha level 0.05). In the simple CL-SQ model, the ASC SQ coefficient was found to be negative and significant which indicates *ceteris paribus* that the respondents had negative preferences for the status quo. This result can be linked with the result presented in Section 8.2 whereby less than 10% of the overall respondents chose the status quo option. A positive sign would have meant that the respondents desire the status quo and they attach some positive utility to the status quo condition. The simple CL-SQ model was also statistically significant with a χ^2 statistic of 525.744, against a critical value 16.919 (with 9 degrees of freedom at alpha level 0.05).

CL-F versus CL-NSQ

Comparison of the two models shows that the number of insignificant attributes did not change and there was a slight decrease in the pseudo-R^2 value from 0.267 in the CL-F model to 0.262 in the CL-NSQ model. In each model, the parameter for Toilet2, Toliet3, Jetty2, CarP100 and PlayG2 were significant at least at the 5% level and had the *a priori* expected sign. As expected, the coefficient on the fee attribute is negative and significant in both models. Interestingly, the significance level of the attribute for tourist information centre (TIC2 and TIC3) had changed in both of the models. The TIC2 attribute that is highly significant in the CL-F model becomes insignificant in the CL-NSQ model. Meanwhile, the TIC3 attribute that is not significant in the CL-F model becomes significant at the 5% level in the CL-NSQ model. The comparison between both results indicate that there is a little difference between the CL-F and CL-NSQ models in terms of goodness-of-fit and the significance of the attribute coefficients.

CL-F versus CL-SQ

Comparison of the two models shows that the number of insignificant parameters did not change with the inclusion of the status quo. Moreover, all the significant parameters in the CL-

F model also remain significant at least at the 10% level in the CL-SQ model. When the specification of the ASC SQ is included in the CL-SQ model, there is only a slight increase in the pseudo-R^2 value from 0.267 to 0.271. In each model, the parameter for Toilet2, Toilet3, Jetty2, CarP100 and PlayG2 were significant at least at the 5% level and had the *a priori* expected sign. The parameter estimate for the TIC2 was also significant in the CL-F model, however, it changed to a negative sign and became significant at the lower level in the CL-SQ model.

The only insignificant variable was TIC3 for both of the models. This result can be related to the majority number of respondents who were repeat visitors to the lake. Therefore, for the repeat visitor they might be less likely to use the tourist information centre service because they already have all the information needed. As expected, the fee coefficient is negative and significant. This indicates that as the entrance fee increases, respondents' utility will decrease. The comparison between both models indicate that there is a little difference between the CL-F and CL-SQ models in terms of goodness-of-fit and the significance of the attribute coefficients.

CL-NSQ versus CL-SQ

Comparison of the two models shows that when the ASC SQ is included, there is only a slight increase in the pseudo-R^2 value from 0.262 to 0.271. Also, the number of insignificant parameters did not change with the inclusion of the ASC SQ. A Log-likelihood Ratio (LLR) test was employed to compare these two nested models and showed that the CL-SQ model does show statistical improvement over the CL-NSQ model with a χ^2 statistic of 15.834, against a critical value 3.841 (with 1 degree of freedom at alpha level 0.05). All the significant parameters in the CL-NSQ model also remain significant at least 5% in the CL-SQ model, except for the tourist information attributes. The TIC2 attribute that was not significant in the CL-NSQ model became significant at 1% level in the CL-SQ model. Meanwhile, the TIC3 attribute that was significant at 5% level in the CL-NSQ model became insignificant in the CL-SQ model. The comparison between both models indicate that there is a little difference between the CL-NSQ model and the CL-SQ model in terms of goodness-of-fit and the significance of the attribute coefficients.

Table 8.2: Parameters Estimate from the Simple CL Model

Attribute	Simple Conditional Logit					
	Forced		Unforced			
	CL-F		CL-NSQ		CL-SQ	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Toilet2	0.658	6.134***	1.059	9.536***	0.828	6.902***
Toilet3	1.301	10.427***	1.749	13.698***	1.488	10.774***
Jetty2	0.672	8.219***	1.216	13.394***	1.041	10.803***
CarP100	0.840	10.005***	1.251	12.680***	1.108	10.942***
TIC2	0.311	2.834***	-0.035	-0.315	-0.216	-1.780*
TIC3	0.076	0.748	0.236	2.181**	0.111	1.018
PlayG2	0.168	2.133**	0.318	3.633***	0.202	2.273**
Fee	-0.172	-10.995***	-0.252	-12.978***	-0.252	-13.343***
ASC SQ	-	-	-	-	-0.774	-3.995***
Summary Statistics						
Log-likelihood function: $LL(\beta_b)$	-538.333		-716.582		-708.665	
Log-likelihood: $LL(\beta_0)$	-734.194		-971.537		-971.537	
Pseudo-R^2	0.267		0.262		0.271	
Adjusted Pseudo-R^2	0.261		0.26		0.268	
Number of observations	1080		1080		1080	

Notes: ***significant at 1%, **significant at 5% and *significant at 10%

8.3.2 Testing for the IIA Violations

In Section 3.4.1, the Independence from Irrelevant Alternatives (IIA) property underlying the CL model was discussed. The IIA property denotes that the ratio of the choice probability between two alternatives is not affected by the availability of other attributes from a third alternative. The test for IIA was conducted for the basic CL model before continuing with further model analysis.

Hausman and McFadden (1984) have introduced a specification test for the existence of the IIA. The test is based on the elimination of some alternatives from the choice set in order to see if the underlying choice behaviour from the restricted choice set conforms to the IIA property. Hausman and McFadden (1984) propose that if a subset of a choice set is truly unrelated or irrelevant, omitting the subset from the model completely will not change the coefficient estimates systematically. The first step to conducting the IIA test is to estimate the unrestricted model namely a model with all alternatives included. Then, the restricted model is estimated with a restricted set of alternatives. The null hypothesis for this test is that the coefficient estimates obtained from the restricted model will not be significantly different from those obtained from the unrestricted model (H_o: $\beta_r = \beta_{ur}$). According to Hausman and McFadden (1984) and Hensher et al., (2015), the test statistic is specified as:

$$(\beta_r - \beta_{ur})' [Covr(\beta_r) - Covr(\beta_{ur})] -1 (\beta_r - \beta_{ur})'$$

where β_r and β_{ur} indicate the estimated coefficients from the restricted and unrestricted models, $Covr(\beta_r)$ and $Covr(\beta_{ur})$ are the estimated variance covariance for the restricted and unrestricted models respectively. The model is asymptotically distributed as chi-squared with *K* degree of freedom.

In this study, the IIA test was conducted for the unforced sample only, as the test cannot be conducted in the forced sample with 2 alternatives. Table 8.3 and Table 8.4 present the results from the IIA test for both unforced-without ASC SQ and unforced-with ASC SQ models. In each model, three subsets were estimated and compared to the basic model estimation. In each subset, one alternative was removed at a time. Based on the Table 8.3 and Table 8.4, Model A presents the basic model, Model B presents the restricted model in which the first alternative (Option 1) was excluded, Model C presents the restricted model in which the second alternative (Option 2) was excluded and Model D presents the restricted model in which the third alternative (Option 3) was excluded. All the models in Table 8.3 were statistically significant with a large value of χ^2 against a critical value 15.507 (with 8 degrees of freedom at alpha level 0.05). In Table 8.4, the models were also statistically significant with a large value of χ^2 against a critical value 16.919 (with 9 degrees of freedom at alpha level 0.05).

Checking the sign and the significance of the coefficient estimates, in Table 8.3, TIC3 is not significant in Model B, Model C and Model D while TIC2 turns to be significant in Model D. The PlayG2 attribute carries an opposite sign and is not significant in Model B. Finally the LLR test comparing the basic model and the subset models was conducted. The difference between -2 log likelihood of Model A and the subset models is large, rejecting the null hypothesis that the coefficient estimates obtained from the restricted model will not be significantly different from those obtained from the unrestricted model with a full set of alternatives. Thus, the IIA does not hold.

Table 8.3: Hausman-McFadden Test for IIA – Unforced Model without ASC SQ

Att.	Model A		Model B		Model C		Model D	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Toilet2	1.059	9.536***	1.071	3.833***	1.07	3.434***	0.913	7.091***
Toilet3	1.749	13.698***	2.007	5.681***	1.284	3.858***	1.626	10.561***
Jetty2	1.216	13.394***	1.296	4.726***	1.323	5.77***	1.125	10.216***
CarP100	1.251	12.680***	1.385	5.662***	1.051	3.42***	1.180	10.259***
TIC2	-0.035	-0.315	0.022	0.065	0.339	1.045	-0.293	-2.217**
TIC3	0.236	2.181**	0.439	1.346	0.111	0.366	0.163	1.423
PlayG2	0.318	3.633***	-0.138	-0.521	0.799	3.035***	0.241	2.543**
Fee	-0.252	-12.978***	-0.235	-5.671***	-0.186	-3.73***	-0.273	-11.746***
Summary Statistics								
Log-likelihood function: $LL(\beta_b)$	-716.582		-191.246		-216.873		-428.648	
Log-likelihood: $LL(\beta_0)$	-971.537		-224.718		-246.76		-681.336	
χ^2 (d.o.f = 8)	509.91		66.944		59.774		505.376	
Pseudo-R^2	0.262		0.149		0.121		0.371	
Adjusted Pseudo-R^2	0.26		0.135		0.11		0.366	
Number of observations	1080		509		653		998	

Notes: ***significant at 1%, **significant at 5% and *significant at 10%
Model A= Basic model; Model B = restricted Option 1; Model C = restricted Option 2, Model D = restricted Option 3
χ^2 is the difference between -2 $LL(\beta_0)$ and $LL(\beta_b)$
At 95% confidence level the critical value for χ^2 distribution is 15.507 with 8 degrees of freedom

The Hausman and McFadden test for the unforced-with ASC SQ model reveals the same result as that achieved in the unforced-without ASC SQ model. Based on Table 8.4, the difference between -2 log likelihood of model A and the subset models is extremely large rejecting the null hypothesis that the coefficient estimates obtained from the restricted model will not be significantly different from those obtained from the unrestricted model. In other words, the IIA does not hold. Checking the sign and the significance of the coefficient estimates, TIC is not significant in Model B and Model C while PlayG2 carries an opposite sign and is not significant in Model B.

The failure in the IIA test for both unforced models in this study suggests that all options are relevant alternatives and need to be included in the choice set presented to the respondents. Also, the failure of the IIA test suggests that it is necessary to consider a less restrictive model that does not impose the IIA assumption, for example, the mixed logit model.

Table 8.4: Hausman-McFadden Test for IIA – Unforced Model with ASC SQ

Attribute	**Model A**		**Model B**		**Model C**	
	Coeff.	**t-stat**	**Coeff.**	**t-stat**	**Coeff.**	**t-stat**
Toilet2	0.828	6.902***	0.66	1.985**	0.847	2.447**
Toilet3	1.488	10.774***	1.568	3.977***	1.133	3.243***
Jetty2	1.041	10.803***	0.944	3.001***	1.093	3.992***
CarP100	1.108	10.942***	1.097	3.96***	0.984	3.175***
TIC2	-0.216	-1.780*	-0.274	-0.754	-0.06	-0.138
TIC3	0.111	1.018	0.198	0.598	-0.281	-0.673
PlayG2	0.202	2.273**	-0.335	-1.185	0.66	2.362**
Fee	-0.252	-13.343***	-0.241	-5.833***	-0.203	-4.054***
ASC SQ	-0.774	-3.995***	-0.981	-2.253**	-0.766	-1.493
Summary Statistics						
Log-likelihood function: $LL(\beta_b)$	-708.665		-188.655		-215.731	
Log-likelihood: $LL(\beta_0)$	-971.537		-224.718		-246.76	
χ^2 (d.o.f = 8)	525.744		72.162		62.058	
Pseudo-R^2	0.271		0.16		0.126	
Adjusted Pseudo-R^2	0.268		0.145		0.114	
Number of observations	1080		509		653	

Notes: ***significant at 1%, **significant at 5% and *significant at 10%
Model A= basic model; Model B = restricted Option 1; Model C = restricted Option 2; Model D cannot be calibrated since most of the attributes turn to be fixed parameter
χ^2 is the difference between -2 $LL(\beta_0)$ and $LL(\beta_b)$
At 95% confidence level the critical value for χ^2 distribution is 16.919 with 9 degrees of freedom

8.3.3 Results for the Conditional Logit Interactions Model

The respondents' socioeconomic data can be introduced into the CL model as interactions with the main attribute. The models resulting from this inclusion are presented in Table 8.5. These interactions help to produce a rich data set about the particular influences of choice on each attribute level used in the study.

In the CL interactions model for the forced and unforced samples, there are 35 interaction variables incorporated, but only significant variables are presented, except for the main attributes. The analysis of the model begins with the inclusion of all of the interaction variables then drops the insignificant variables. This step continues until all the interaction variables are significant.

CL Interactions - Forced Model

The CL interactions model for the forced sample was statistically significant with a χ^2 statistic of 422, against a critical value 22.362 (with 13 degrees of freedom at alpha level 0.05). The interaction of the socioeconomic variables with the main attribute into the model has a positive influence on model fit. The log-likelihood value has increased from -538.333 in the simple CL-F model (Table 8.2) to -523.194 (Table 8.5) in the CL interaction-F model, demonstrating that a more precise model specification has been achieved. Improvements in the interactions model are also proved by the increases in the pseudo-R^2 value from 0.267 to 0.287.

There are some notable features of the interactions model for the forced sample reported in Table 8.5. The inclusion of the interactions between attributes into the estimation process has the effect of generating a model whereby six variables, Toilet2, Jetty2, CarP100, TIC2, PlayG2 and Fee in the primary attributes, become significant. Comparison of the interactions model with the simple CL-F model in Table 8.2 indicates that the Toilet3 attribute becomes insignificant in the interactions model. Moreover, the variables Toilet2 and PlayG2 show a low level of significance compared to being highly significant in the simple CL-F model. The implications of this are that there are some interaction effects within socioeconomic attributes with the primary attributes. As expected the coefficient for the fee attribute was negative and significant.

The inclusion of the socioeconomic variables has produced substantial detail about the relations between the characteristics of the respondents and choice for tourist facilities attributes at Kenyir Lake. Gender was significant and shows positive sign on Toilet3 attribute

(TLT3_GEN), indicating that males have more interest than females in toilet facilities that offer a bathroom and a babies changing room. The positive sign of household number with Toilet2 attribute (TLT2_HHN) indicates that respondents with a large household number prefer the provision of the toilet that includes the bathroom facilities.

The positive signs of education with the toilet attributes indicate that the higher educated respondents give greater support for the provision of toilet; either with the bathroom facilities (TLT2_EDU) or the bathroom and babies changing room facilities (TLT3_EDU). Meanwhile, the higher educated respondents contributed positively towards supporting the provision of one hundred parking lots (C100_EDU).

CL Interactions – Unforced Model (NSQ)

The CL interaction for the unforced model without the specification of the ASC SQ was statistically significant with a χ^2 statistic of 579.652, against a critical value 23.684 (with 14 degrees of freedom at alpha level 0.05). The interaction of the socioeconomic variables with the main attribute into the unforced model without ASC SQ has a positive influence on model fit. The log-likelihood value has increased from -716.582 in the simple CL-NSQ model (Table 8.2) to -681.711 (Table 8.5) in the CL interaction-NSQ model, demonstrating that a more precise model specification has been achieved. Improvements in the interactions model are also proved by the increases in the pseudo-R^2 value from 0.262 to 0.298.

The inclusion of the interactions between attributes into the estimation process has the effect of generating a model whereby all the primary attributes become significant. As expected the fee coefficient was negative and significant. Comparison of the interactions model with the simple CL-NSQ model in Table 8.2 indicates that the TIC2 attribute becomes positive and significant in the interactions model. Meanwhile, the TIC3 attribute becomes negative in sign in the interactions model.

All interaction variables were significant at least at 5% level. The positive sign for education coefficient for the provision of one hundred parking slots (C100_EDU) indicates that the higher educated respondents prefer additional slots for the car park. Respondents with a higher level of education also prefer the provision of two jetties (JTY2_EDU), superior tourist information centre services (TIC3_EDU) and the bigger playground (PLY2_EDU).

The younger people had a greater preference than older people for the provision of a medium level of tourist information service (TIC2_AGE). Income variable has negative sign on the provision of two jetties (JTY2_INC). The negative sign coefficients implied that low-income respondents support the provision of two jetties.

CL Interactions – Unforced Model (SQ)

The CL interaction for the unforced model with the specification of ASC SQ was statistically significant with a χ^2 statistic of 628.484, against a critical value 32.670 (with 21 degrees of freedom at alpha level 0.05). The interaction of the socioeconomic variables with the main attribute into the model also produces the same result as that achieved in the forced model in terms of goodness-of-fit of the model. The log-likelihood value in the simple CL-SQ model (Table 8.2) has increased from -708.665 to -657.295 in the interactions model (Table 8.5) and the pseudo-R^2 value increased from 0.271 to 0.323. Therefore, the inclusion of the socio-economic variables had a positive influence on model fit. Furthermore, improvement of the model was also indicated by the increase in the pseudo-R^2 value.

There are some notable features of the interactions model for the unforced sample reported in Table 8.5. For the primary attributes, there was only one attribute which became significant and had a positive sign, namely TIC2. In a comparison of this model and the simple CL-SQ model in Table 8.2, it can be seen that Toilet2, CarP100 and PlayG2 have changed to be insignificant and negative in signs. This implies that there is strong relationship affected by the interaction variables to the main attributes. Meanwhile, the fee coefficient was significant and had the expected negative sign.

All interaction variables were significant at least 5% level except for C100_AGE, JTY2_INC and TIC3_INC. The positive sign for education coefficient for the provision of one hundred parking slots (C100_EDU) indicates that the higher educated respondents prefer additional slots in the car park. Respondents with a higher level of education also prefer the provision of two jetties (JTY2_EDU), superior tourist information centre services (TIC3_EDU) and the bigger playground (PLY2_EDU).

The older people had a greater preference than younger people for the provision of one hundred slots in the car park (C100_AGE) and the bigger playground size (PLY2_AGE). Meanwhile, the negative sign coefficient of TIC2_AGE implies that younger people rather than older people support the provision of the toilet with the bathroom facilities.

Income variables, TLT2_INC and TLT3_INC, were positive and significant with the level of toilet attributes. However, it has negative signs on the provision of two jetties (JTY2_INC), superior tourist information centre services (TIC3_INC) and big playground (PLY2_INC). The positive sign for income coefficients for toilet attributes indicates that high-income respondents had a greater preference than low-income respondents for the improvement in the toilet services; either additional bathroom facilities or bathroom and babies changing room facilities. Meanwhile, the negative sign coefficients implied that low-income respondents support the provision of two jetties, a superior tourist information centre and a bigger playground.

Comparison of the CL Interactions Model – Forced and Unforced Samples

Comparison between the CL interaction – forced model and CL interaction – unforced model without ASC SQ reveals that the pseudo-R^2 value was slightly higher in the unforced model compared to the forced model. Moreover, all the insignificant parameters for the main attributes in the forced model changed to be significant in the unforced model.

Comparison between the CL interaction – forced model and CL interaction – unforced model with ASC SQ reveals that the pseudo-R^2 value was higher in the unforced model compared to the forced model. However, the number of significant parameters for the main attributes was dramatically changed in the unforced model with SQ. The attributes Toilet2, Jetty2, CarP100 and PlayG2 became insignificant in the unforced model, although it was significant in the forced model. The only attribute which was significant in the unforced model was TIC2. However, TIC2 decreased to being significant at the 10% level in the unforced model compared to 1% level in the forced model. In the unforced model with SQ, the ASC SQ coefficient was found to be negative and significant which indicates *ceteris paribus* that the respondents had negative preferences for the status quo option.

Table 8.5: Parameters Estimate from the CL Interactions Model

Attribute	CL Interactions Model					
	Forced		Unforced			
	F		NSQ		SQ	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Toilet2	-0.653	-1.803*	1.178	10.108***	-0.478	-1.099
Toilet3	-0.538	-1.234	1.907	14.027***	0.173	0.374
Jetty2	0.708	8.423***	0.658	2.011**	0.516	1.543
CarP100	0.472	2.091**	0.498	1.736*	-0.101	-0.254
TIC2	0.346	3.08***	0.481	1.722*	0.557	1.876*
TIC3	0.083	0.798	-0.871	-2.435**	-0.554	-1.328
PlayG2	0.16	1.989*	-0.5	-1.738*	-0.377	-0.882
Fee	-0.177	-11.04***	-0.269	-13.176***	-0.282	-13.74***
ASC SQ	-	-	-	-	-0.883	-4.366***
TLT3_GEN	0.466	2.337**	-	-	-	-
TLT2_HHN	0.136	3.199***	-	-	-	-
TLT2_EDU	0.174	2.186**	-	-	-	-
TLT3_EDU	0.330	3.622***	-	-	-	-
C100_EDU	0.109	1.852*	0.208	2.946***	0.244	3.347***
JTY2_EDU	-	-	0.371	4.098***	0.342	3.703***
TIC3_EDU	-	-	0.288	3.235***	0.425	3.6***
PLY2_EDU	-	-	0.226	3.19***	0.554	5.127***
C100_AGE	-	-	-	-	0.14	1.714*
TIC2_AGE	-	-	-0.197	-1.96**	-0.307	-2.847***
PLY2_AGE	-	-	-	-	0.233	2.597***
TLT2_INC	-	-	-	-	0.393	3.317***
TLT3_INC	-	-	-	-	0.408	3.249***
JTY2_INC	-	-	-0.231	-2.149**	-0.197	-1.746*
TIC3_INC	-	-	-	-	-0.259	-1.749*
PLY2_INC	-	-	-	-	-0.579	-4.373***
Summary Statistics						
Log-likelihood function: $LL(\beta_b)$	-523.194		-681.711		-657.295	
Log-likelihood: $LL(\beta_0)$	-734.194		-971.537		-971.537	
Pseudo-R^2	0.287		0.298		0.323	
Adjusted Pseudo-R^2	0.279		0.294		0.317	
Number of observations	1080		1080		1080	

Notes: ***significant at 1%, **significant at 5% and *significant at 10%

8.4 Mixed Logit Model Estimation for the Status Quo Issue

The mixed logit model is a highly flexible discrete choice model that relaxes many of the assumptions of the CL and MNL model (Revelt and Train, 1998; Bhat, Eluru and Copperman, 2008). For example, the MXL model relaxes the assumption of homogeneous preferences across respondents for all non-price attributes. In other words, the MXL can be used to approximate any random heterogeneity in preferences by allowing the taste parameter to vary across respondents. Moreover, the MXL model fully relaxes the independent irrelevant alternatives (IIA) property (Section 3.4.1), and this model is also able to handle a more flexible substitution pattern across the choice alternative.

In this study, there are two stages of the MXL model estimation. Firstly, the simple MXL models for both forced and unforced samples were estimated and analysed. Then, the existence of taste heterogeneity around the population mean parameter was determined by looking at the significant standard deviation coefficients from the mean parameter.

Secondly, the estimation of MXL model also allowed the primary attributes and interaction attributes to enter the indirect utility specification. Estimates were derived for both forced and unforced samples of respondents. These interactions models reveal the influence of the characteristics of respondents on the preferences distribution. The results derived from the simple and interaction MXL models for both of the samples are then compared with the results of the simple and interaction CL models in the previous section, using the likelihood ratio test.

For both samples of respondents, the taste coefficients of all attributes used in the MXL model estimations were assumed to be normally distributed, except for the entrance fee attribute. As explained in Section 4.3, a fixed price coefficient was used to help the analysts to interpret the results. Therefore, the coefficient of entrance fee was assumed to be fixed. The MXL model was estimated with simulated maximum likelihood using 100 Halton draws as recommend by Bhat (2001). Even though other distributions can be specified for the taste coefficient, the normal distribution is chosen since the other distributions tested in this study provide comparable mean estimates, except for the lognormal distribution. The analysis in Chapter 10 validates the results of this finding.

8.4.1 Results for the Simple MXL Model

Table 8.6 presents the results of the simple MXL model for the forced and unforced samples. The results specify the estimated taste coefficient values for the means of preferences and the estimated standard deviation of the distribution of the taste parameter for each of the tourist facility attributes in the sample. The results revealed that the model based on 100 Halton draws provided sufficiently good approximations for the estimates from the forced and unforced samples.

The simple MXL - forced model (MXL-F) is specified to account for the respondents' choice between two hypothetical alternatives of tourist facilities. The unforced model presents two hypothetical options and one status quo option and this model was divided into two; (1) the simple MXL - unforced model without the specification of the ASC SQ (MXL-NSQ), and (2) the simple MXL - unforced model with the specification of the ASC SQ (MXL-SQ). The MXL-NSQ model is specified to account for the respondents' choice between tourism facilities options solely as a function of the attributes. Meanwhile, the MXL-SQ model is specified to account for the status quo effects.

Based on Table 8.6, the simple MXL-F model was statistically significant with a χ^2 statistic of 433.276, against a critical value 24.995 (with 15 degrees of freedom at alpha level 0.05). Meanwhile, the simple MXL-NSQ model was statistically significant with a χ^2 statistic of 1032.48, against a critical value 24.995 (with 15 degrees of freedom at alpha level 0.05). The simple MXL-SQ model was also statistically significant with a χ^2 statistic of 1156.468, against a critical value 27.587 (with 17 degrees of freedom at alpha level 0.05). In terms of model fit, the pseudo-R^2 value in the MXL-F model was 0.289. Meanwhile, in the MXL-NSQ and MXL-SQ models, the pseudo-R^2 value were 0.435 and 0.487 respectively.

In comparison to the simple CL model in Table 8.2, the results of the LLR test for the forced sample did not permit the conclusion that the simple MXL-F model fit better than the simple CL-F model. The LLR value was 12.744, against a critical value 14.067 (with 7 degrees of freedom at alpha level 0.05). In addition, the model fit as measured by the pseudo-R^2 value demonstrates a slight improvement compared to the simple CL-F model in Table 8.2 (increases from 0.267 to 0.289). This small improvement indicates that the explanatory power of the simple MXL-F model is not much different from that of the simple CL-F model.

Meanwhile, the simple MXL-NSQ model fitted better than the simple CL-NSQ model with LLR value of 92.642, against a critical value 14.067 (with 7 degrees of freedom at alpha level 0.05). Furthermore, the model fit as measured by the pseudo-R^2 value demonstrates a considerable improvement compared to the simple CL-NSQ model in Table 8.2 (increases from 0.262 to 0.435). The simple MXL-SQ model does show statistical improvement over the simple

CL-SQ model with a χ^2 statistic of 200.796, against a critical value 15.507 (with 8 degrees of freedom at alpha level 0.05). Also, the pseudo-R^2 value shows a large improvement compared to the simple CL-SQ model in Table 8.2 (increases from 0.271 to 0.487). This result indicates that the explanatory power of the simple MXL-SQ model is higher than the simple CL-SQ model and can be considered as improved.

All the mean parameters in the simple MXL models for both forced and unforced samples have signs identical to those observed in the simple CL models. The mean parameter of the fee for all of the simple MXL models was negative and highly significant as expected. Interpretation of the results in the simple MXL models and the simple CL models is similar, except for the estimated standard deviation coefficients. The estimated standard deviation coefficients indicate whether a heterogeneity exists across the estimated mean coefficients. The statistical significance of the standard deviation reveals the presence of heterogeneity in the model. By referring to the Table 8.6, the results suggest the existence of heterogeneity in the coefficients of Jetty2 and CarP100 in the simple MXL-F model, and Jetty2, CarP100, TIC3, PlayG2 and ASC SQ in the MXL-SQ model. The mean parameter of TIC3 in the MXL-SQ model, however, was not statistically significant. Meanwhile, in the simple MXL-NSQ model, the results suggest the existence of heterogeneity in all attributes.

MXL-F versus MXL-NSQ

Comparison of the two models in Table 8.6 shows that the number of insignificant attributes had changed and the pseudo-R^2 value increases from 0.289 in the simple MXL-F model to 0.435 in the simple MXL-NSQ model. In each model, the parameter for Toilet2, Toliet3, Jetty2, CarP100 and PlayG2 were significant at least at the 5 % level and had the *a priori* expected sign. As expected, the parameter on the fee attribute is negative and significant in both MXL models. The TIC2 attribute which was highly significant at 1% level in the MXL-F model become insignificant in the MXL-NSQ model. The comparison between both results indicate that there is a considerable difference between the MXL-F and MXL-NSQ models in terms of goodness-of-fit of the model.

MXL-F versus MXL-SQ

Comparison of the two models in Table 8.6 shows that the number of insignificant parameters did not change with the inclusion of the status quo. Moreover, all the significant parameters in the MXL-F model also remain significant at least 5% in the MXL-SQ model. Comparison of the pseudo-R^2 value shows that the value increases from 0.289 in the MXL-F model to 0.487 in the MXL-SQ model. In each model, the parameters for Toilet2, Toilet3, Jetty2, CarP100, and PlayG2 were significant at least at the 5% level and had the *a priori* expected sign. The parameter estimate for the TIC2 was also significant in the MXL-F model; however, it changed to a negative sign and became significant at the lower level in the MXL-SQ model. The only insignificant variable was TIC3 for both of the models. As expected, the fee coefficient is negative and significant. The comparison between both models indicates that there is a difference between the MXL-F and MXL-SQ models in terms of goodness-of-fit. However, there is no significant difference in terms of the significance of the attribute coefficients.

MXL-NSQ versus MXL-SQ

Comparison of the two models in Table 8.6 shows that the number of insignificant attributes had changed and there is a small increase in the pseudo-R^2 value from 0.435 in the simple MXL-NSQ model to 0.487 in the simple MXL-SQ model. The LLR test between these two nested models showed that the MXL-SQ model does show statistical improvement over the MXL-NSQ model with a $\chi 2$ statistic of 123.988, against a critical value 5.991 (with 2 degree of freedom at alpha level 0.05). In both models, the parameter for Toilet2, Toliet3, Jetty2, CarP100 and PlayG2 were significant at least at the 5% level and had the a priori expected sign. As expected, the parameter on the fee attribute is negative and significant in both MXL models.

The TIC2 attribute which was not significant in the MXL-NSQ model turns to be negative and significant at 5% level in the MXL-SQ model. The comparison between both results indicate that there is a little difference between the MXL-NSQ and MXL-SQ models in terms of goodness-of-fit and the significance of the attribute coefficients. The SQ coefficient in the simple MXL-SQ model was found to be negative and significant which indicates *ceteris paribus* that the respondents had negative preferences for the status quo.

Table 8.6: Parameters Estimate from the Simple MXL Model

Attribute	**Simple MXL**					
	Forced		**Unforced**			
	MXL-F		**MXL-NSQ**		**MXL-SQ**	
Random Parameters (mean)	**Coeff.**	**t-stat**	**Coeff.**	**t-stat**	**Coeff.**	**t-stat**
Toilet2	0.715	5.434***	1.673	7.563***	1.297	6.277***
Toilet3	1.449	8.436***	2.74	9.701***	2.19	8.255***
Jetty2	0.766	6.391***	1.907	9.247***	1.493	7.947***
CarP100	0.961	7.759***	1.883	8.638***	1.54	8.54***
TIC2	0.376	2.954***	-0.088	-0.486	-0.322	-1.977**
TIC3	0.085	0.732	0.242	1.144	0.163	1.036
PlayG2	0.203	2.046**	0.455	2.603***	0.31	2.535**
ASC SQ	-	-	-	-	-3.828	-5.092***
Non-random Parameters						
Fee	-0.199	-8.217***	-0.421	-9.594***	-0.377	-9.763***
Standard Deviations						
Toilet2	0.271	0.735	1.083	2.855***	0.171	0.452
Toilet3	0.271	0.735	1.083	2.855***	0.171	0.452
Jetty2	0.762	4.45***	1.106	2.556**	0.878	4.086***
CarP100	0.452	2.073**	1.458	4.853***	0.818	3.696***
TIC2	0.107	0.338	0.745	1.986**	0.157	0.281
TIC3	0.031	0.06	1.419	5.07***	0.932	3.692***
PlayG2	0.019	0.067	1.059	4.489***	0.494	1.937*
ASC SQ	-	-	-	-	4.098	6.587***
Summary Statistics						
Log-likelihood function: $LL(\beta_b)$	-531.961		-670.261		-608.267	
Log-likelihood: $LL(\beta_0)$	-748.599		-1186.501		-1186.501	
Pseudo-R^2	0.289		0.435		0.487	
Adjusted Pseudo-R^2	0.28		0.431		0.484	
Number of observations	1080		1080		1080	

Notes: ***significant at 1%, **significant at 5% and *significant at 10%

8.4.2 Results for the MXL Interactions Model

There were 35 interaction variables incorporated in the MXL interactions model for the forced and unforced samples. However, only significant variables are presented, except for the main attributes. The analysis of the model begins with the inclusion of all of the interaction variables then drops the insignificant variables until all the interaction variables were significant.

Table 8.7 presents the interactions model between the main attributes and the socioeconomic variables of the respondents. The table shows the estimated mean and standard deviations of the distribution of the taste coefficient for both the main variables and the interaction variables.

MXL Interactions – Forced Model

The MXL interactions model for the forced sample was statistically significant with a χ^2 statistic of 473.684, against a critical value 40.113 (with 27 degrees of freedom at alpha level 0.05). The interaction of the socioeconomic variables with the main attributes in the model has a positive influence on model fit. The log-likelihood value rises in this model compared to the simple MXL-F model in Table 8.6 (from -531.961 to -511.757). Improvements in the interactions model are also proved by the increases in the pseudo-R^2 value from 0.289 to 0.316. This model does pass the LLR test when compared with the simple MXL-F model. The LLR test value was 40.408, which is higher than the chi-squared valued statistic with 12 degrees of freedom at 5% of significance level. This finding suggests that respondents' taste for tourist facilities attributes will vary across the sample.

There were two variables with mean parameters that were significant at the 1% level and have positive expected sign; Jetty2 and TIC2. The mean parameter of Toilet2 was negative and significant at 10% level only. Comparison of the interactions model with the simple MXL-F model in Table 8.6 indicates that the Toilet3, CarP100 and PlayG2 attributes becomes insignificant. The mean for all interaction variables has significance at least 10% levels. The significance of the standard deviation for the Jetty2 attribute specifies that the preferences for the unobserved factors for this variable vary significantly across the sample of the respondents.

MXL Interactions – Unforced Model (NSQ)

The MXL interactions for the unforced model without the specification of the ASC SQ was statistically significant with a χ^2 statistic of 1110.07, against a critical value 40.113 (with 27 degrees of freedom at alpha level 0.05). The log-likelihood value has increased from -670.261 in the simple MXL-NSQ model (Table 8.6) to -631.466 (Table 8.7) in the MXL interactions-NSQ model, demonstrating that a more precise model specification has been achieved. Improvements in the interactions model are also proved by the increases in the pseudo-R^2 value from 0.435 to 0.468. This model does pass the LLR test when compared with the simple MXL-NSQ model. The LLR value of 77.59 is higher than the chi-squared valued statistic with 12 degrees of freedom at 5% of significance level.

The inclusion of the interactions between attributes into the estimation process has the effect of generating a model whereby four variables, CarP100, TIC2, TIC3 and PlayG2 become significant. As expected the fee coefficient was negative and significant. Comparison of the interactions model with the simple MXL-NSQ model in Table 8.6 indicates that the TIC2 and TIC3 attributes become significant in the interactions model. Meanwhile, the mean parameters for Toilet2, Toilet3 and Jetty2 turn to be insignificant in the interactions model. The mean for all interaction variables has significance at least at 5% level. All the main attributes have a significant standard deviation, except for the TIC2 attribute.

MXL Interactions – Unforced Model (SQ)

The MXL interactions model for the unforced sample with the specification of the ASC SQ was statistically significant with a χ^2 statistic of 1213.042, against a critical value 44.985 (with 31 degrees of freedom at alpha level 0.05). The pseudo-R^2 value is slightly higher than the simple MXL-SQ in Table 8.6 from 0.487 to 0.511. This result means that the MXL interactions model has a better explanatory power than the simple MXL for the unforced sample. This model does pass the LLR test when compared with the simple MXL-SQ. The LLR value of 56.574 is higher than the chi-squared valued statistic with 14 degrees of freedom at 5% of significance level.

There are several specific features of the estimation results of the MXL interactions model for the unforced sample presented in Table 8.7. All the significant mean parameters for the main attribute in the simple MXL (Table 8.6) became insignificant in the MXL interactions model, except for the PlayG2 attribute. However, the variable PlayG2 turns to negative in sign, although it was positive in the simple MXL model. The mean parameter for variable TIC3 was negative and significant at 5% level compared to being insignificant in the simple MXL-SQ in Table 8.6. As expected, the fee parameter was negative and highly significant. The mean for all interaction variables has significance at least 5% levels. From seven main attributes, only TIC3 has a significant standard deviation in the model.

Table 8.7: Parameters Estimate from the MXL Interactions Model

Attribute	MXL Interactions					
	Forced		Unforced			
	MXL-F		MXL-NSQ		MXL-SQ	
Random Parameters (mean)	**Coeff.**	**t-stat**	**Coeff.**	**t-stat**	**Coeff.**	**t-stat**
Toilet2	-0.845	-1.908*	0.030	0.042	-0.621	-0.944
Toilet3	-0.931	-1.608	0.761	0.978	-0.191	-0.259
Jetty2	0.862	6.713***	0.702	1.158	0.381	0.839
CarP100	0.441	1.545	1.982	8.219***	0.301	0.645
TIC2	0.435	3.16***	0.975	1.978**	0.546	1.182
TIC3	0.086	0.682	-1.521	-2.23**	-1.358	-2.353**
PlayG2	-0.271	-0.905	-1.194	-1.909*	-0.899	-1.903*
ASC SQ	-	-	-	-	-3.395	-4.59***
TLT3_GEN	0.726	2.594***	-	-	-	-
PLY2_GEN	0.352	1.768*	-	-	-	-
TLT2_HHN	0.163	2.981***	-	-	-	-
TLT2_EDU	0.238	2.353**	-	-	-	-
TLT3_EDU	0.433	3.466***	-	-	-	-
C100_EDU	0.185	2.312**	-	-	0.373	2.929***
JTY2_EDU	-	-	0.409	2.637***	0.322	2.67***
TIC3_EDU	-	-	0.487	2.691***	0.393	2.635***
PLY2_EDU	-	-	0.473	2.94***	0.360	2.906***
TIC2_AGE	-	-	-0.403	-2.255**	-0.338	-2.019**
TLT2_INC	-	-	0.537	2.539**	0.608	3.139***
TLT3_INC	-	-	0.670	2.927**	0.790	3.489***
Non-random Parameters						
Fee	-0.228	-8.93***	-0.468	-9.529***	-0.443	-9.29***
Standard Deviations						
Toilet2	0.000	0.004	0.676	2.071**	0.157	0.546
Toilet3	0.000	0.004	0.676	2.071**	0.157	0.546
Jetty2	0.877	4.941***	1.402	4.707***	0.055	0.181
CarP100	0.410	1.532	1.404	4.995***	0.463	0.833
TIC2	0.265	0.685	0.426	0.806	0.516	1.458
TIC3	0.063	0.176	1.193	2.153**	1.111	3.44***
PlayG2	0.082	0.309	0.912	2.318**	0.516	1.611
ASC SQ	-	-	-	-	3.649	7.363***
TLT3_GEN	0.206	1.121	-	-	-	-
PLY2_GEN	0.057	0.406	-	-	-	-
TLT2_HHN	0.037	0.655	-	-	-	-
TLT2_EDU	0.128	2.068**	-	-	-	-

Table 8.7 (continued): Parameters Estimate from the MXL Interactions Model

Atribute	MXL Interactions					
	Forced		Unforced			
	MXL-F		MXL-NSQ		MXL-SQ	
Standard Deviations						
TLT3_EDU	0.165	2.620***	-	-	-	-
C100_EDU	0.087	1.509	-	-	0.126	0.989
JTY2_EDU	-	-	0.179	2.317**	0.281	4.709***
TIC3_EDU	-	-	0.353	2.556**	0.032	0.189
PLY2_EDU	-	-	0.273	3.402***	0.105	1.327
TIC2_AGE	-	-	0.23	1.223	0.178	1.393
TLT2_INC	-	-	0.095	0.947	0.088	1.139
TLT3_INC	-	-	0.37	3.173***	0.226	2.196**
Summary Statistics						
Log-likelihood function: $LL(\beta_b)$	-511.757		-631.466		-579.98	
Log-likelihood: $LL(\beta_0)$	-748.599		-1186.501		-1186.501	
Pseudo-R^2	0.316		0.468		0.511	
Adjusted Pseudo-R^2	0.299		0.461		0.504	
Number of observations	1080		1080		1080	

Notes: ***significant at 1%, **significant at 5% and *significant at 10%

Comparison of the MXL Interactions Model – Forced and Unforced Samples

Comparison of these two MXL interactions models in Table 8.7 reveals that the pseudo-R^2 value was higher in the unforced models compared to the forced model. Nevertheless, the number of significant mean parameters for the main attributes was dramatically changed in the unforced models. The attributes Toilet2 and Jetty2 became insignificant in the unforced models compared to being significant in the forced model. Meanwhile, the attributes TIC3 and PlayG2 became negative and significant in the unforced models compared to being insignificant in the forced model. As expected, the ASC SQ parameter in the unforced model was found to be negative and significant which indicates *ceteris paribus* that the respondents had negative preferences for the status quo option.

8.5 Latent Class Model Estimation for the Status Quo Issue

Latent class model is an alternative model that can be used to identify the heterogeneity of preferences in choice model data. The discussion of the LCM to examine the status quo issue is presented in two sections. It begins with the discussion on how to determine the number of classes or segments that should be specified in the study, followed by the model estimation for the forced and unforced samples.

8.5.1 Number of Segments

Table 8.8 reports the value of pseudo-R^2 for different segments. The results show that the value of pseudo-R^2 increases when the number of segments for both forced and unforced models increase. This finding indicates the existence of heterogeneity in the data.

For example, in the forced sample the value increases from 0.267 to 0.309 when there was an increase from one to two segments. When more segments were added to the model, the pseudo-R^2 value for the forced sample, however, started to flatten. The model only showed an increase of 0.006 for the pseudo-R^2 when an additional segment was added from two segments to three segments.

In the UF-NSQ sample, the pseudo-R^2 increased by 42.3% by moving from one segment (0.262) to a two segments (0.454). The value slightly increases to 0.474 in the three segments model and 0.494 in the four segments model. Meanwhile, in the UF-SQ sample, the pseudo-R^2 increased by 51.3% by moving from one segment (0.271) to a two segments (0.41). The value slightly increases to 0.418 in the three segments model and 0.425 in the four segments model.

Although the pseudo-R^2 results (as shown in Table 8.8) reveal the existence of heterogeneity in the choice data and reveal that segments in both samples could be identified, this does not specify the number of segments that should be used in the choice model estimation. A common approach applied by analysts to determine the number of the segment is to use the statistical information criteria. This includes AIC, AIC-3 and BIC (e.g. Boxall and Adamowicz, 2002; Dias, 2006; Ruto et al., 2008; Campbell, Hensher and Scarpa, 2011; Garrod et al., 2012). The information criterion with the lowest value should be preferred, because the lower the value of information criterion, the better the model fit (Provencher, Baerenklau and Bishop, 2002).

The LCM models for the forced and unforced samples were estimated initially over two, three and four classes. The results for the statistical information criterion based on the number of segments presented in Table 8.8 were not consistent with the forced model. The AIC and AIC-3 criterions in the forced model favour the two segments respectively, whereas the BIC criterion favour one segment only. In the UF-NSQ model, the AIC and AIC-3 criterions favour the four segments, whereas the BIC criterion favour two segments only. For the UF-SQ model, the AIC, AIC-3 and BIC criterions favour only one segment although the pseudo-R^2 value indicates the existence of heterogeneity in the data when the segment is added to the model. The statistical information criterion results for the forced sample are shown in Figure 8.3. Meanwhile, the statistical information criterion results for the unforced sample – with and without the specification of the SQ are shown in Figure 8.4 and Figure 8.5 respectively.

Since there is no specific guidance to determine which criterion should be preferred, the combination of statistical information criterion and detail interpretation of the model result should be used to decide the number of segments (Walker and Li, 2007). In this study, this is applied by identifying the number of significant coefficients in different segments. The results from both of the samples show that the number of significant coefficients decreased once the number of segments was increased from two to three. Therefore, for the estimation purposes, the two segment model was employed for both of the samples. The segmentation derived from the LCM provides additional information, as it can be used to identify a number of different group of people with particular preferences (Garrod et al., 2012).

Table 8.8: Comparison of Pseudo-R^2 in Different Segment – Forced and Unforced Samples

Number of Segments	**1**			**2**		
	F	**UF-NSQ**	**UF-SQ**	**F**	**UF-NSQ**	**UF-SQ**
Log-likelihood	-538.33	-716.582	-708.67	-516.94	-647.59	-700.17
No. of Parameters	8	8	9	17	17	19
No. of Observation	1080	1080	1080	1080	1080	1080
AIC	1092.66	1449.164	1435.34	1067.88	1329.18	1438.34
AIC-3	1638.99	2173.746	2153.01	1601.81	1993.77	2157.52
BIC	1132.54	1489.04	1480.19	1152.62	1413.92	1533.05
Pseudo-R^2	0.267	0.262	0.271	0.309	0.454	0.410

Notes: F = Forced sample, UF = Unforced Sample

Table 8.8 (continued): Comparison of Pseudo-R^2 in Different Segment – Forced and Unforced Samples

Number of Segments	**3**			**4**		
	F	**UF-NSQ**	**UF-SQ**	**F**	**UF-NSQ**	**UF-SQ**
Log-likelihood	-512.55	-624.169	-689.74	-510.72	-600.307	-682.06
No. of Parameters	26	26	29	35	35	39
No. of Observation	1080	1080	1080	1080	1080	1080
AIC	1077.10	1300.338	1437.48	1091.44	1270.614	1442.12
AIC-3	1615.64	1950.507	2156.22	1637.16	1905.921	2163.18
BIC	1206.70	1429.941	1582.04	1265.91	1445.079	1636.52
Pseudo-R^2	0.315	0.474	0.418	0.318	0.494	0.425

Notes: F = Forced sample, UF = Unforced Sample

Figure 8.3: Comparison of the Different Information Criterion Statistics for the Forced Sample

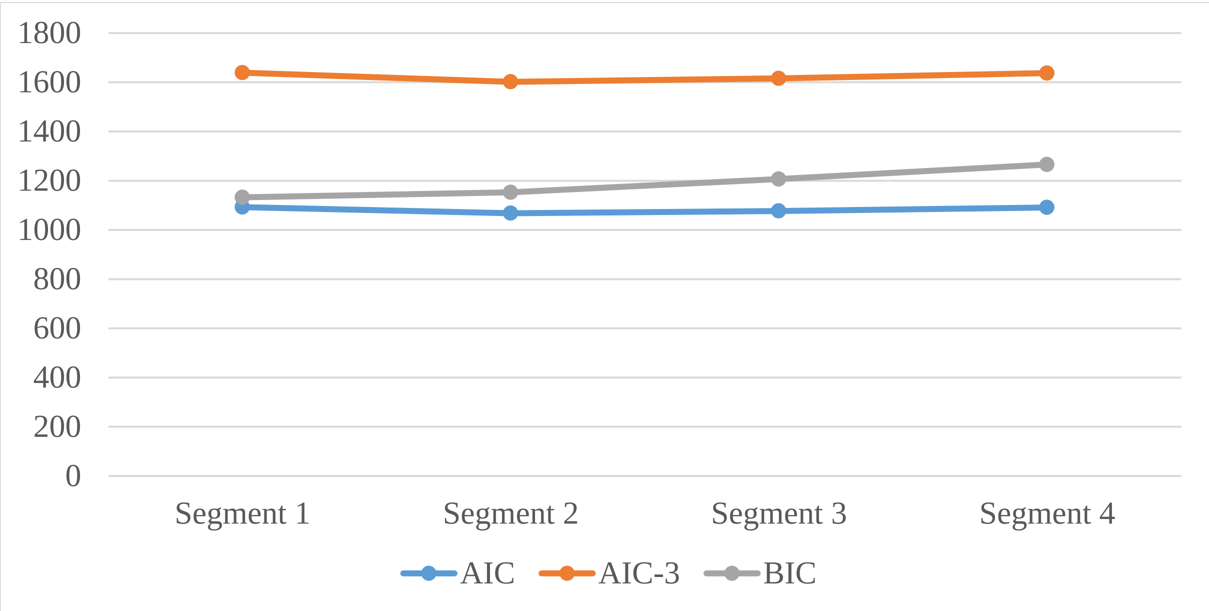


Figure 8.4: Comparison of the Different Information Criterion Statistics for the Unforced Sample - SQ

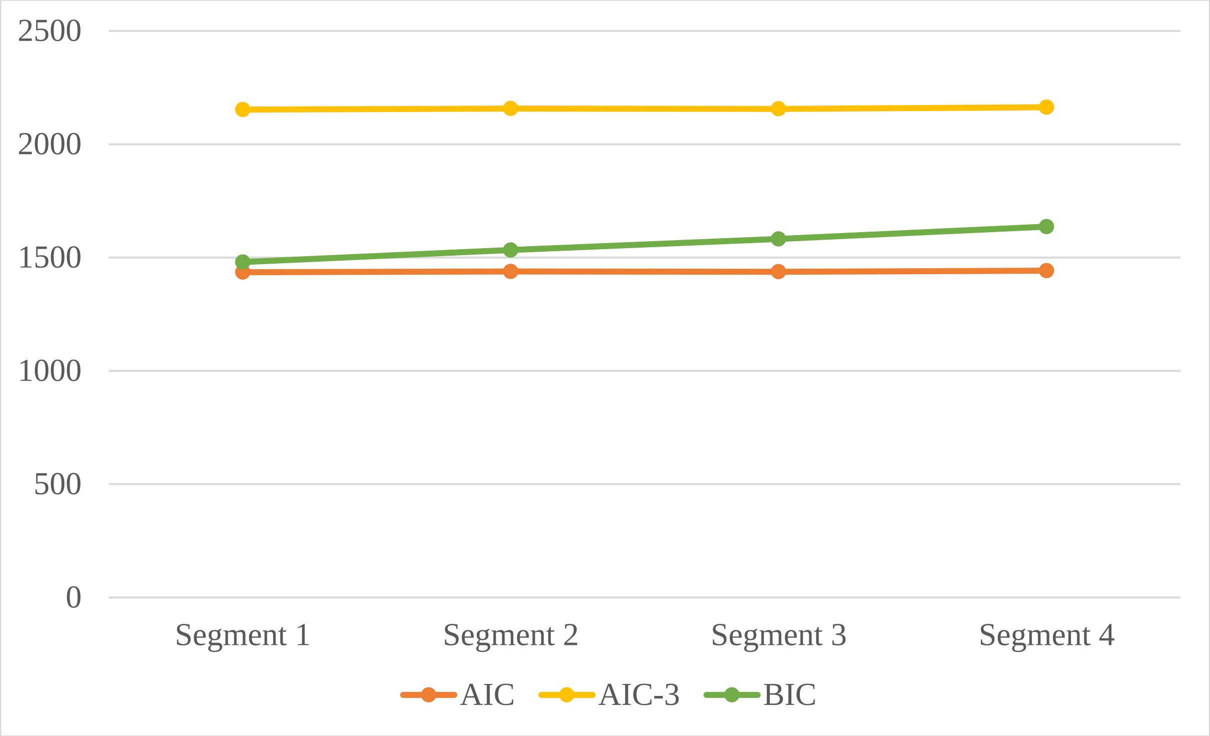
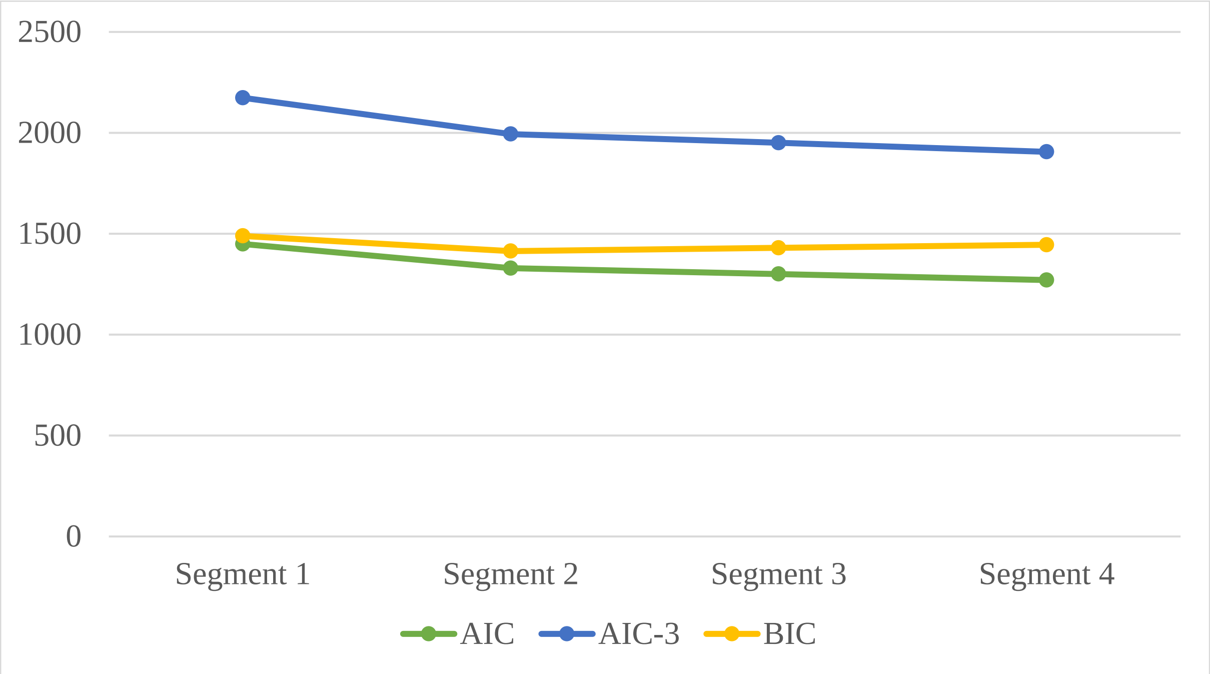


Figure 8.5: Comparison of the Different Information Criterion Statistics for the Unforced Sample - NSQ



8.5.2 Results for the Latent Class Model

The two-segment LCM results are presented in Table 8.9. The LCM was estimated with the maximum likelihood procedure, as shown in Equation 3.28. In general, the choice data in the forced and unforced samples exhibit heterogeneity of preferences for the attributes used in the study. This can be seen from the differences in magnitude and significance of the estimated parameters. Both unforced models recorded a high pseudo-R^2 value compared to the forced model.

Forced Sample

The 2-segment model for the forced sample was statistically significant with a χ^2 statistic of 463.322, against a critical value 27.587 (with 17 degrees of freedom at alpha level 0.05). Segment 1 of the 2-segment LCM represents 70% of the total sample while segment 2 represents 30% of the sample. Based on the estimation results for the 2-segment model, there were differences in preference between the two segments.

Respondents in segment 1 prefer tourist facilities that offer: both levels of the toilet facilities (Toilet2 and Toilet3), two jetties (Jetty2), and one hundred slots in the car park (CarP100). Meanwhile, respondents in segment 2 prefer tourist facilities that offer: both levels of the toilet facilities (Toilet2 and Toilet3), one hundred parking slots (CarP100), medium level of tourist information centre service (TIC2), and bigger playground (PlayG2). Segment 1 had three parameters which were not statistically significant while segment 2 had only two insignificant parameters. The fee parameter for both segments was negative and significant.

The most highly significant parameter estimate for both of the segments indicates that respondents in both segments have the strongest preference for the provision of superior toilet facilities (Toilet3). Also, both segments had similar preferences for some attributes.

Unforced Sample - NSQ

The 2-segment LCM was statistically significant with a χ^2 statistic of 1077.82, against a critical value 27.587 (with 17 degrees of freedom at alpha level 0.05). Segment 1 of the 2-segment LCM represents 91.3% of the total sample while segment 2 represents 8.7% of the sample. Estimation results for the 2-segment LCM showed that there were differences between the two segments.

Respondents in segment 1 were likely to choose facilities which have: both level of the toilet facilities (Toilet2 and Toilet3), two jetties (Jetty2), one hundred parking slots (CarP100), superior tourist information service (TIC3) and a big playground (PlayG2). Meanwhile, in segment 2, respondents had positive preferences for the superior toilet facilities (Toilet3), two jetties (Jetty2) and one hundred parking slots (CarP100). Respondents in segment 2 had negative preference for the superior level of tourist information centre (TIC3) and big playground (PlayG2). The fee parameters for both segments were negative and statistically significant.

Unforced Sample - SQ

The 2-segment LCM was statistically significant with a χ^2 statistic of 1139.094, against a critical value 30.143 (with 19 degrees of freedom at alpha level 0.05). Segment 1 of the 2-segment LCM represents 89.8% of the total sample while segment 2 represents 10.2% of the sample. Estimation results for the 2-segment LCM showed that there were differences between the two segments.

Respondents in segment 1 were likely to choose facilities which have: both levels of the toilet facilities (Toilet2 and Toilet3), two jetties (Jetty2), one hundred parking slots (CarP100) and a big playground (PlayG2). Respondents expressed negative preferences for TIC2 attribute. Meanwhile, in segment 2, respondents have positive preferences for the superior toilet facilities (Toilet3), two jetties (Jetty2) and one hundred parking slots (CarP100). The fee parameters for both segments were negative and statistically significant. Interestingly, the respondents in segment 1 had a negative preference for the status quo while the respondents in segment 2 had a positive preference for the status quo.

The LCM results from the forced and unforced samples suggest that there is considerable unobserved heterogeneity of preferences within the respondents. The results show in Table 8.9 also indicate that all the attributes are suitable for the LCM analysis. The estimated coefficients are then used to account for the implicit price or WTP values. The WTP results for the LCM are presented in Table 8.14.

Table 8.9: Parameters Estimates of Two Segments Latent Class Models – Forced and Unforced Samples

Attribute	Forced				Unforced - NSQ				Unforced - SQ			
	Segment 1		Segment 2		Segment 1		Segment 2		Segment 1		Segment 2	
	Coeff.	t-stat.	Coeff.	t-stat.	Coeff	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.
Toilet2	1.045	4.42***	0.433	3.394***	1.410	10.915***	-0.441	-0.954	0.953	7.264***	0.318	0.713
Toilet3	2.236	6.46***	0.782	5.571***	2.146	14.19***	0.796	1.816*	1.645	10.61***	1.331	2.871***
Jetty2	1.636	5.712***	-0.110	-1.075	1.491	13.45***	1.241	3.77***	1.139	10.24***	1.339	4.395***
CarP100	1.672	5.542***	0.429	4.501***	1.485	12.615***	0.754	2.274**	1.199	10.3***	1.093	3.470**
TIC2	-0.009	-0.038	0.413	2.674**	0.045	0.364	-0.325	-0.892	-0.312	-2.308**	0.192	0.532
TIC3	-0.014	-0.086	0.102	0.767	0.411	3.419***	-1.079	-1.934*	0.186	1.599	-0.782	-1.556
PlayG2	0.171	1.167	0.437	4.093***	0.519	5.292***	-0.963	-2.237**	0.285	2.963***	-0.533	-1.447
Fee	-0.361	-5.59***	-0.078	-4.55***	-0.281	-11.83***	-0.622	-6.08***	-0.272	-11.85***	-0.52	-6.036***
ASC SQ	-	-	-	-	-	-	-	-	-2.097	-6.608***	1.24	2.360**
Statistical Information												
Log-likelihood function: $LL(\beta_b)$	-516.938				-647.59				-616.954			
Log-likelihood: $LL(\beta_0)$	-748.599				-1186.501				-1186.501			
Pseudo-R^2	0.309				0.454				0.48			
Adjusted Pseudo-R^2	0.298				0.45				0.475			
Number of observations	1080				1080				1080			

Note: ***significant at 1%, **significant at 5% and *significant at 10%

8.6 WTP Estimate

Willingness to pay can be interpreted as the maximum amount an individual is willing to pay to secure the benefit or worth of having goods or to avoid unwanted goods. The WTP for each attribute is calculated as the ratio of the attribute coefficients with the fee coefficient using the Wald procedure (Delta method) in Limdep 8.0.

8.6.1 WTP Estimates for the CL Model – Simple and Interactions

Table 8.10 and 8.11 presents the WTP values (in Ringgit Malaysia) for the main attribute in the forced and unforced samples for the simple CL model and the CL interactions model respectively.

WTP for the Simple CL

In the simple CL – forced model (Table 8.10), the results show that the respondents express their highest WTP value of RM 7.577 for the toilet services which have additional bathrooms and babies changing room facilities, followed by RM 4.893 for one hundred parking slots and RM 3.912 for the provision of two jetties. In the simple CL-NSQ model, the respondents express their highest WTP value of RM 6.93 for the superior toilet service, followed by RM 4.957 for one hundred parking slots and RM 4.817 for the provision of two jetties. Meanwhile, in the simple CL-SQ model, the respondents also express their highest WTP value of RM 5.905 for the toilet services which have additional bathrooms and babies changing room facilities, followed by RM 4.397 for one hundred parking slots and RM 4.133 for the provision of two jetties. These findings reveal that both of the forced and unforced (NSQ and SQ) models have the same relative importance ranking of WTP estimates (Toilet3 → CarP100 → Jetty2).

The results in Table 8.10 also show that the WTP value for TIC2 turns to be negative and significant at a lower level (10% level) in the simple CL-SQ model, although it was positive and highly significant at 1% level in the simple CL-F model. The negative sign indicates that an additional unit of certain attributes will decrease the consumer's willingness to pay for those goods (Wagner, 2012). In the simple CL-NSQ model, the respondents were not willing to pay for the TIC2 attribute since this attribute was not significant. Meanwhile, the WTP values for TIC3 were not significant in all models, except for the simple CL-NSQ model.

Focusing only on similar significant attributes, comparison of the results in Table 8.10 reveals that the WTP values in the simple CL-F model were lower than the WTP values in the simple

CL-NSQ model, except for the Toilet3 attribute. The difference, however, is very small. For example, the WTP values of CarP100 attribute in the simple CL-F model and simple CL-NSQ model were RM 4.893 and RM 4.957 respectively. The difference of these two WTP values is only RM 0.064 (RM 4.957 - RM 4.893).

Meanwhile, the WTP values in the simple CL-F model were higher than the WTP in the simple CL-SQ model, except for the Jetty2 attribute. The difference, however, is small for most of the significant attributes. For example, the difference of PlayG2 attribute in the CL-F model and the CL-SQ model is only RM 0.175 (RM 0.978 – RM 0.803). Meanwhile, the difference of Jetty2 attribute in the CL-SQ model and the CL-F model is only RM 0.221 (RM 4.133 – RM 3.912).

WTP for the CL Interactions Model

As shown in Table 8.11, the respondents in the CL interaction - forced model had the highest WTP of RM 3.994 for the provision of two jetties, followed by RM 2.66 for one hundred parking slots and RM 1.954 for the tourist information service which offers the video presentation to the visitors. On the other hand, the respondents in the CL interaction - NSQ model had the highest WTP value of RM 7.089 for the provision of superior toilet facilities, followed by RM 4.381 for the provision of medium toilet facilities and RM 2.446 for the provision of two jetties. Meanwhile, the CL interaction – SQ model had the highest WTP of RM 1.974 for the tourist information service which offers a video presentation to the visitors.

Table 8.10: Marginal WTP Estimates (in RM) from the Simple CL Model for the Status Quo Issue: Forced and Unforced Samples

Attribute	Simple CL				Simple CL				Simple CL			
	Forced				Unforced (NSQ)				Unforced (SQ)			
	WTP	t-stat	95% confidence limits		WTP	t-stat.	95% confidence limits		WTP	t-stat.	95% confidence limits	
Toilet2	3.831	5.686***	2.510	5.151	4.196	8.56***	3.235	5.157	3.285	6.52***	2.297	4.271
Toilet3	7.577	8.715***	5.873	9.281	6.930	12.696***	5.860	7.999	5.905	10.553***	4.808	7.001
Jetty2	3.912	7.813***	2.930	4.893	4.817	13.152***	4.099	5.535	4.133	10.971***	3.394	4.871
CarP100	4.893	9.26***	3.857	5.928	4.957	13.907***	4.258	5.655	4.397	12.217***	3.691	5.102
TIC2	1.810	2.679***	0.485	3.133	-0.141	-0.317	-1.010	0.729	-0.856	-1.817*	-1.778	0.067
TIC3	0.444	0.75	-0.716	1.603	0.938	2.179**	0.094	1.781	0.440	1.020	-0.406	1.286
PlayG2	0.978	2.135**	0.080	1.875	1.259	3.734***	0.598	1.920	0.803	2.318**	0.123	1.481

Notes: ***significant at 1%, **significant at 5% and *significant at 10%

Table 8.11: Marginal WTP Estimates (in RM) from the CL Interactions Model for the Status Quo Issue: Forced and Unforced Samples

Attributes	CL Interaction Forced				CL Interaction Unforced with NSQ				CL Interaction Unforced with SQ			
	WTP	t-stat	95% confidence limits		WTP	t-stat	95% confidence limits		WTP	t-stat	95% confidence limits	
Toilet2	-3.681	-1.800*	0.327	-7.689	4.380	9.056***	5.326	3.433	-1.693	-1.100	1.325	-4.711
Toilet3	-3.032	-1.229	1.803	-7.867	7.089	13.286***	8.133	6.045	0.610	0.374	3.808	-2.588
Jetty2	3.994	8.001***	4.972	3.016	2.446	2.022**	4.815	0.077	1.826	1.551	4.132	-0.48
CarP100	2.660	2.078**	3.101	2.219	1.852	1.746*	3.931	-0.227	-0.359	-0.254	2.408	-3.126
TIC2	1.954	2.898***	3.275	0.633	1.787	1.697*	3.850	-0.276	1.974	1.852*	4.061	-0.113
TIC3	0.465	0.799	1.605	-0.675	-3.239	-2.421**	-0.619	-5.859	-1.961	-1.325	0.939	-4.861
PlayG2	0.900	1.990**	1.785	0.015	-1.859	-1.725*	0.251	-3.969	-1.333	-0.879	1.64	-4.306

Notes: ***significant at 1%, **significant at 5% and *significant at 10%

8.6.2 WTP Estimates for the MXL Model – Simple and Interactions

Table 8.12 and 8.13 presents the WTP values for the primary attributes in the forced and unforced samples for the simple MXL model and MXL interactions model respectively.

WTP for the Simple MXL

In the simple MXL – forced model (Table 8.12), the results demonstrate that the respondents express their highest WTP value of RM 7.296 for the toilet services which have additional bathrooms and babies changing room facilities, followed by RM 4.835 for one hundred parking slots and RM 3.855 for the provision of two jetties. In the simple MXL-SQ model, the respondents also express their highest WTP value of RM 5.807 for the toilet services which have additional bathrooms and babies changing room facilities, followed by RM 4.084 for one hundred parking slots and RM 3.957 for the provision of two jetties. These results revealed that the respondents in both samples had the same magnitude for WTP ranking estimates for three attributes; Toilet3, CarP100 and Jetty2, similar to that reported in the simple CL model. However, in the simple MXL-NSQ model, the WTP ranking is slightly different where the highest WTP value is for the Toilet3 attribute, followed by Jetty2 and CarP100.

Comparison of the results in Table 8.12 reveals that the WTP values in the simple MXL-F model were not much different than the WTP values in the simple MXL-NSQ model. Meanwhile, the WTP values in the simple MXL-F model were higher than the WTP in the simple MXL-SQ model, except for the Jetty2 attribute. The difference, however, is small for most of the significant attributes. For example, the difference of Toilet2 attribute in the MXL-F model and the MXL-SQ model is only RM 0.159 (RM 3.598 – RM 3.439).

WTP for the MXL Interactions Model

As presented in Table 8.13, the respondents in the MXL interaction - forced model had the highest WTP value of RM 3.781 for the provision of two jetties and followed by RM 1.908 for the medium level of tourist information service. The respondents however had a negative WTP for the Toilet2 attribute. In the MXL interaction-NSQ model, the highest WTP value is RM 4.232 (CarP100), and followed by RM 2.081 (TIC2). All the significant WTP values in the MXL interaction - forced model became insignificant in the MXL interaction - SQ model. Moreover, the WTP values for all of the attributes in the MXL interaction – SQ model were not significant, except for TIC3. However, the WTP value for TIC3 was negative.

Table 8.12: Marginal WTP Estimates (in RM) from the Simple MXL Model for the Status Quo Issue: Forced and Unforced Samples

Attributes	Simple MXL				Simple MXL				Simple MXL			
	Forced				Unforced (NSQ)				Unforced (SQ)			
	WTP	t-stat	95% confidence limits		WTP	t-stat.	95% confidence limits		WTP	t-stat.	95% confidence limits	
Toilet2	3.598	5.436***	2.301	4.896	3.978	8.238***	3.033	4.922	3.439	7.237***	2.508	4.370
Toilet3	7.296	8.325***	5.578	9.013	6.516	11.450***	5.400	7.631	5.807	10.835***	4.757	6.854
Jetty2	3.855	6.824***	2.747	4.961	4.535	11.271***	3.747	5.322	3.957	10.370***	3.209	4.703
CarP100	4.835	9.012***	3.783	5.887	4.478	11.026***	3.682	5.273	4.084	11.724***	3.401	4.766
TIC2	1.892	2.927***	0.625	3.159	-0.208	-0.489	-1.042	0.626	-0.854	-2.012**	-1.685	0.808
TIC3	0.427	0.733	-0.716	1.571	0.575	1.162	-0.395	1.545	0.432	1.038	-0.384	1.251
PlayG2	1.019	2.165**	0.096	1.942	1.082	2.659***	0.284	1.879	0.821	2.404***	0.151	1.490

Notes: ***significant at 1%, **significant at 5% and *significant at 10%

Table 8.13: Marginal WTP Estimates (in RM) from the MXL Interactions Model for the Forced and Unforced Samples

Attributes	MXL Interaction Forced				MXL Interaction Unforced (NSQ)				MXL Interaction Unforced (SQ)			
	WTP	t-stat	95% confidence limits		WTP	t-stat	95% confidence limits		WTP	t-stat	95% confidence limits	
Toilet2	-3.706	-1.908**	0.033	-7.445	0.066	0.042	-3.022	3.154	-1.402	-0.952	0.463	-3.267
Toilet3	-4.083	-1.625	-0.898	-7.268	1.626	0.973	-1.651	4.903	-0.432	-0.259	0.075	-0.939
Jetty2	3.781	6.8***	-9.547	17.109	1.499	1.171	-1.009	4.007	0.859	0.844	-0.795	2.513
CarP100	1.935	1.532	-1.067	4.937	4.232	10.996***	3.48	4.984	0.680	0.646	-0.586	1.946
TIC2	1.908	3.047***	-4.064	7.88	2.081	1.963**	0.004	4.158	1.232	1.187	-1.094	3.558
TIC3	0.377	0.684	-0.963	1.717	-3.247	-2.247**	-6.079	-0.415	-3.065	-2.372**	1.584	-7.714
PlayG2	-1.190	-0.904	0.581	-2.961	-2.550	-1.943*	-5.121	0.021	-2.028	-1.929	1.752	-5.808

Notes: ***significant at 1%, **significant at 5% and *significant at 10%

8.6.3 WTP Estimates for the LCM

The WTP results for the LCM for both forced and unforced samples are presented in Table 8.14. For the forced model, the respondents in segment 1 had the highest WTP estimate of RM 6.190 in order to have the superior toilet service, followed by RM 4.628 for one hundred parking slots and RM 4.528 for the provision of two jetties. On the other hand, the respondents in segment 2 had expressed their highest WTP value of RM 9.965 for the superior toilet service, followed by RM 5.577 for a big playground and RM 5.512 for the provision of the toilet with bathroom facilities.

The WTP results for the unforced-NSQ reveal that the respondents in segment 1 had the highest WTP value of RM 7.633 for the superior toilet service, followed by RM 5.302 for the provision of two jetties and RM 5.283 for one hundred parking slots. In contrast, respondents in segment 2 expressed their highest WTP value of RM 1.994 for the provision of two jetties, followed by RM 1.279 for the superior toilet service and RM 1.211 for the provision of one hundred parking slots. The results in Table 8.14 also show that the respondents in segment 1 in the unforced-SQ model had the highest WTP value of RM 6.034 for the toilet services that offer bathroom and babies changing room facilities, followed by RM 4.401 for one hundred parking slots provided at the lake and RM 4.181 for the provision of two jetties. In segment 2, the respondents expressed their highest WTP value of RM 2.690 for the provision of two jetties, followed by RM 2.561 for the superior toilet service and RM 2.103 for the provision of one hundred car park slots.

Based on the WTP results for the LCM presented in Table 8.14, it can be concluded that the magnitude of the WTP values differ between the segments in each model and between the models. Meanwhile, the comparison of the WTP values between the forced and unforced-NSQ models reveals that the WTP values in the unforced-NSQ model are higher compared to the WTP values in the forced model for the attributes in segment 1. On the other hand, in segment 2, the WTP values in the forced model are higher compared to the WTP values in the unforced-NSQ model. For example, in segment 2, the WTP values of CarP100 attribute in the forced and unforced-NSQ model were RM 5.467 and RM 1.211 respectively. The difference of these two WTP values is also large; RM 5.467 - RM 1.211 = RM 4.256.

The comparison of the WTP values between the forced and unforced-SQ models reveals that the WTP values in the forced model are slightly higher compared to the WTP values in the unforced-SQ model, for some attributes in segment 1 (e.g. Toilet3, Jetty2 and CarP100).

However, much larger differences were observed in segment 2. For example, the difference between the WTP value of Toilet3 attribute in both forced and unforced-SQ models was RM 7.404 in segment 2 (RM 9.965 – RM 2.561).

Table 8.14: Marginal WTP Estimates (in RM) from LCM for the Status Quo Issue: Forced and Unforced Samples

Att.	Forced				Unforced - NSQ				Unforced - SQ			
	Segment 1				Segment 1				Segment 1			
	WTP	t-stat.	95% confidence limits		WTP	t-stat.	95% confidence limits		WTP	t-stat.	95% confidence limits	
Toilet2	2.892	4.681***	1.491	4.293	5.016	9.516***	3.980	6.052	3.496	6.907***	2.503	4.488
Toilet3	6.190	8.354***	4.435	7.945	7.633	13.12***	6.488	8.778	6.034	10.815***	4.935	7.133
Jetty2	4.528	10.54***	3.609	5.447	5.302	13.77***	4.544	6.058	4.181	11.085***	3.439	4.922
CarP100	4.628	11.79***	3.738	5.518	5.283	14.66***	4.575	5.989	4.401	12.671***	3.720	5.082
TIC2	-0.025	-0.03	-1.989	1.938	0.161	0.36	-0.717	1.041	-1.147	-2.412**	-2.084	-0.209
TIC3	-0.040	-0.086	-1.182	1.100	1.461	3.349***	0.605	2.318	0.683	1.601	-0.153	1.521
PlayG2	0.474	1.245	-0.432	1.381	1.845	5.457***	1.181	2.508	1.048	3.061***	0.376	1.720
Att.	**Segment 2**				**Segment 2**				**Segment 2**			
	WTP	**t-stat.**	**95% confidence limits**		**WTP**	**t-stat.**	**95% confidence limits**		**WTP**	**t-stat.**	**95% confidence limits**	
Toilet2	5.512	2.839***	-1.622	12.646	-0.708	-0.933	-2.696	1.279	0.612	0.7	-1.848	3.072
Toilet3	9.965	3.485***	-0.260	20.191	1.279	1.874*	-0.497	3.057	2.561	2.644***	-0.016	5.139
Jetty2	-1.411	-1.028	-7.800	4.978	1.994	3.576***	0.486	3.501	2.690	3.765***	0.563	4.818
CarP100	5.467	3.258***	-0.299	11.234	1.211	2.381**	-0.289	2.712	2.103	3.043***	0.111	4.094
TIC2	5.269	2.39***	-3.059	13.597	-0.522	-0.9	-2.279	1.234	0.370	0.521	-1.656	2.398
TIC3	1.305	0.765	-5.503	8.114	-1.733	-1.895*	-3.829	0.362	-1.504	-1.526	-3.838	0.829
PlayG2	5.577	2.925***	-1.866	13.021	-1.546	-2.12**	-3.515	0.422	-1.025	-1.421	-2.983	0.329

Notes: ***significant at 1%, **significant at 5% and *significant at 10%

8.7 Summary and Discussion

An important question in the design of choice experiment concerns the decision whether to include or exclude a status quo option in the choice card. Under certain conditions, it is possible that the forced choice question which excludes the status quo option might be more suitable to be applied than the unforced choice question. In particular, if respondents believe that procrastination is detrimental, or a choice must be made sooner or later, they might prefer not to have the status quo option (Dhar and Simonson, 2003). Briefly, the forced choice design that excludes the status quo option is found to be a better approach compared to the unforced choice design that includes this option. This justification is based on several important points of evidence revealed in this chapter. Before going further, it is important to bear in mind that the results presented in this chapter are data specific and for the case in this study only.

To start with, the chapter began with the analysis of the choice card responses for both forced and unforced CE questionnaires. This study is the first to introduce the supplementary question to compare the responses of the choice cards and to determine if any bias in choice occurs as a result of presenting a split sample design of CE question to the respondents. The results of the choice card responses highlight some important findings. In the forced sample, the results showed that only a small percentage of the respondents (3.33%) felt forced to make a choice because they were not given an option to vote for no change (status quo). Meanwhile, some of the respondents (25.56%) tended to choose the lowest price option because of the unavailability of the status quo option on the choice cards. These findings suggest that some of the respondents in the forced sample would have a tendency to choose the status quo option if this option was available on the choice card.

If the respondents in a hypothetical WTP survey are being given a choice between two options but would actually not pick any and are not given an opportunity to express this preference within a status quo option, the possible consequence is that they would make a forced choice which in truth would be a misrepresentation or falsification of their underlying utility function. In other words, the choices made by these respondents are biased and do not present their true utility. The biased responses would lead the researchers drawing an erroneous conclusion for use within economic valuation. However, there is only a small percentage of respondents who indicate that the choices made by them are driven by the absence of the status quo. Hence, this small bias response in the forced sample is not likely to significantly affect the overall results.

Meanwhile, in the unforced sample, more than half (53.89%) of the respondents claimed that it was difficult to make a choice with three alternatives. Choice difficulty denotes the complexity of the choice experiment question. As discussed in the literature, complexity often leads to a delay of choice, bias responses and adds noise to choices (Beshears, Choi, Laibson, Madrian, 2008). The complexity of the task induces response error, thus, decreasing the statistical accuracy of the econometric model (Regier, Watson, Burnett and Ungar, 2014).

Therefore, the results from the choice card responses in Section 8.1 reveal that both forced and unforced CE designs have a tendency to induce bias responses which could affect the accuracy of the result. Specifically, the bias responses in the forced CE is due to the unavailability of the SQ option on the choice card. Meanwhile, in the unforced sample, the bias responses that might occur are due to the difficulty of making a choice between three alternatives presented in the choice card. Thus, it is obvious that both CE designs have their own impact which needs to be carefully considered by the researchers. For this case study, the results reveal that the bias responses are likely to be higher in the unforced sample due to the choice difficulty compared to the forced sample. Thus, the forced CE design, which excludes the status quo option, is considered to be better compared to the unforced CE design, since the bias response is minimal in the forced design.

The empirical work carried out in Section 8.2 also supports the justification as to why the forced choice design is better in comparison to the unforced choice design, for the case study conducted in this research. When given the option to remain with the current situation (status quo), only a very small amount of respondents (8.1%) in the unforced sample chose to do so. This has led to the choice shares of the two hypothetical options in the forced and unforced samples being insignificantly different. The results also signify that the respondents are willing to pay or keen to respond to the changes presented. Thus, it seems unimportant to offer the status quo option when in reality, the respondents want a change from the current situation.

The choice responses from the forced and unforced CE questionnaires were further analysed by using the logit family of CE. The analysis began with the simple CL model. The basic finding across the three simple CL models in both forced and unforced samples was that the model fit and welfare estimates were not significantly different. In order to explore the presence of unobserved taste heterogeneity, the MXL model and the LCM model were specified for both samples. The goodness-of-fit of the MXL models are better compared to the CL models, especially in the unforced samples (with and without ASC SQ). The interaction of the socioeconomics variables with main attributes in the CL and MXL models were also analysed in this study. However, the discussion of these models, i.e. the comparison between forced and unforced samples, was not reported in this section since some of the main attributes became insignificant or had changed in sign when the socioeconomics variables were incorporated into the models.

The significant standard deviation estimates in the MXL models and the presence of segments in the LCM models show the presence of unobserved taste heterogeneity. In the simple MXL model, particularly in the forced sample, heterogeneity was less noticeable where the standard deviations on only two parameters (Jetty2 and CarP100) were statistically significant. Meanwhile, in the unforced sample, heterogeneity in preferences for more attributes was noticeable in both simple MXL models, with and without the specification of the ASC SQ. These results indicate that the degree of heterogeneity is found to depend on the choice card design (with and without the constant alternative). In the forced and unforced (without ASC SQ) samples, a 2-segment LCM provided a significant improvement in model fit over the CL and MXL model specifications. In the unforced sample with ASC SQ, both MXL model and LCM produced the same model fit and provided a significant improvement over the CL model.

Similar to that achieved in the CL models, the welfare estimates in the MXL models for both forced and unforced choice survey formats were not significantly different. Thus, the results of the MXL models suggest that there are no significant differences in the welfare estimates between the survey versions with and without the status quo option, except that the version including the status quo option reveals greater unobserved heterogeneity, similar to the findings of Carlsson et al., (2007). This indicates that including the status quo option increases the variance but does not have an effect on welfare estimates. However, larger differences were observed for the WTP estimates in the LCM models; between the segments and the samples. Further research should explore whether the difference in the results of the LCM models between the segments and the samples is related to the different characteristics of the respondents.

The findings reported above highlight several important considerations related to the application of the choice experiment method in the future. Firstly, it should be noted that choice experiment studies based on both forced and unforced questions have different consequences and limitations, and the researchers must choose the design that is best suited for each case study or possibly employ both methods. Therefore, to determine which method is best for a particular case study, it is important to undertake a more significant pilot study in order to uncover several things, for example, to examine the extent to which the forced and unforced

CE designs have a tendency to induce higher bias in responses, and to examine whether the respondents favoured the status quo option like the other options. In other words, it is worth assessing the trade-off between applying a forced choice card or unforced choice card at the start of the research, so that the consequences of taking the forced or unforced approaches can be carefully considered. Thus, for another case study, whether the status quo is relevant or not as one of the alternatives in the CE choice set can be empirically determined through the pilot test before deciding whether to include it or not in the main survey.

Secondly, if the forced choice is going to be used in the main survey, it is still important for the future study to investigate the bias responses that might occur due to the absence of the status quo option in the choice card. This is so these bias responses can be excluded from the analysis to produce a more representative estimate. Thus, providing a supplementary question regarding the responses of the choice card seems to be crucial in order to detect the bias responses due to the absence of the status quo option in the forced CE design.

The case study conducted in this research could also be expanded in the future in different ways. The split sample design of CE applied in this study could be compared with a dual response choice experiment design to evaluate if different choice card designs impact on the respondents' choice for the status quo option.

The WTP estimates derived from CL, MXL and LCM models were further examined in order to derive policy recommendations for improvements to tourist facilities attributes. The basic finding across the two samples of respondents (forced and unforced) was that, with the proposed entrance fees ranged from RM1 to RM 10, the respondents expressed the positive WTP values for most of the attributes presented in the study. Thus, the results indicate that the respondents accept the proposed entrance fee and they realise the benefit that they will get from the implementation of an entrance fee system. The implementation of the entrance fee is the most significant policy implication in this study. In other words, this study is concerned with the use of private money to enhance the quality and quantity of the tourist facilities attributes at Kenyir Lake. This allows policy makers to justify why private money needs to be invested in recreational sites. With the increase in the number of visitors every year, the Department of KETENGAH should consider imposing an entrance fee or other charges for future visitors as a viable way of increasing revenues to cover the development and maintenance of the tourist facilities.

In addition, it is clear from the results that the status quo is not a preferred option by the respondents; with only 8.1% of the respondents (Table 8.1) in the unforced sample choosing this option. In other words, providing a status quo option does not result in a significant proportion of responses falling into this category. This may be conditioned upon the majority of respondents wanting a change from the SQ at the prices offered. Furthermore, the ASC SQ coefficient shows a negative sign in all of the model estimations (except in Segment 2 LCM Unforced – SQ). These results suggest that the respondents had negative preferences for the status quo, giving some useful hints to the policy maker at Kenyir Lake, i.e. an urgent need to improve the tourist facilities attributes from the current situation which underpins the visitors' experience and satisfaction.

The WTP estimates derived from this study provide useful evidence to inform policy makers regarding how financial allocation can be optimally invested to improve tourist facilities based on public's need. In many cases, managers of public parks face difficulties allocating the limited amount of money. As a result, it is common to find that financial allocations for public parks is invested unwisely. For example, some parks provide tourist facilities that do not meet the needs of the public. In the worst case scenario, unneeded or unimportant facilities provided in parks might involve high maintenance costs and can be unfeasible to maintain in the long term.

Based on the WTP estimates, the results of the CL and MXL models indicated that the respondents in the forced and unforced samples were willing to pay higher for Toilet3, Jetty2 and CarP100 compared to the other attributes levels. Meanwhile, the highest WTP estimate in the CL, MXL and LCM (except for the segment 2 in the LCM with and without the ASC SQ) was for the Toilet3 attribute. This implies that it is the most important facilities that should be improved by policy makers. With the increasing number of tourists that come to the lake every year, the provision of toilet services that have an additional bathroom and baby changing room is crucial.

Chapter 9: Attribute Non-Attendance Analysis

9.0 Introduction

The purpose of this chapter is to present the analysis for the attribute non-attendance issue. It begins with Section 9.1 which presents the results of the attribute responses. As explained in more detail in Section 4.2.2, the stated non-attendance approach uses a follow-up question to explore whether respondents ignored any attributes when responding to the choice experiment question. Therefore, with the purpose of identifying how respondents pay attention on the attribute presented in the choice card, a follow-up question regarding their responses towards each attribute is provided at the end of the choice cards. The information gathered from the follow-up question is subsequently used in the mixed logit model estimation. The follow-up question is prepared based on the previous studies and the outcome from the focus group discussion as described in Section 6.1.3. By presenting this supplementary question, the issues of whether the respondents ignored certain attributes or not, or whether they just actually assigned them as being of lesser importance (given less emphasis), as explained in Section 4.2.4, can be examined.

Section 9.2 presents the cross tabulation analysis. Following this, the summary of attribute attendance and non-attendance and the estimation of the mixed logit model for the stated non-attendance issue are presented in Section 9.3 and Section 9.4 respectively. The analysis of the willingness to pay estimates is provided in Section 9.5. Finally, Section 9.6 provides the summary and discussion of the chapter.

9.1 Attribute Responses

For the attribute responses, this study presents a novel contribution by incorporating a new supplementary question regarding how respondents attend to each of the attributes used in the study; as a way of distinguishing between ignored and less important attributes (as explained in Section 4.2.4). For the first response offered ‘Did you ignore this attribute because it is not important to you?’ this study refers to Carlsson et al., (2010) and Alemu et al., (2013), and also the feedback from the focus group meetings. According to Carlsson et al., (2010), respondents might state that they have ignored certain attributes just because they are not willing to pay for the suggested change in that attribute.

The second response offered 'Did you put less emphasis on this attribute because there were more important attributes in the choice set?' was generated based on the discussion in the focus group meetings and the finding by Hess and Hensher (2010) who found that the respondents who claimed to have ignored a specific attribute may simply have assigned it lesser importance. Response three 'Did you give the same weight as all the other attributes in reaching your choice?' and response four 'Did you put more emphasis on this attribute because it is more important than other attributes?' were generated based on the suggestion and recommendation from the focus group meetings. Although it might be argued that many other possible options could be offered in the list of how respondents attended to each of the attributes, this study chooses to apply only these four response options in order to reduce the cognitive burden of the respondents.

Table 9.1 and 9.2 present the results of the attribute responses for the forced and unforced samples. The responses given by each respondent are based on each attribute used in the study. Based on Table 9.1, the most ignored attribute in the forced sample was the tourist information centre (37.2%) and followed by the children's playground (15.6%). Meanwhile, in the unforced sample (Table 9.2), the most ignored attribute was also the tourist information centre (41.6%) and followed by the children's playground (15%).

For the toilet, jetty and car park attributes in the forced sample, most of the respondents stated that they gave the same weight as all other attributes in reaching their choices with 69.4%, 77.2% and 85.6% respectively. Meanwhile, for the children's playground, most of the respondents stated that they put less emphasis on this attribute because there were more important attributes in the choice set (40%). For the entrance fee attribute, half of the respondents (50%) indicated that they gave the same weight as all other attributes in reaching their choices and 43.9% of the respondents stated that they put more emphasis on this attribute because it was more important compared to the other attributes. In the unforced sample, more than half of the respondents gave the same weight to the toilet (76.1%), jetty (76.7%) and car park (86.1%) attributes as all other attributes when making their choices. There were 42.2% of the respondents who put less emphasis on the children's playground attribute because there were more important attributes in the choice set.

The results from both forced and unforced samples produce evidence that some of the respondents do in fact ignore certain attributes when making their decision. Besides, some of the respondents put less emphasis on certain attributes when making the trade-off between all attributes in the choice cards. Thus, a supplementary question provided in this study has allowed the respondents to express their different responses between the ignored and the less important attributes. A common criticism in the ANA literature is that respondents may indicate an attribute as ignored, whilst in the real situation it is only regarded as less important. Therefore, the results obtained from the supplementary questions provided in this study assure that the respondents who stated that they ignored certain attributes really have ignored them. To account for the effect of ignored attributes and less emphasis attributes on the estimates and subsequently welfare measures, further analysis is conducted in Section 9.4 and Section 9.5 respectively.

There are a lot of factors that can induce or cause the individuals to employ attribute processing strategies in CE. Internal factors, for instance, the complexity of the CE task (DeShazo and Fermo, 2002; Scarpa et al., 2009; Weller, Oehlmann, Mariel and Meyerhoff, 2014) or the relevance of the attributes incorporated in the experiment (Hensher, 2006a), are possible explanations for an individual employing attribute processing strategies. External factors, for example, the cognitive ability of the individuals, beliefs, strength of attitude and other demographic characteristics of the individuals are also likely to have an impact on the use of lexicographic decision-making rules (Rosenberger, Peterson, Clarke and Brown, 2003). The next section discusses the demographic characteristics that influence the respondents to ignore the attribute in this study. Meanwhile, Section 9.3 discusses the complexity of the CE task (in terms of the number of alternatives) that influences the ANA.

Table 9.1: Attribute Responses for the Forced Sample

Response	**Answer (%)**					
	Toilet	**Jetty**	**Car Park**	**TIC**	**Playground**	**Fee**
Did you ignore this attribute because it is not important to you?	0.6	1.7	0.6	37.2	15.6	0.6
Did you put less emphasis on this attribute because there were more important attributes in the choice set?	2.8	1.7	3.2	29.4	40	5.5
Did you give the same weight as all other attributes in reaching your choice?	69.4	77.2	85.6	19.5	38.3	50
Did you put more emphasis on this attribute because it is more important than other attributes?	27.2	19.4	10.6	13.9	6.1	43.9
Total	**100**	**100**	**100**	**100**	**100**	**100**

Table 9.2: Attribute Responses for the Unforced Sample

Response	Answer (%)					
	Toilet	**Jetty**	**Car Park**	**TIC**	**Playground**	**Fee**
Did you ignore this attribute because it is not important to you?	-	1.7	-	41.6	15	0.6
Did you put less emphasis on this attribute because there were more important attributes in the choice set?	1.1	0.6	3.3	23.9	42.2	2.2
Did you give the same weight as all other attributes in reaching your choice?	76.1	76.7	86.1	30.6	41.7	46.1
Did you put more emphasis on this attribute because it is more important than other attributes?	22.8	21	10.6	3.9	1.1	51.1
Total	**100**	**100**	**100**	**100**	**100**	**100**

9.2 Cross Tabulation Analysis between Attribute Responses and Respondents' Characteristics

Analysts have been exploring factors as to why individuals employ attribute processing strategies (Hensher 2006a; Campbell et al., 2006; Alemu et al., 2013). One of the factors is related to the socioeconomic characteristics of the respondents (Hensher 2006a; Carlsson et al., 2010). Briefly, the socioeconomic characteristics of respondents influence the inclusion or exclusion of specific attributes during the decision making process. Therefore, in order to examine the impact of the characteristics of respondents towards the attribute responses, a cross tabulation analysis between attribute responses and socioeconomics information is conducted for the tourist information centre attribute and the playground attribute. The TIC attribute is the most ignored attribute by the respondents. Meanwhile, most of the respondents put less emphasis on the playground attribute compared to the other attributes in both samples (forced and unforced). Thus, it is worth attempting to identify what the characteristics of the respondents are that influenced their decision to ignore or put less emphasis on these attributes.

9.2.1 Cross Tabulation Analysis between Attribute Responses and the Characteristics of the Respondents in the Forced Sample

(a) Tourist Information Centre

The results from Table 9.3 revealed that 37.2% [(10+42+15)/180 x 100] of respondents in the forced sample ignored the TIC attribute because this attribute was not important to them. Approximately only 17.2% of the first time visitors ignored this attribute. Meanwhile, the majority of respondents who had visited the lake for 2-5 times and 6-10 times ignored the TIC attribute with 46.7% and 46.8% respectively. A Chi-Square Test of Independence was computed in order to understand the variables that may have impacted the frequency of attribute responses for the TIC attribute. The Chi-Square result revealed that the frequency of attribute responses does depend on the number of visits (*Chi-square (3) = 27.122, p < 0.05*). No statistically significant dependencies were found between attribute responses and gender (*Chi-square (3) = 1.47, p > 0.05*), age (*Chi-square (12) = 8.882, p > 0.05*), household number (*Chi-square (9) = 12.402, p > 0.05*) and income (*Chi-square (12) = 20.464, p > 0.05*).

Table 9.3: Cross Tab Attribute Responses of TIC and Characteristics of the Respondents in the Forced Sample

	Tourist Information Centre								Total	
	Ignored		Less Emphasis		Same Weight		More emphasis			
Number of Visits	***n***	***%***	***n***	***%***	***n***	***%***	***n***	***%***	***n***	***%***
First time visit	10	17.2	15	25.9	16	27.6	17	29.3	58	100
2-5 times	42	46.7	28	31.1	14	15.5	6	6.7	90	100
6-10 times	15	46.8	10	31.3	5	15.6	2	6.3	32	100
Pearson Chi-Square Value = 27.122, df = 3, Asymptotic Significance (2-sided) =0.000										
Gender										
Male	37	37.4	28	28.3	22	22.2	12	12.1	99	100
Female	30	37	25	30.9	13	16	13	16	81	100
Pearson Chi-Square Value = 1.47, df = 3, Asymptotic Significance (2-sided) = 0.689										
Age										
18-24	11	28.9	14	36.8	8	21.1	5	13.2	38	100
25-34	26	40	22	33.8	8	12.3	9	13.8	65	100
35-44	20	41.7	9	18.7	11	22.9	8	16.7	48	100
45-54	7	31.8	6	27.3	7	31.8	2	9.1	22	100
55 and above	3	42.8	2	28.6	1	14.3	1	14.3	7	100
Pearson Chi-Square Value = 8.882, df = 12, Asymptotic Significance (2-sided) = 0.713										

Table 9.3 (continued): Cross Tab Attribute Responses of TIC and Characteristics of the Respondents in the Forced Sample

	Tourist Information Centre								Total	
	Ignored		Less Emphasis		Same Weight		More emphasis			
Household Number										
2 persons or fewer	6	50	4	33.4	1	8.3	1	8.3	12	100
3-5 persons	36	35	31	30.1	17	16.5	19	18.4	103	100
6-8 persons	20	36.4	14	25.5	17	30.9	4	7.3	55	100
More than 8	5	50	4	40	-	-	1	10	10	100
Pearson Chi-Square Value = 12.402, df = 9, Asymptotic Significance (2-sided) = 0.192										
Income										
Low (< RM 2000)	15	62.4	2	8.3	3	12.5	4	16.7	24	100
Medium (RM 2001-RM 4000)	41	32	44	34.4	24	18.8	19	14.8	128	100
High (> RM 4001)	11	39.3	7	25	8	28.6	2	7.1	28	100
Pearson Chi-Square Value = 20.464, df = 12, Asymptotic Significance (2-sided) = 0.059										

(b) Playground

The results from Table 9.4 revealed that 40% [(19+40+13)/180 x 100] of respondents in the forced sample put less emphasis on the playground attribute because there were more important attributes in the choice set. Approximately 32.8% of the first time visitors put less emphasis on this attribute. Meanwhile, the majority of respondents who had visited the lake for 2-5 times and 6-10 times put less emphasis on this attribute with 44.4% and 40.6% respectively. About 44.4% of the female respondents and 45.8% of the respondents in the 35-44 years age category put less emphasis on the playground attribute. Based on the Chi-Square results, no statistically significant dependencies were found between attribute responses of the playground and the number of visits (*Chi-square (3) = 2.697, p > 0.05*), gender (*Chi-square (3) = 2.145, p > 0.05*), age (*Chi-square (12) = 8.673, p > 0.05*), household number (*Chi-square (9) = 5.783, p > 0.05*) and income (*Chi-square (12) = 12.955, p > 0.05*).

Table 9.4: Cross Tab Attribute Responses of Playground and Characteristics of the Respondents in the Forced Sample

	Playground								Total	
	Ignored		Less Emphasis		Same Weight		More emphasis			
Number of Visits	*n*	%	*n*	%	*n*	%	*n*	%	*n*	%
First time visit	12	20.7	19	32.8	23	39.7	4	6.8	58	100
2-5 times	11	12.2	40	44.4	35	38.9	4	4.44	90	100
6-10 times	5	15.6	13	40.6	11	34.4	3	9.4	32	100
Pearson Chi-Square Value = 2.697, df = 3, Asymptotic Significance (2-sided) = 0.441										
Gender										
Male	16	16.2	36	36.4	42	42.4	5	5.1	99	100
Female	12	14.8	36	44.4	27	33.3	6	7.4	81	100
Pearson Chi-Square Value = 2.145, df = 3, Asymptotic Significance (2-sided) = 0.543										
Age										
18-24	8	21.1	12	31.6	14	36.8	4	10.5	38	100
25-34	11	16.9	28	43.1	22	33.8	4	6.2	65	100
35-44	3	6.3	22	45.8	21	43.8	2	4.2	48	100
45-54	5	22.7	7	31.8	9	40.9	1	4.55	22	100
55 and above	1	14.3	3	42.9	3	42.9	-	-	7	100
Pearson Chi-Square Value = 8.673, df = 12, Asymptotic Significance (2-sided) = 0.731										
Household Number										
2 persons or fewer	1	8.3	3	25	7	58.3	1	8.3	12	100
3-5 persons	16	15.5	44	42.7	37	35.9	6	5.8	103	100
6-8 persons	11	20	21	38.2	20	36.4	3	5.5	55	100
More than 8	-	-	4	40	5	50	1	10	10	100
Pearson Chi-Square Value = 5.783, df = 9, Asymptotic Significance (2-sided) = 0.761										
Income										
Low (< RM 2000)	3	12.5	12	50	8	33.3	1	4.2	24	100
Medium (RM 2001-RM 4000)	24	18.8	47	36.7	48	37.5	9	7	128	100
High (> RM 4001)	1	3.6	13	46.4	13	46.4	1	3.6	28	100
Pearson Chi-Square Value = 12.955, df = 12, Asymptotic Significance (2-sided) = 0.372										

9.2.2 Cross Tabulation Analysis between Attribute Responses and the Characteristics of the Respondents in the Unforced Sample

(a) Tourist Information Centre

The results from Table 9.5 revealed that 41.6% [(21+34+20)/180 x 100] of respondents in the unforced sample ignored the TIC attribute because this attribute was not important to them. Approximately 36.2% of the first time visitors ignored this attribute. Meanwhile, the majority of respondents who had visited the lake for 2-5 times and 6-10 times ignored the TIC attribute with 39.1% and 57.1% respectively. About 44.1% of the male respondents and 55.8% of the respondents who had a household number of between 6-8 persons ignored this attribute. Employing the Chi-Square Test of Independence revealed that attribute responses of TIC does depend on the number of visits (*Chi-square (3) = 17.815, $p < 0.05$*) and income (*Chi-square (3) = 21.814, $p < 0.05$*). No statistically significant dependencies were found between attribute responses and gender (*Chi-square (3) = 0.796, $p > 0.05$*), age (*Chi-square (12) = 18.922, $p > 0.05$*) and household number (*Chi-square (9) = 18.496, $p > 0.05$*).

Table 9.5: Cross Tab Attribute Responses of TIC and Characteristics of the Respondents in the Unforced Sample

	Tourist Information Centre								Total	
	Ignored		Less Emphasis		Same Weight		More emphasis			
Number of Visits	***n***	***%***	***n***	***%***	***n***	***%***	***n***	***%***	***n***	***%***
First time visit	21	36.2	6	10.3	29	50	2	3.4	58	100
2-5 times	34	39.1	31	35.6	17	19.5	5	5.7	87	100
6-10 times	20	57.1	6	17.1	9	25.7	-	-	35	100
Pearson Chi-Square Value = 17.815, df = 3, Asymptotic Significance (2-sided) = 0.000										
Gender										
Male	49	44.1	26	23.4	32	28.8	4	3.6	111	100
Female	26	37.7	17	24.6	23	33.3	3	4.3	69	100
Pearson Chi-Square Value = 0.796 , df = 3 , Asymptotic Significance (2-sided) = 0.85										
Age										
18-24	15	57.7	4	15.4	6	23.1	1	3.8	26	100
25-34	26	35.6	24	32.9	21	28.8	2	2.7	73	100
35-44	19	37.3	9	17.6	20	39.2	3	5.9	51	100
45-54	12	63.2	5	26.3	2	10.5	-	-	19	100
55 and above	3	27.3	1	9.1	6	54.5	1	9.1	11	100
Pearson Chi-Square Value = 18.922 , df = 12 , Asymptotic Significance (2-sided) = 0.9										

Table 9.5 (continued): Cross Tab Attribute Responses of TIC and Characteristics of the Respondents in the Unforced Sample

	Tourist Information Centre								Total	
	Ignored		Less Emphasis		Same Weight		More emphasis			
Household Number	*n*	*%*	*n*	*%*	*n*	*%*	*n*	*%*	*n*	*%*
2 persons or fewer	3	37.5	2	25	3	37.5	-	-	8	100
3-5 persons	43	36.1	34	28.6	38	31.9	4	3.36	119	100
6-8 persons	29	55.8	6	11.5	14	26.9	3	5.8	52	100
More than 8	-	-	1	100	-	-	-	-	1	100
Pearson Chi-Square Value = 18.496, df = 21, Asymptotic Significance (2-sided) = 0.617										
Income										
Low (< RM 2000)	12	63.2	4	21.1	2	10.5	1	5.3	19	100
Medium (RM 2001-RM 4000)	44	35.5	33	26.6	43	34.7	4	3.2	124	100
High (> RM 4001)	19	51.4	6	16.2	10	27	2	5.4	37	100
Pearson Chi-Square Value = 21.814, df = 12, Asymptotic Significance (2-sided) = 0.04										

(b) Playground

The results from Table 9.6 revealed that 42.2% [(17+43+16)/180 x 100] of respondents in the forced sample put less emphasis on the playground attribute because there were more important attributes in the choice set. Approximately 29.3% of the first time visitors put less emphasis on this attribute. Meanwhile, the majority of respondents who had visited the lake for 2-5 times and 6-10 times put less emphasis on this attribute with 49.4% and 45.7% respectively. About 44.1% of the male respondents and 47.1% of the respondents in the 35-44 years age category put less emphasis on the playground attribute. A Chi-Square Test of Independence revealed that the frequency of attribute responses does depend on the number of visits (*Chi-square (3) = 15.2, p < 0.05*). No statistically significant dependencies were found between attribute responses of the playground and gender (*Chi-square (3) = 0.523, p > 0.05*), age (*Chi-square (12) = 9.008, p > 0.05*), household number (*Chi-square (21) = 22.62, p > 0.05*) and income (*Chi-square (12) = 17.466, p > 0.05*).

Table 9.6: Cross Tab Attribute Responses of Playground and Characteristics of the Respondents in the Forced Sample

	Playground								Total	
	Ignored		Less Emphasis		Same Weight		More emphasis			
Number of Visits	*n*	*%*	*n*	*%*	*n*	*%*	*n*	*%*	*n*	*%*
First time visit	5	8.6	17	29.3	36	62.1	-	-	58	100
2-5 times	15	17.2	43	49.4	28	32.2	1	1.1	87	100
6-10 times	7	20	16	45.7	11	31.4	1	2.9	35	100
Pearson Chi-Square Value = 15.2 , df = 3, Asymptotic Significance (2-sided) = 0.02										
Gender										
Male	16	14.4	49	44.1	45	40.5	1	1	111	100
Female	11	15.9	27	39.1	30	43.5	1	1.4	69	100
Pearson Chi-Square Value = 0.523, df = 3 , Asymptotic Significance (2-sided) = 0.914										
Age										
18-24	4	15.4	10	38.5	12	46.2	-	-	26	100
25-34	13	17.8	28	38.4	31	42.5	1	1.4	73	100
35-44	6	11.8	24	47.1	21	41.2	-	-	51	100
45-54	2	10.5	11	57.9	5	26.3	1	5.3	19	100
55 and above	2	18.2	3	27.3	6	54.5	-	-	11	100
Pearson Chi-Square Value = 9.008, df = 12 , Asymptotic Significance (2-sided) = 0.702										
Household Number										
2 persons or fewer	1	12.5	3	37.5	4	50	-	-	8	100
3-5 persons	19	16	47	39.5	52	43.7	1	0.8	119	100
6-8 persons	7	13.5	25	48.1	19	36.5	1	1.9	52	100
More than 8	-	-	1	100	-	-	-	-	1	100
Pearson Chi-Square Value = 22.62, df = 21, Asymptotic Significance (2-sided) = 0.365										
Income										
Low (< RM 2000)	7	36.8	8	42.1	3	15.8	1	5.3	19	100
Medium (RM 2001-RM 4000)	15	12.1	49	39.5	59	47.6	1	0.8	124	100
High (> RM 4001)	5	13.5	19	51.4	13	35.1	-	-	37	100
Pearson Chi-Square Value = 17.466, df = 12 , Asymptotic Significance (2-sided) = 0.133										

9.3 Summary of Attribute Attendance and Non-attendance

How often each of the six attributes is ignored as a single attribute, and as an ignored attribute in combinations, is reported in Table 9.7 and Table 9.8 for the forced and unforced samples respectively.

Table 9.7 shows that out of the 180 respondents in the forced sample, 87 (48.4%) respondents stated that they did not ignore any of the attributes presented in the choice sets. This result reveals that these respondents considered all the attributes presented in the choice sets, completely adhering to the continuity axioms assumption which is commonly assumed in a choice experiment. However, the remaining 93 (51.6%) respondents stated that they ignored at least one attribute, indicating that these respondents had discontinuous preferences behaviour when making choices. It is not unusual to discover that less than half of the respondents fully consider all the attributes presented in the choice cards (e.g. Carlsson et al., 2010; Alemu et al., 2013). Thus, maintaining the passive bounded rationality assumption by depending on respondents assessing all attribute information provided in the choice sets, might result in biased welfare estimates. Table 9.7 also shows that the most often ignored single attribute is the tourist information centre (N=60; 33.3%). Meanwhile, the most commonly ignored attribute combinations are tourist information centre together with children's playground (N=7; 3.8%).

Table 9.7: Number of Respondents Who Ignored One or Several Attributes in the Forced Sample

Number of Attributes Ignored	Number of Respondents (N)	Share of Respondents (%)
Zero	87	48.4
One	85	47.2
Ignored only jetty	2	1.1
Ignored only car park	1	0.6
Ignored only tourist information centre	60	33.3
Ignored only children's playground	21	11.6
Ignored only entrance fee	1	0.6
Two	8	4.4
Ignored toilet and jetty	1	0.6
Ignored tourist information centre and children's playground	7	3.8
Total	**180**	**100**

Table 9.8 presents the attribute non-attendance results for the unforced sample. The table shows that out of 180 respondents, 98 (54.44%) stated that they did not ignore any of the attributes presented in the choice sets. This finding suggests that more than half of the respondents in the unforced sample fully adhered to the continuity axiom of consumer behaviour assumption. The remaining 82 (45.56%) respondents stated that they ignored at least one attribute, indicating that these respondents had discontinuous preferences behaviour when making choices. The most commonly ignored single attribute was the tourist information centre (N=52; 28.9%). Meanwhile, the two ignored attribute combinations were tourist information centre together with children's playground (N=22; 12.2%) and the three ignored attribute combinations were jetty along with tourist information centre and children's playground (N=1; 0.56%).

Table 9.8: Number of Respondents Who Ignored One or Several Attributes in the Unforced Sample

No. of Attributes Ignored	No. of Respondents	Share of Respondents (%)
Zero	98	54.44
One	59	32.8
Ignored only jetty	2	1.1
Ignored only tourist information centre	52	28.9
Ignored only children's playground	4	2.2
Ignored only entrance fee	1	0.6
Two	22	12.2
Ignored tourist information centre and children's playground	22	12.2
Three	1	0.56
Ignored jetty, tourist information centre and children's playground		
Total	**180**	**100**

The results presented in Table 9.7 and Table 9.8 clearly reveal that some of the respondents did not attend to all attributes presented in the CE question. This means that, as a consequence, attributes are being ignored by the respondents. This violates the continuity axiom assumption on which the theory of CE is built. The results also reveal that the number of respondents who do not ignore any attributes in the choice card is slightly higher in the unforced sample compared to the forced sample.

The complexity of the choice experiment question is one of the reasons identified as to why individuals employ attribute processing strategies (DeShazo and Fermo, 2002; Hensher 2006a). This complexity can be described in terms of the number of alternatives presented to the respondents. A larger number of alternatives make the choice tasks in a CE more complex. In complex situations, individuals adopt simplified decision rules (DeShazo and Fermo, 2002). In this study, between forced (2 hypothetical alternatives) and unforced CE questions (2 hypothetical alternatives + status quo), more respondents are expected to adopt simplifying strategies in the unforced sample compared to the forced sample.

However, the results from Table 9.7 and Table 9.8 reveal a contradiction to what is expected. A slightly higher percentage of respondents who did not ignore any of the attributes were observed in the CE with three alternatives, in comparison to the CE with two alternatives. This is interesting because it clearly contradicts the assumption of ANA based on the number of alternatives presented, i.e. respondents ignore more attributes when presented with a larger number of alternatives. Instead, in this case study, the larger number of alternatives (2 hypothetical alternatives + status quo) did not influence their ANA decision. This further signifies that the availability of the SQ alternative in the choice card does not influence the ANA decision made by the respondents.

9.3.1 Hypothesis Test for the Difference between Two Sample Proportions

The hypothesis test for the difference between two proportions can be used to determine if the proportion of the respondents who ignored the attribute in the forced sample is significantly different to the respondents who ignored the attribute in the unforced sample. The test statistic to compare these two proportions can be derived by referring to Drozdenko and Drake (2002).

The hypothesis to be tested:

Two-tailed test:

H_0: The proportion of the respondents who ignored the attribute in the forced sample is equal to the proportion of the respondents who ignored the attribute in the unforced sample; or, $\hat{p}_f - \hat{p}_{uf} = d$

H_1: The proportion of the respondents who ignored the attribute in the forced sample is not equal to the proportion of the respondents who ignored the attribute in the unforced sample; or, $\hat{p}_f - \hat{p}_{uf} \neq d$

Following Drozdenko and Drake (2002), the test statistic is used to decide whether to accept or reject the null hypothesis H_0.

$$\text{Test Statistic} = \frac{[(\hat{p}f - \hat{p}uf) - d\,]}{(S\hat{p}f - \hat{p}uf)}$$

Where:

$S\hat{p}_f - \hat{p}_{uf}$ is the standard deviation associated with the difference in proportions and is equal to:

$$= \sqrt{[(\bar{p})(1-\bar{p})][\left(\frac{1}{nf}\right) + (\frac{1}{nuf})]}$$

and

$\bar{p} = \frac{[(\hat{p}f)(nf)+(\hat{p}uf)(nuf)]}{(nf+nuf)}$ is called the averaged proportion.

For a two-tailed test, if the absolute value of the test statistic is greater than z (where z is equal to 1.96 for 95% confidence level), the null hypothesis H_0 is rejected in favour of the alternative hypothesis H_1.

Therefore, in this study,

$\hat{p}_f$ = 0.516 (the proportion of respondents who ignored the attribute in the forced sample)

$\hat{p}_{uf}$ = 0.4556 (the proportion of respondents who ignored the attribute in the unforced sample)

n_f = 180 (sample size forced)

n_{uf} = 180 (sample size unforced)

The averaged population, $\bar{p} = \frac{[(\hat{p}f)(nf)+(\hat{p}uf)(nuf)]}{(nf+nuf)}$

$$\bar{p} = \frac{[(0.516)(180)+(0.4556)(180)]}{(180+180)}$$

$$\bar{p} = \frac{[(92.88)+(82.008)]}{(360)}$$

$$\bar{p} = \frac{(174.888)}{(360)}$$

$$\bar{p} = 0.4858$$

The standard deviation, $S\hat{p}_{f} - \hat{p}_{uf} = \sqrt{[(\bar{p})(1-\bar{p})][\left(\frac{1}{nf}\right) + (\frac{1}{nuf})]}$

$$= \sqrt{[(0.4858)(1-0.4858)][\left(\frac{1}{180}\right) + (\frac{1}{180})]}$$

$$= \sqrt{[(0.4858)(0.5142)][(0.00555) + (0.00555)]}$$

$$= \sqrt{(0.24979)(0.0111)}$$

$$= 0.05265$$

Thus, test statistic = $\frac{[(\hat{p}f - \hat{p}uf) - d\ ]}{(S\hat{p}f - \hat{p}uf)}$

$$= \frac{[(0.516 - 0.4556) - 0\ ]}{(0.05265)}$$

$$= 1.147$$

The decision rule is to reject the null hypothesis if the absolute value of the test statistic is greater than z = 1.96. Based on the result, the absolute value of the test statistic is 1.147, which is less than 1.96 (test statistic < z). Therefore, we cannot reject the null hypothesis; that the proportion of the respondents who ignored the attribute in the forced sample is equal to the proportion of the respondents who ignored the attribute in the unforced sample. The two proportions of the respondents who ignored the attribute do not differ, at the 95% confidence level. Therefore, it can be concluded that the forced and unforced CE choice cards have the same influence on the ANA decision employed by the respondents. This also means that the availability of the SQ alternative in the choice card does not influence the ANA decision made by the respondents.

9.4 Mixed Logit Model Estimation for the Stated ANA Issue

The MXL model was applied in the analysis of the stated ANA, following research in previous studies (see Table 4.2).

To demonstrate the impact of ANA on valuation, this study estimates and compares four different specifications of MXL models:

Model 1: standard model or benchmark model which assumes full attribute attendance or no restriction on the coefficients (1080 observations).

Model 2: model which restricts the coefficient of the ignored attributes to zero based on the information from the supplementary question. This method is the standard way of dealing with attribute non-attendance which has been applied by the previous researchers. In the likelihood function, the probabilities were thus only a function of the attribute coefficients which were considered by the respondents[10] (1080 observations).

Model 3: model which excluded the respondents who ignored the tourist information centre attribute, since the tourist information centre was the most commonly ignored as a single attribute (Forced sample = 678 observations; Unforced sample = 630 observations).

Model 4: model which excluded the respondents who ignored any attribute presented in the choice cards (Forced sample = 522 observations; Unforced sample = 588 observations).

All models were estimated with the simulated maximum likelihood using 100 Halton draws and the models were estimated using Nlogit 4.0. All attribute coefficients were specified as random parameters with a normal distribution, except for the entrance fee attribute.

[10] According to Carlsson et al., (2010), this is exactly the same as setting the attribute levels of the ignored attribute to zero. Thus, this technique was applied in this study whereby the attribute levels for the ignored attributes for each respondent were set to zero in the data.

Some interactions models were also tested to explore the interaction between the socioeconomic characteristics of the respondents and the main attributes. Particularly, the interaction between the number of visits variable and the TIC attribute was tested in Model 1 and Model 2 for both forced and unforced samples. The results of these MXL interactions models are discussed in the final section of this chapter.

9.4.1 MXL Model Estimation for the Forced Sample

Table 9.9 reports the results of the simple MXL models with four different specifications for the forced sample. Model 1 was statistically significant with a χ^2 statistic of 433.276, against a critical value 24.996 (with 15 degrees of freedom at alpha level 0.05). Model 2 was statistically significant with a χ^2 statistic of 424.988, against a critical value 24.996 (with 15 degrees of freedom at alpha level 0.05). Model 3 was also statistically significant with a χ^2 statistic of 263.992 against a critical value 24.996 (with 15 degrees of freedom at alpha level 0.05), and Model 4 was statistically significant with a χ^2 statistic of 188.128, against a critical value 24.996 (with 15 degrees of freedom at alpha level 0.05).

Comparison of the results achieved under the standard way of dealing with ANA (Model 2) with the results achieved in the benchmark model where ANA is not taken into account (Model 1) reveals only minor differences. The PlayG2 attribute, which was significant at 5% level in Model 1, became insignificant in Model 2. This result can be linked with the attribute responses result presented in Table 9.1 (Section 9.1) whereby the playground attribute was the second most ignored attribute by a majority of respondents. In other words, many respondents did not care about the playground attribute and this behaviour lead to the insignificant coefficient estimate of the PlayG2 attribute in Model 2. Discounting the fact that the PlayG2 attribute is insignificant in Model 2, the overall conclusions reached in these two models are relatively similar. Similar to Carlsson et al., (2010), the model fit decreased in the restricted model. However, the decrease in pseudo-R^2 value is very small (0.289 to 0.283). In contrast to the finding of Campbell et al., (2008), Campbell and Lorimer (2009) and Kosenius (2013), accounting for non-attendance attribute did not improve the performance of the estimated model in the forced sample.

Even though it has been debated that the respondents might put less weight on the attribute they claim to have ignored (e.g. Hess and Hensher, 2010; Hess, 2014), the results obtained from this study cannot be argued. This is because the respondents who stated that they ignored certain attributes were genuine and were differentiated from the respondents who put less emphasis on certain attributes (based on the attribute responses in Table 9.1). However, the results in Table 9.9 reveal that the highest percentage of the less emphasis attribute in the forced sample, which is the PlayG2 attribute, turn out to be insignificant in Model 2.

In addition, based on the attribute responses results in Section 9.1, the most ignored attribute in the forced sample was the tourist information centre. If many respondents do not care about this attribute, then the coefficient estimated for the tourist information attribute in Model 2 should be statistically insignificant. However, the statistical evidence of the respondents' choices indicate otherwise. The results presented in Model 2 revealed that the TIC2 attribute was highly significant at 1% level and TIC3 attribute was not significant, similar to that achieved in Model 1. These results suggest that, instead of completely ignoring the tourist information attribute, respondents might only ignore the individual level of this attribute, which is the TIC3 attribute level whilst still considering the TIC2 attribute level. Thus, setting the value of the coefficients of the ignored attributes equal to zero in the analysis might not be appropriate, since the respondents do place importance on the different levels of the attribute. This raises the question as to whether the non-attendance statement should be offered for each level of attributes.

Accounting for ANA in Model 2 would be expected to have an impact on the overall model performance, considering some coefficients which are excluded from contributing to the likelihood function. However, the results reveal no significant difference between Model 1 and Model 2. The imperative question here is whether or not the standard way of dealing with ANA, by restricting the coefficient of the ignored attributes to zero, is the appropriate approach to represent preferences? Or perhaps even more specifically, do the estimates obtained from Model 2 represent the attribute non-attendance effect? Hess and Hensher (2010) and Campbell and Lorimer (2009) argue that it is not appropriate to depend on stated ignoring information by fixing the value of the concerned coefficients equal to zero. Therefore, Model 3 and Model 4 are intended to present the different modelling approaches in dealing with attribute non-attendance.

To explore the effect of the most ignored attribute on the coefficient estimates in greater detail, the respondents who ignored the tourist information attribute were excluded from the analysis. Thus, the results in Model 3 only represent the respondents who considered the tourist information attribute together with the other attributes. The comparison between Model 1 and Model 3 reveals only minor differences in terms of the pseudo-R^2 value. The TIC2 which was highly significant in Model 1 at 1% level remains significant with the same significance level in Model 3. Meanwhile, the TIC3 attribute remains insignificant in Model 3. Thus, the exclusion of the highest group of respondents who ignored certain attributes; which in this study is the tourist information attribute, did not have a significant effect on the overall model performance.

When a respondent does not consider all attributes presented in the choice set, this behaviour leads to the violation of the continuity axiom and the assumption of compensatory decision-making. Accounting for the respondents who attend to all attributes in the choice cards is considered important in the choice experiment study. Thus, the comparison between Model 1, which assumed all respondents attended to every attribute presented in the choice cards, and Model 4 which only included the respondents who attended to all attributes was done to reveal whether these two models produced a different model estimate.

Based on Table 9.9, the comparison between Model 1 and Model 4 shows that there is a notable decrease in the pseudo-R^2 value from 0.289 in Model 1 to 0.259 in Model 4. *Ceteris paribus*, dropping the number of observations in a dataset would be expected to decrease the explanatory power of the model. Thus, considering a number of observations which were excluded from contributing to the likelihood in Model 4, it may not be surprising to see the decrease in the pseudo-R^2 value. All the significant variables in Model 1 remain significant in Model 4, except for the PlayG2 attribute. This means that, even when the respondents say they attend to all attributes in Model 4, it does not mean that they necessarily prefer all attributes or that all attributes will be statistically significant. The standard deviation estimates suggest the existence of heterogeneity in the coefficients of Jetty2 and CarP100 in Model 1. Meanwhile, in Model 4, the result suggests the existence of heterogeneity in CarP100 only. Summarising, there is a significant difference between the results in both of the models.

The comparison between Model 2 and Model 4 is considered interesting because both of the models applied different techniques of dealing with non-attendance attribute. Even though the technique applied in Model 2 is widely used in the previous study, there is an argument raised about the appropriateness of this technique (e.g. Campbell and Lorimer, 2009; Hess and Hensher, 2010). Therefore, the comparison between Model 2 and Model 4 is worth conducting in order to examine whether these two techniques produce different results. From a review of literature on this issue, this is the first study that undertakes a comparison between these two MXL specifications. The pseudo-R^2 value was decreased in Model 4 from Model 2 (0.283 to 0.259). All the significant variables in Model 2 remain significant in Model 4 with the same significance level. Coefficients in Model 4 that are statistically significant, are, with one exception, higher than those in Model 2. Meanwhile, the standard deviation results in both models suggest the existence of heterogeneity in Jetty2 and CarP100, with the exception of

Jetty2 in Model 4. Overall, there is a significant difference between the results in both of the models.

Table 9.9: Estimated MXL Models with Different Specifications for the ANA Issue - Forced Sample

Attribute	**1**		**2**		**3**		**4**	
Random Parameters (mean)	**Coeff.**	**tstat.**	**Coeff.**	**tstat.**	**Coeff.**	**tstat.**	**Coeff.**	**tstat.**
Toilet2	0.715	5.434***	0.712	5.692***	0.806	4.514***	0.901	4.093***
Toilet3	1.449	8.436***	1.426	9.014***	1.669	6.502***	1.747	5.247***
Jetty2	0.766	6.391***	0.727	6.586***	0.849	5.139***	0.838	4.191***
CarP100	0.961	7.759***	0.934	8.564***	0.905	5.565***	0.834	4.269***
TIC2	0.376	2.954***	0.409	2.614***	0.490	2.799***	0.547	2.601***
TIC3	0.085	0.732	0.065	0.442	0.104	0.677	0.172	0.944
PlayG2	0.203	2.046**	0.155	1.571	0.254	2.035**	0.205	1.412
Non-random Parameters								
Fee	-0.199	-8.217***	-0.194	-9.466***	-0.165	-5.765***	-0.142	-4.272***
Standard Deviations								
Toilet2	0.271	0.735	0.085	0.134	0.388	1.160	0.470	1.282
Toilet3	0.271	0.735	0.085	0.134	0.388	1.160	0.470	1.282
Jetty2	0.762	4.45***	0.713	4.493***	0.588	2.484**	0.477	1.557
CarP100	0.452	2.073**	0.426	1.998**	0.634	2.564**	0.660	2.190**
TIC2	0.107	0.338	0.044	0.094	0.076	0.205	0.096	0.224
TIC3	0.031	0.06	0.384	1.170	0.447	1.030	0.628	1.526
PlayG2	0.019	0.067	0.149	0.422	0.037	0.135	0.040	0.134
Summary Statistics								
LL(β_b)	-531.961		-536.105		-337.957		-267.758	
LL(β_0)	-748.599		-748.599		-469.953		-361.822	
Pseudo-R^2	0.289		0.283		0.280		0.259	
Adjusted Pseudo-R^2	0.28		0.274		0.265		0.239	
Number of Observations	1080		1080		678		522	

Notes: ***significant at 1%, **significant at 5% and *significant at 10%

9.4.2 MXL Model Estimation for the Unforced Sample (with ASC SQ)

Table 9.10 reports the results of the simple MXL models with four different specifications for the unforced sample with the inclusion of the ASC SQ. Model 1 was statistically significant with a χ^2 statistic of 1156.468, against a critical value 27.587 (with 17 degrees of freedom at alpha level 0.05). Model 2 was statistically significant with a χ^2 statistic of 1148.362, against a critical value 27.587 (with 17 degrees of freedom at alpha level 0.05). Model 3 was also statistically significant with a χ^2 statistic of 628.904 against a critical value 27.587 (with 17 degrees of freedom at alpha level 0.05), and Model 4 was statistically significant with a χ^2 statistic of 573.846, against a critical value 27.587 (with 17 degrees of freedom at alpha level 0.05).

The comparison between the results in Model 2 and Model 1 reveals that the TIC2 attribute becomes insignificant in Model 2, in contrast to being significant at 5% level in Model 1. This result can be linked with the attribute responses result presented in Table 9.1 (Section 9.1) whereby the TIC attribute was the most ignored attribute by a majority of respondents. In other words, many respondents did not care about the TIC attribute and this behaviour lead to the insignificant coefficient estimate of the TIC attribute in Model 2. Besides, a majority of respondents were return visitors (based on Table 7.2, Section 7.2) and highly educated (based on Table 7.1, Section 7.1), suggesting that the TIC attribute would not add much value to their experience and offered low or zero utility.

Meanwhile, the standard deviation of the PlayG2 attribute becomes insignificant in Model 2, whilst being significant in Model 1 at 10% level. There is only a slight decrease in the pseudo-R^2 value from Model 1 to Model 2 (0.487 to 0.483). Thus, accounting for the non-attendance attribute did not improve the performance of the estimated model in the unforced sample with ASC SQ. However, when accounting for ANA the most ignored attribute (TIC) becomes insignificant. Meanwhile, the ASC SQ was found to be negative and significant in both models, signifying that the respondents found the SQ or current situation alternative as less desirable than the experimentally designed alternatives.

The comparison between Model 1 and Model 3 reveals that the pseudo-R^2 value was decreased in Model 3 from Model 1 (0.487 to 0.454). Thus, excluding the highest group of respondents who ignored certain attributes; which in this study is the TIC attribute, can be seen to impact on the model performance. The TIC2 which was significant in Model 1 at 5% became insignificant in Model 3. The standard deviation estimates suggest the existence of heterogeneity in the coefficients of ASC SQ, Jetty2, CarP100, TIC3 and PlayG2 in Model 1. Meanwhile, in Model 3, the result suggests the existence of heterogeneity in all attributes, except for TIC2 and PlayG2 attributes. Summarising, there is a significant difference between the results in both of the models.

The comparison between Model 1 and Model 4 shows that the pseudo-R^2 value decreases from 0.487 in Model 1 to 0.444 in Model 4. All the significant variables in Model 1 remain significant in Model 4, except for the TIC2 attribute. The standard deviation estimates suggest the existence of heterogeneity in the coefficients of ASC SQ, Toilet2, Toilet3, CarP100 and TIC3 in Model 4 which differ with Model 1. Summarising, there is a significant difference between the results in both of the models.

The comparison between Model 2 and Model 4, which are two different techniques of dealing with non-attendance attribute, reveals a significant difference in model fit. The pseudo-R^2 value decreased from Model 2 to Model 4 (0.483 to 0.444). However, all the significant variables in Model 2 remain significant in Model 4 with the same significance levels. Meanwhile, the standard deviation results suggest the existence of heterogeneity in only four attributes (ASC SQ, Jetty2, CarP100 and TIC3) in Model 2 compared to five attributes (ASC SQ, Toilet2, Toilet3, CarP100 and TIC3) in Model 4. Overall, there is a significant different between the results in both of the models.

Table 9.10: Estimated MXL Models with Different Specifications for the ANA Issue - Unforced Sample (with ASC SQ)

Attribute	**1**		**2**		**3**		**4**	
Random Parameters (mean)	**Coeff.**	**tstat.**	**Coeff.**	**tstat.**	**Coeff.**	**tstat.**	**Coeff.**	**tstat.**
ASC SQ	-3.828	-5.092***	-3.922	-4.704***	-2.811	-3.253***	-2.855	-3.000***
Toilet2	1.297	6.277***	1.293	6.86***	1.294	4.499***	1.183	4.560***
Toilet3	2.19	8.255***	2.153	8.504***	2.083	5.840***	1.835	5.870***
Jetty2	1.493	7.947***	1.438	8.454***	1.362	5.477***	1.292	6.015***
CarP100	1.54	8.54***	1.475	8.481***	1.621	5.885***	1.477	6.209***
TIC2	-0.322	-1.977**	-0.185	-0.890	-0.198	-0.861	-0.112	-0.466
TIC3	0.163	1.036	0.090	0.455	0.282	1.278	0.224	1.016
PlayG2	0.31	2.535**	0.269	2.029**	0.501	2.445**	0.372	1.943**
Non-random Parameters								
Fee	-0.377	-9.763***	-0.356	-9.983***	-0.445	-6.961***	-0.416	-8.033**
Standard Deviations								
ASC SQ	4.098	6.587***	4.019	6.534***	3.903	4.609***	3.518	5.028***
Toilet2	0.171	0.452	0.343	1.412	0.924	3.055***	0.626	2.064**
Toilet3	0.171	0.452	0.343	1.412	0.924	3.055***	0.626	2.064**
Jetty2	0.878	4.086***	0.920	4.511***	0.775	2.475**	0.599	1.511
CarP100	0.818	3.696***	0.894	4.629***	0.849	3.065***	0.836	2.690**
TIC2	0.157	0.281	0.399	1.055	0.543	1.214	0.581	1.271
TIC3	0.932	3.692***	0.640	1.719*	0.698	1.760**	0.737	2.018**
PlayG2	0.494	1.937*	0.387	1.360	0.560	1.399	0.554	1.565
Summary Statistics								
LL(β_b)	-608.267		-612.320		-377.673		-359.061	
LL(β_0)	-1186.501		-1186.501		-692.125		-645.984	
Pseudo-R^2	0.487		0.483		0.454		0.444	
Adjusted Pseudo-R^2	0.484		0.480		0.447		0.436	
Number of Observations	1080		1080		630		588	

Notes: ***significant at 1%, **significant at 5% and *significant at 10%

9.4.3 MXL Model Estimation for the Unforced Sample (without ASC SQ)

Table 9.11 reports the results of the simple MXL models with four different specifications for the unforced sample, without the inclusion of the ASC SQ. It is worth noting here that the MXL model without the inclusion of the ASC SQ was included in this study, in order to show whether this model makes a big difference or not compared to the MXL model with ASC SQ. Comparison between Model 1 – MXL with ASC SQ in Table 9.10, and Model 1 – MXL without ASC SQ in Table 9.11, revealed that the coefficient values of all attributes were higher in the MXL without ASC SQ. This result suggests that including the ASC SQ tends to decrease the estimated values of the coefficients.

Based on Table 9.11, Model 1 was statistically significant with a χ^2 statistic of 1032.48, against a critical value 24.996 (with 15 degrees of freedom at alpha level 0.05). Model 2 was statistically significant with a χ^2 statistic of 1026.574, against a critical value 24.996 (with 15 degrees of freedom at alpha level 0.05). Model 3 was also statistically significant with a χ^2 statistic of 580.054 against a critical value 24.996 (with 15 degrees of freedom at alpha level 0.05), and Model 4 was statistically significant with a χ^2 statistic of 536.32, against a critical value 24.996 (with 15 degrees of freedom at alpha level 0.05).

The comparison between the results in Model 2 and Model 1 reveals that there is only a slight decrease in the pseudo-R^2 value from Model 1 to Model 2 (0.435 to 0.432). All the significant attributes in Model 1 remain significant in Model 2 with the same significance level, except for PlayG2. The PlayG2 attribute, which was highly significant at 1% level in Model 1, became significant at a lower level (5% level) in Model 2. The statistical significance of the standard deviation reveals the presence of heterogeneity in the model. Referring to the Table 9.11, the results suggest the existence of heterogeneity in all of the attributes in Model 1 and Model 2. Therefore, accounting for non-attendance attribute did not have a significant impact on the overall model performance.

The comparison between Model 1 and Model 3 reveals that there was a decrease in the pseudo-R^2 value from Model 1 to Model 3 (0.435 to 0.419). The PlayG2 attribute, which was highly significant at 1% level in Model 1, became significant at a lower level (10% level) in Model 3. Meanwhile, the standard deviation of TIC2, which was significant at 5% level in Model 1, became insignificant in Model 3. Therefore, by excluding the respondents who ignored the TIC attribute from the analysis, there was a decrease in the overall model performance.

The comparison between Model 1 and Model 4 shows that there is a notable decrease in the pseudo-R^2 value from 0.435 in Model 1 to 0.415 in Model 4. All the significant variables in Model 1 remain significant in Model 4, except for the PlayG2 attribute. Meanwhile, the TIC3 attribute, which was not significant in Model 1, became significant at 5% level in Model 4. The standard deviation estimates suggest the existence of heterogeneity in all of the coefficients in Model 1 and Model 4. Summarising, there is a significant difference between the results in both of the models.

The comparison between Model 2 and Model 4 reveals a significant difference in the goodness-of-fit of the model. The pseudo-R^2 value was decreased from Model 2 to Model 4 (0.432 to 0.415). The TIC3 attribute which was not significant in Model 2 became significant at 5% level in Model 4. Meanwhile, the PlayG2 attribute which was significant at 5% level in Model 2 became insignificant in Model 4. The standard deviation results suggest the existence of heterogeneity in all of the attributes in both of the models.

Table 9.11: Estimated MXL Models with Different Specifications for the ANA Issue - Unforced Sample (without ASC SQ)

Attribute	**1**		**2**		**3**		**4**	
Random Parameters (mean)	**Coeff.**	**tstat.**	**Coeff.**	**tstat.**	**Coeff.**	**tstat.**	**Coeff.**	**tstat.**
Toilet2	1.673	7.563***	1.692	8.144***	1.811	4.694***	1.738	3.959***
Toilet3	2.74	9.701***	2.747	10.213***	2.773	6.703***	2.999	5.667***
Jetty2	1.907	9.247***	1.848	9.687***	1.747	5.779***	2.396	5.071***
CarP100	1.883	8.638***	1.841	8.908***	2.032	5.950***	2.166	5.090***
TIC2	-0.088	-0.486	-0.131	-0.586	0.09	0.317	0.417	1.114
TIC3	0.242	1.144	0.062	0.243	0.503	1.619	0.958	2.426**
PlayG2	0.455	2.603***	0.404	2.242**	0.552	1.878*	0.389	1.220
Non-random Parameter								
Fee	-0.421	-9.594***	-0.399	-10.200***	-0.526	-7.689***	-0.649	-5.973***
Standard Deviations								
Toilet2	1.083	2.855***	1.084	4.008***	2.181	4.572***	2.914	4.403***
Toilet3	1.083	2.855***	1.084	4.008***	2.181	4.572***	2.914	4.403***
Jetty2	1.106	2.556**	1.097	3.181***	1.448	3.524***	1.753	3.845***
CarP100	1.458	4.853***	1.429	6.417***	1.535	4.471***	2.468	4.209***
TIC2	0.745	1.986**	0.729	1.647*	0.821	1.525	1.693	3.181***
TIC3	1.419	5.07***	1.258	3.634***	1.451	4.027***	1.589	3.081***
PlayG2	1.059	4.489***	1.074	4.470***	1.748	4.679***	2.086	5.340***
Summary Statistics								
LL(β_b)	-670.261		-673.214		-402.098		-377.824	
LL(β_0)	-1186.501		-1186.501		-692.125		-645.984	
Pseudo-R^2	0.435		0.432		0.419		0.415	
Adjusted Pseudo-R^2	0.431		0.307		0.412		0.408	
Number of Observations	1080		1080		630		588	

Notes: ***significant at 1%, **significant at 5% and *significant at 10%

9.5 Estimation of WTP for the Stated ANA Issue

9.5.1 WTP Estimates for the Forced Sample

Based on Table 9.12, the comparison between the results from Model 1 and Model 2 in the forced sample reveals that the respondents in both models have the same relative importance ranking of WTP estimates. The highest WTP value was Toilet3, followed by CarP100 and Jetty2 for both of the models. The respondents in Model 2 were not willing to pay for the PlayG2 attribute since this attribute was not significant in comparison to being significant at 5% level in Model 1 with the WTP value of RM 1.019. Focusing only on similar significant attributes in both of the models, the WTP values for all of the significant attributes were quite comparable. Overall the evidence suggests that the WTP estimates derived from the model accounting for ANA by restricting the ignored attribute to zero are not statistically different to those estimated by the model that assumed full attribute attendance. This finding is similar to the findings of Carlsson et al., (2010) and Nguyen et al., (2015), but it is in sharp contrast to the findings of Hensher et al., (2005a), Hensher et al., (2007), Campbell (2008), Puckett and Hensher (2008) and Campbell and Lorimer (2009).

The comparison between the results in Model 1 and Model 3 revealed that the highest WTP value was Toilet3, followed by CarP100 and Jetty2 for both of the models. It is noticeable that the WTP values were higher in Model 3 compared to Model 1 for all of the significant attributes. For example, the WTP values of the Toilet3 attribute in Model 1 and Model 3 were RM 7.296 and RM 10.098 respectively. The difference of these two WTP values was large; RM 10.098 – RM 7.296 = RM 2.802. Thus, excluding the respondents who ignored the tourist information centre attribute from the analysis has a significant effect to the WTP estimates.

The comparison between Model 1 and Model 4 revealed that the respondents in Model 4 were not willing to pay for the PlayG2 attribute since this attribute was not significant in comparison to being significant at 5% level in Model 1. In addition, both of the models had a different relative importance ranking of WTP estimates. In Model 1, the highest WTP value was Toilet3, followed by CarP100 and Jetty2. On the other hand, in Model 4, the highest WTP value was Toilet3, followed by Toilet2 and Jetty2. Even though most of the significant variables in Model 1 remained significant in Model 4, the WTP values in Model 4 were much higher than the WTP values in Model 1. For example, the difference between the WTP value of the Toilet3 attribute in Model 4 and Model 1 was RM 4.957 (RM 12.253 – RM 7.296). In other words, the WTP value for Toilet3 in Model 4 increased by 67.9% compared to Model 1 when accounting for the respondents who attended to all attributes presented in the choice sets. Therefore, excluding the respondents who did not consider all attributes given in the choice cards significantly affects welfare estimates.

The comparison between Model 2 and Model 4 reveals that the WTP values in Model 4 were high compared to Model 2. For example, the difference between the WTP value of the Toilet3 attribute in Model 4 and Model 2 was large, i.e. RM 4.924 (RM 12.253 – RM 7.329). Thus, accounting for ANA by restricting the coefficient of the ignored attribute to zero against accounting for ANA by excluding all the respondents who ignored any of the attributes indeed produced statistically different WTP results. The relative importance ranking of WTP estimates also differed.

Table 9.12: WTP Estimates (in RM) from the MXL for the Stated ANA Issue – Forced Sample

Attribute	Willingness-to-pay Value											
	Model 1			Model 2			Model 3			Model 4		
	WTP	95% confidence limits		WTP	95% confidence limits		WTP	95% confidence limits		WTP	95% confidence limits	
Toilet2	3.598 (5.436***)	2.301	4.896	3.659 (5.551***)	2.366	4.951	4.876 (4.505***)	2.755	6.996	6.323 (4.113***)	3.310	9.335
Toilet3	7.296 (8.325***)	5.578	9.013	7.329 (8.401***)	5.619	9.038	10.098 (6.340***)	6.976	13.219	12.253 (5.198***)	7.633	16.872
Jetty2	3.855 (6.824***)	2.747	4.961	3.736 (6.567***)	2.622	4.849	5.140 (5.473***)	3.299	6.980	5.879 (4.465***)	3.297	8.460
CarP100	4.835 (9.012***)	3.783	5.887	4.799 (8.952***)	3.748	5.849	5.474 (5.940***)	3.668	7.279	5.852 (4.596***)	3.356	8.347
TIC2	1.892 (2.927***)	0.625	3.159	2.103 (2.585***)	0.509	3.697	2.968 (2.855***)	0.931	5.004	3.839 (2.684***)	1.036	6.641
TIC3	0.427 (0.733)	-0.716	1.571	0.338 (0.442)	-1.163	1.839	0.634 (0.677)	-1.202	2.470	1.206 (0.936)	-1.318	3.730
PlayG2	1.019 (2.165**)	0.096	1.942	0.796 (1.588)	-0.185	1.780	1.542 (2.169**)	0.148	2.935	1.442 (1.509)	-0.429	3.313

Notes: ***significant at 1%, **significant at 5% and *significant at 10%; t-statistics are in brackets.

9.5.2 WTP Estimates for the Unforced Sample (with ASC SQ)

Based on Table 9.13, the comparison between the results from Model 1 and Model 2 reveals that the respondents in both models have the same relative importance ranking of WTP estimates. The highest WTP value was Toilet3, followed by CarP100 and Jetty2 for both of the models. The respondents in Model 2 were not willing to pay for the TIC2 attribute since this attribute was not significant compared to being significant at 5% level in Model 1. However, in Model 1, the WTP value for TIC2 attribute was negative and this implies that an additional unit of the tourist information centre attribute decreased the respondents' willingness to pay value.

In both Model 1 and Model 2, the WTP values for all of the significant attributes were quite comparable. Thus, the evidence suggests that the WTP estimates derived from the model accounting for ANA are not statistically different to those estimated by the model that assumed full attribute attendance. This finding is in sharp contrast to the findings of Hensher et al., (2005a), Hensher et al., (2007), Puckett and Hensher (2008), Campbell (2008), and Campbell and Lorimer (2009), but it is similar to the findings of Carlsson et al., (2010) and Nguyen et al., (2015).

The comparison between the model which assumed full attribute attendance (Model 1) and the model which excluded the respondents who ignored the tourist information attribute (Model 3) revealed that the respondents in Model 3 were not willing to pay for the TIC2 attribute. Accordingly, this attribute was not statistically significant compared to being significant at 5% level in Model 1. Both of the models also had the same relative importance ranking of WTP estimates. The highest WTP value was Toilet3, followed by CarP100 and Jetty2. The comparison between Model 1 and Model 3 reveals that the WTP value in Model 1 was high compared to Model 3 for one attribute, i.e. Toilet3, while for the other significant attributes the WTP values were quite comparable.

The comparison of the WTP values between Model 1, which assumed all respondents attended to every attribute presented in the choice cards, and Model 4 which only included the respondents who attended to all attributes, revealed that both of the models had the same relative importance ranking of WTP estimates. The highest WTP value was Toilet3, followed by CarP100 and Jetty2. Also, it is apparent from the table that the WTP values in Model 1 are quite comparable with the WTP values in Model 4 for most of the significant attributes, except for the Toilet3 attribute. The WTP value for the Toilet3 attribute was higher in Model 1 compared to model 4.

The comparison between Model 2 and Model 4 reveals that the WTP value in Model 2 was high compared to Model 4 for one attribute: Toilet3, whilst for the other significant attributes the WTP values were quite comparable. For example, the difference between the WTP value of CarP100 attribute in Model 2 and Model 4 was only RM 0.591 (RM 4.136 – RM 3.545).

Table 9.13: WTP Estimates (in RM) from the MXL for the Stated ANA Issue – Unforced Sample with ASC SQ

Attribute	Willingness-to-pay Value											
	Model 1			Model 2			Model 3			Model 4		
	WTP	95% confidence limits		WTP	95% confidence limits		WTP	95% confidence limits		WTP	95% confidence limits	
Toilet2	3.439 (7.237***)	2.508	4.370	3.625 (7.798***)	2.714	4.533	2.905 (5.112***)	1.790	4.017	2.839 (4.82***)	1.684	3.993
Toilet3	5.807 (10.835***)	4.757	6.854	6.034 (11.048***)	4.963	7.104	4.675 (7.608***)	3.470	5.877	4.405 (6.67***)	3.110	5.697
Jetty2	3.957 (10.370***)	3.209	4.703	4.031 (10.408***)	3.272	4.789	3.062 (7.376***)	2.248	3.875	3.102 (7.17***)	2.254	3.947
CarP100	4.084 (11.724***)	3.401	4.766	4.136 (11.109***)	3.406	4.865	3.639 (8.99***)	2.846	4.431	3.545 (7.92***)	2.667	4.420
TIC2	-0.854 (-2.012**)	-1.685	0.808	-0.519 (-0.899)	-1.651	0.613	-0.444 (-0.875)	-1.439	0.551	-0.269 (-0.47)	-1.397	0.859
TIC3	0.432 (1.038)	-0.384	1.251	0.255 (0.455)	-0.841	1.349	0.635 (1.313)	-0.311	1.581	0.538 (1.02)	-0.494	1.570
PlayG2	0.821 (2.404***)	0.151	1.490	0.754 (2.057**)	0.036	1.471	1.125 (2.766***)	0.329	1.920	0.894 (2.06**)	0.045	1.742

Notes: ***significant at 1%, **significant at 5% and *significant at 10%; t-statistics are in brackets.

9.5.3 WTP Estimates for the Unforced Sample (without ASC SQ)

Based on Table 9.14, the comparison between Model 1 and Model 2 reveals that there is no significant difference between the WTP estimates derived from both models. The WTP value for the PlayG2 attribute which was highly significant at 1% level in Model 1 became significant at a lower level (5% level) in Model 2. Both of the models had the same relative importance ranking of WTP estimates. The highest WTP value was Toilet3, followed by Jetty2 and CarP100. Even though the WTP values in Model 2 were slightly higher compared to Model 1 for most of the significant attributes, the values were quite comparable.

The comparison between the model which assumed full attribute attendance (Model 1) and the model which excluded the respondents who ignored the tourist information attribute (Model 3) revealed that the respondents in both models had a different relative importance ranking of WTP estimates. In Model 1, the highest WTP value was Toilet3, followed by Jetty2 and CarP100. On the other hand, the highest WTP value in Model 3 was Toilet3, followed by CarP100 and Toilet2. In addition, the respondents in Model 3 were willing to pay for the TIC3 attribute since this attribute was significant at 10% level, whereas it was insignificant in Model 1. Meanwhile, the WTP value for the PlayG2 attribute which was highly significant at 1% level in Model 1 became significant at a lower level (5% level) in Model 3. It is apparent from the table that the WTP values in Model 1 are higher compared to Model 3 for two attributes; Toilet3 and Jetty2. For the other significant attributes, the values were quite comparable.

Meanwhile, the comparison between Model 1 and Model 4 reveals that both of the models had the same relative importance ranking of WTP estimates. The highest WTP value was Toilet3, followed by Jetty2 and CarP100. Focusing only on the similar significant attributes in both models, it is apparent from the table that the WTP values in Model 1 are higher compared to Model 4. For example, the difference between the WTP value of the Toilet3 attribute in Model 1 and Model 4 was RM 1.899 (RM 6.516 – RM 4.617). Hence, excluding respondents who did not consider all attributes presented in the choice cards significantly affects welfare estimates.

The comparison between Model 2 and Model 4 reveals that both of the models had the same relative importance ranking of WTP estimates. The highest WTP value was Toilet3, followed by Jetty2 and CarP100. Focusing only on the similar significant attributes in both models, it is apparent from the table that the WTP values in Model 2 are higher compared to Model 4. For example, the difference between the WTP value of the Toilet3 attribute in Model 2 and Model 4 was RM 2.259 (RM 6.876 – RM 4.617). Overall, the evidence suggests that there is a significant difference between accounting for ANA by restricting the coefficient of the ignored attribute to zero and accounting for ANA by excluding all the respondents who ignored any of the attributes from the data.

Table 9.14: WTP Estimates (in RM) from the MXL for the Stated ANA Issue – Unforced Sample without ASC SQ

Attribute	Willingness-to-pay Value											
	Model 1			Model 2			Model 3			Model 4		
	WTP	95% confidence limits		WTP	95% confidence limits		WTP	95% confidence limits		WTP	95% confidence limits	
Toilet2	3.978	3.033	4.922	4.235	3.306	5.163	3.444	2.142	4.745	2.676	1.388	3.963
	(8.238***)			(8.94***)			(5.183***)			(4.074***)		
Toilet3	6.516	5.400	7.631	6.876	5.786	7.965	5.272	3.803	6.740	4.617	3.374	5.859
	(11.45***)			(12.35***)			(7.033***)			(7.282***)		
Jetty2	4.535	3.747	5.322	4.628	3.826	5.429	3.323	2.380	4.265	3.689	2.787	4.590
	(11.271***)			(11.31***)			(6.9***)			(8.019***)		
CarP100	4.478	3.682	5.273	4.608	3.807	5.408	3.863	2.851	4.874	3.336	2.440	4.231
	(11.026***)			(11.27***)			(7.476***)			(7.297***)		
TIC2	-0.208	-1.042	0.626	-0.329	-1.422	0.763	0.172	-0.894	1.238	0.642	-0.441	1.725
	(-0.489)			(-0.59)			(0.316)			(1.16)		
TIC3	0.575	-0.395	1.545	0.156	-1.102	1.414	0.956	-0.167	2.079	1.475	0.481	2.468
	(1.162)			(0.243)			(1.668*)			(2.909***)		
PlayG2	1.082	0.284	1.879	1.014	0.142	1.883	1.05	0.001	2.098	0.6	-0.338	1.538
	(2.659***)			(2.28**)			(1.96**)			(1.252)		

Notes: ***significant at 1%, **significant at 5% and *significant at 10%; t-statistics are in brackets.

9.6 Summary and Discussion

The fact that survey respondents ignore certain attributes, or do not attend to all the attributes presented in CE choice cards, is fast becoming a critical issue in CE studies. This issue is referred to in the CE literature as attribute non-attendance. A growing number of CE studies have acknowledged that accounting for attribute non-attendance behaviour in stated choice analysis is important and have documented that ignoring this behaviour leads to biased WTP estimate and welfare measures (Hensher, 2006a; Hensher and Rose, 2009; Carlsson et al., 2010; Scarpa et al., 2010). This study adds to this evidence presenting results from a CE concerning the visitors' preferences for the tourist facilities attributes in Kenyir Lake, Malaysia.

The common practice in identifying attribute non-attendance in CE studies is by directly asking individuals (through the supplementary questions) whether they have ignored certain attributes in reaching their choices. However, it seems inadequate to simply ask respondents whether they have ignored some attributes or not, since there is evidence that the respondents who claimed to have ignored certain attributes did not actually ignore them. Instead, they have simply assigned the ignored attribute as of lower importance. Or in other words, they put less emphasis on the attribute they claimed to have ignored. Furthermore, questions relating to how individuals attend to information given in the CE choice cards, and the best methods to capture such behaviour, are still somewhat unanswered. To dig deeper into these issues, this study suggests a new method aimed at eliciting respondents' stated non-attendance behaviour by introducing a new ANA follow-up question at the end of the choice tasks. Respondents are given a chance to express which attribute they ignored, and which attribute they put less emphasis based on in this new ANA follow-up question.

The outcomes of the ANA analysis presented in this chapter reveal some interesting evidence regarding the responses of the respondents towards the choice cards. The results presented in Section 9.1 and Section 9.3 reveal that the respondents in both forced and unforced samples do ignore certain attributes when making their decisions. This indicates that the respondents do not make the assumed trade-offs between all attributes and levels presented in the choice cards. The most ignored attribute in both forced and unforced samples was tourist information centre. Interestingly, the results also reveal that some of the respondents do indeed put less emphasis on certain attributes when making the trade-off between all attributes in the choice cards. Hence, it seems to be crucial to differentiate between low degrees of consideration being given to an attribute in some choice situations, and giving no attention to it at all (Hess, Stathopoulos, Campbell, O'Neill and Caussade, 2013).

The different characteristics of the respondents have been identified as one of the sources of ANA behaviour in the CE literature. The cross tabulation analysis between attribute responses and the characteristics of the respondents presented in Section 9.2 revealed that the different characteristics of the respondents influenced the exclusion of the TIC attribute (highest percentage of the ignored attribute) during the decision making process. For example, based on Table 9.3 and Table 9.5, the TIC attribute has been ignored mostly by the repeat visitors compared to the first time visitor. This means that the TIC attribute is not important or not relevant to the repeat visitors at Kenyir Lake. Therefore, the relevance of the attributes used in this study is somewhat related to the different categories of visitors to the lake.

Thus, it is recommended that future work should attempt to investigate what types of attribute facilities are relevant to the repeat visitors and the first time visitor, because these two categories of visitors might prefer different combinations of attribute facilities. The construction of the different CE choice cards can be completed based on this information. In other words, the repeat visitor and the first time visitor will receive CE choice cards which differ in terms of the combination of attribute levels. The relevance of attributes to the repeat visitors and the first time visitors may cause respondents to consider all attributes presented to them. Finally, the comparison of the estimation results between these two types of visitors will not only reveal the preference for the tourist facilities attribute but also will provide additional information to the policy maker regarding the preferences between two different categories of visitors. Thus, this information will help the policy maker to determine if different policy implementation should be taken based on the needs of different categories of visitors to the lake.

The complexity of a CE question is one of the factors identified as to why individuals ignore attributes. Thus, between the forced and unforced CE questions, it is expected that more respondents will employ attribute processing strategies in the unforced sample compared to the forced sample, since they have to evaluate more alternatives. However, the results presented in Section 9.3 do not find that the complexity of the CE influences the respondents’ ANA decision, since a slightly higher percentage of respondents who consider all attributes are observed in the unforced sample compared to the forced sample. Thus, the evidence from this study suggests that the characteristics of the respondents and the relevancy of the attributes are the sources of heterogeneity which induce attribute processing in this study. The results presented in Section 9.3 also denote another important finding, i.e. there is no significant difference between the proportion of the respondents who ignored the attribute in both forced and unforced samples. This means that the complexity of the CE question in terms of the availability of the status quo alternative presented in the choice cards does not influence the ANA behaviour. Whether the status quo option could have a significant impact on the ANA behaviour employed by the respondents has not been revealed yet by any study, and this issue could be further investigated in future research.

To explore whether taking non-attendance into account can significantly affect survey results, the ANA information gathered from the supplementary question is subsequently used to improve the estimation of the MXL model to be compared with a benchmark model that assumes continuous preferences, as presented in Section 9.4. Three different specifications of MXL models that account for ANA were estimated and compared with a benchmark model for both forced and unforced samples.

In the forced sample several findings are reported. The estimations reveal that Model 2, which takes ANA into account by restricting the coefficient of the ignored attributes to zero, did not result in a better performance compared to the benchmark model (Model 1). The model fit is slightly lower in Model 2 compared to Model 1. Similar results were observed in the unforced sample with and without ASC SQ. With respect to the WTP estimates, no significant difference was found between the WTP values in Model 1 and Model 2 for the forced sample, similar to that achieved in the unforced sample with and without ASC SQ. Future research could investigate whether eliciting ANA at the choice task level may provide similar results to the current approach applied (serial level) in terms of preferences and welfare estimates.

The results in Model 2 in the forced sample also reveal that there is a contradiction between what respondents declare and what was actually undertaken. This is referred to the TIC attribute, which is the most ignored attribute in the forced sample. When most of the respondents declared that they ignored the TIC attribute, the coefficient of this attribute should be statistically insignificant in Model 2. However, the results showed that only TIC3 was insignificant and the TIC2 was positive and highly significant at 1% level in Model 2. These results suggest that the respondents might only ignore the TIC3 attribute, and that they consider the TIC2 attribute during the decision making process. Thus, the standard way of setting the coefficient of the ignored attribute to zero in the analysis in Model 2 seems inappropriate when in fact the respondents do not ignore the whole attribute.

As stated by Erdem, Campbell and Hole (2015), it is possible that respondents actually ignore a subset of the attribute's levels while attending to the attribute. In this case, assuming that ANA applies to the full attribute would be untrue and could lead to erroneous policy recommendations. Thus, to fully account for ANA behaviour in CE studies, one should take into consideration the ANA response; not only at the attribute level but also at the different levels of the attribute. It is recommended that future research should provide the ANA supplementary question based on the level of each attribute. To the best of researcher's knowledge, whilst previous CE studies have only investigated stated ANA at the attribute level, no other study has examined the ANA at the levels of the attribute, except Caputo, Nayga Jr, Sacchi and Scarpa (2016). Meanwhile, Erdem et al., (2015) examined both attribute level and levels of ANA behaviour through inferred ANA. Hence, more research is needed to examine the stated ANA at the level of the attribute.

Model 3 is the model that specifically accounts for the effect of the most ignored attribute in the estimation. In the forced sample, the results in Model 3 reveal that excluding the respondents who ignored the TIC attribute from the analysis did not improve the model fit compared to Model 1; similar to that achieved in the unforced sample (with and without ASC SQ). However, the WTP estimates were increased for each significant attribute in Model 3 in the forced sample. Different WTP estimates were observed in the unforced sample (with and without ASC SQ) whereby the values were decreased for most of the significant attributes in Model 3 compared to Model 1. Overall, the results suggest that excluding a number of respondents who ignored the most unimportant attribute has an impact on the WTP estimates. This result also can be linked with the results in Section 9.2, whereby the TIC attribute was the most ignored attribute by the repeat visitors. Again, this raises the issue of attribute relevance to the different categories of visitors which affects the ANA decision and subsequently affects the WTP results.

The assumption of different MXL specifications to consider the ANA has a big impact on respondent's preferences estimations and on WTP measures. Therefore, this study found an important issue to be considered, methodologically, in CE research: whether ANA should be taken into account by restricting the coefficient of the ignored attribute to zero (as applied by many researchers) or by excluding all the respondents who ignored any attribute presented in the choice cards from the analysis. The important theoretical assumption in CE is that respondents are assumed to consider all attributes and make their choice based on trade-offs between all attributes presented in the choice card, known as continuity axiom of consumer behaviour. Continuity also implies compensatory decision making. If the respondents do not consider all attributes presented in the choice set, this behaviour leads to non-compensatory strategies which also violate the axiom of consumer choice theory in CE. Therefore, to fully adhere to the axiom of consumer choice theory in CE, only those who consider all the attributes presented in the choice cards should be accounted for in the analysis. In practical use, Model 4 is the model that fully adheres to the axiom in CE.

In addition, the comparison between Model 2 and Model 4 reveals that there is a significant difference in model performance between Model 2 and Model 4 for both forced and unforced samples. With respect to the WTP estimates, the results reveal that the WTP values for all of the attributes in Model 4 were higher compared to Model 2 in the forced sample. In the unforced sample (ASC SQ), the WTP value in Model 2 was higher compared to Model 4 for one attribute, i.e. Toilet3, while for the other significant attributes the WTP values were quite comparable. Meanwhile, in the unforced sample (without ASC SQ), the WTP values in Model 2 were higher compared to Model 4.

If Model 4 is going to be used to account for ANA, there are a number of important aspects that need to be considered, e.g. whether the remaining percentage of respondents (who fully consider all attributes presented in the choice cards) is adequate enough to be counted in the analysis and whether there is a possibility that none of the respondents consider all attributes presented in the choice task. If the remaining percentage of respondents is too small, or if all of the respondents apply non-compensatory behaviour, Model 4 is not suitable or is not applicable for the analysis. Thus, a bigger sample size is recommended if the study would like to apply Model 4 to account for ANA behaviour.

Summarising, the respondents in this study ignored attributes because the attributes were not important for them, or in other words, they had zero utility for the attribute ignored. This finding is in line with the result of Ryan, Watson and Entwistle (2009) who found that a number of respondents ignored attributes just because the attributes were not relevant to them, i.e. they had zero preferences. However, this study acknowledges that attribute ignorance might occur for a host of other reasons, for example, choice complexity. In this case, the respondents ignore attribute not because they have zero utility for that attribute, but because they adopt a simplifying heuristic decision.

The estimated utility values deliver a quantitative measure of the preference for each attribute and level. Ignoring discontinuous preferences in CE could potentially create overestimation of the WTP results. This is because the estimation of the model assumes that all attributes contribute to the utility of the respondents to some degree, but in reality, some of the attributes do not. Thus, the WTP estimates are likely to be overestimated. In addition, the results from previous studies implied that ignoring discontinuous preferences in the estimation of the CE models could potentially create inflated WTP (e.g Campbell et al., 2008; Campbell and Lorimor, 2009).

It is not possible to distinguish between respondents who ignored attributes because they had zero utility for them, and those who ignored attributes as a result of the complexity of the cognitive task, without the use of the follow-up questions regarding the reasons for ignoring attributes, for example, as applied by Alemu et al., (2013). In this study, only the statement 'Did you ignore this attribute because it is not important to you?' was provided to the respondents to choose. This is because, during the focus group meetings and pilot test, respondents did not reveal any other reasons for ignoring the attribute. The only reason why they ignored the attribute was that the attribute was not important for them. Therefore, in the actual survey, when the respondents choose the statement "Did you ignore this attribute because it is not important to you?", they are assumed to ignore the attribute because the attribute was not important for them, and not because of any other reasons. Thus, it is worth noting here that the approaches used to deal with ANA in this study might not be suitable to apply to other CE studies where ANA is more likely to be based around the cognitive challenges of the choice rather than the presence of irrelevant attributes.

The analysis from this chapter also reveals that the most important non-monetary attribute (respondents put more emphasis based on Table 9.1 and 9.2) which is the Toilet attribute, receives the highest preference ranking in the WTP estimate in all MXL models for both forced and unforced samples. The second highest most important non-monetary attribute, the Jetty attribute, was also included in the top three highest WTP ranking estimates in all MXL models for both forced and unforced samples. These results reveal that the WTP ranking of respondents towards the facilities improvement for some attributes is consistent, regardless of the different MXL specifications applied to account for ANA. The results also signify that the visitors are aware of the quality of services and facilities and are willing to pay for better services and facilities. Meanwhile, the highest less emphasis attribute which is the playground attribute receives the lowest preference ranking of WTP estimates or becomes insignificant in certain models in both forced and unforced samples. These findings suggest that the ANA self-reporting is relatively consistent with the choice behaviour that was actually adopted by the respondents. Therefore, this information is useful for the policy maker in considering which attribute is important and which attribute is less important to the visitors, and thus the allocation of budget for the improvement of facilities can take this into account.

This study also explores the interaction between the number of visits variable and the TIC attribute in order to see if there is a significant relationship between the socioeconomic characteristic of the respondents and the main attribute. As revealed in Section 9.2, different types of visitors (first time visitors and repeat visitors) influenced the exclusion of the TIC attribute during the decision making process. Specifically, the tourist information centre attribute has mostly been ignored by the repeat visitors compared to the first time visitors. The interaction between the number of visits and the TIC attributes (TIC2_VST and TIC3_VST) was tested in Model 1 and Model 2 for both forced and unforced samples. Overall, all interactions models revealed that the number of visits variables, TIC2_VST and TIC3_VST, were not significant with the level of tourist information centre attributes, except for Model 2 Unforced (with ASC SQ). Specifically, the interaction variable TIC2_VST was positive and significant in Model 2 Unforced (with ASC SQ). This result indicated that the first time visitors had a greater preference for the provision of medium tourist information centre than the repeat visitors. However, the pseudo-R^2 value of this interactions model does not permit the conclusion that this model is better than the model which does not account the interaction of TIC2_VST.

Due to the lack of a rich data set on the characteristics of respondents, this study is unable to fully explore the significant relationship that might exist between other characteristics of respondents and the main attribute in the model estimation. For example, since this study did not collect the information on the number of children, a significant relationship which might exist between the PlayG2 attribute and the number of children cannot be explored. Thus, it is suggested for future study to collect a richer data set on the characteristics of respondents which can be used in the interactions model with the main attributes.

Another suggestion for future work is to employ an alternative functional form in order to investigate the issue of non-attendance to attributes. For example, Meyerhoff and Liebe (2009b) and Alemu et al., (2013) employed an Error Component Logit (ECL) model to examine the ANA issue. According to Train (2003), the error components specification is used in studies where the primary goal is to appropriately represent substitution patterns by identifying variables that can induce correlations over alternatives in a parsimonious fashion. The experimentally designed hypothetical alternatives are expected to share an extra error component because of potential correlations between the stochastic portions of utility. Thus, this may be captured by a specification with additional errors accounting for this difference in correlation across utilities.

Chapter 10: Different Distributional Assumptions of Random Parameters Analysis

10.0 Introduction

The purpose of this chapter is to present the analysis of the different distributional assumptions of random parameters. In the MXL specification, it is necessary to make an assumption about the distribution of random parameters. Even though the most common assumption of the random parameters is a normal distribution, theoretically any of the distributions expected to fit the estimated parameters can be selected. Thus, various MXL models were analysed with different distributional assumptions of random parameters such as normal, lognormal, triangular and uniform. The simulation was performed using 100 Halton draws and all parameters except the entrance fee were assumed as random. The comparison across MXL models with different types of distributions is made based on the variation of the goodness-of-fit and the marginal WTP values. Section 10.1 presents the MXL estimates obtained for the forced model. Following this, Section 10.2 and Section 10.3 present the MXL estimates for the unforced model without ASC SQ and unforced model with ASC SQ. Section 10.4 presents the WTP estimates for all of the models presented in this chapter. Finally, Section 10.5 provides concluding remarks of the chapter.

10.1 Mixed Logit Model with Different Distributional Assumptions Analysis - Forced Sample

Table 10.1 presents the MXL model estimation results with normal (I), lognormal (II), uniform (III) and triangular (IV) distributions of random parameters for the forced sample. Model I was statistically significant with a χ^2 statistic of 433.276, against a critical value 24.996 (with 15 degrees of freedom at alpha level 0.05). Model II was statistically significant with a χ^2 statistic of 428.838, against a critical value 24.996 (with 15 degrees of freedom at alpha level 0.05). Model III was also statistically significant with a χ^2 statistic of 432.49 against a critical value 24.996 (with 15 degrees of freedom at alpha level 0.05), and Model IV was statistically significant with a χ^2 statistic of 432.972, against a critical value 24.996 (with 15 degrees of freedom at alpha level 0.05).

It seems that all the estimates of the pseudo-R^2 and log-likelihood value are comparable, whatever the distributional assumptions. In addition, all the significant variables in Model I remain significant, with the same significance levels in Model III and IV. The only insignificant variable in Model I, III and IV was TIC3. All the estimates of the mean of β (attribute coefficients) were comparable whether a normal, uniform or triangular distribution was employed. This is similar to the findings of Colombino and Nese (2009). In contrast to Model I, III and IV, only four random variables were significant in Model II, namely, Toilet2, Toilet3, Jetty2 and TIC2. From these variables, only Toilet3 was positive and according to the expected sign. The standard deviation estimates suggest the existence of heterogeneity in the coefficients of Jetty2 and CarP100 in Model I, III and IV. Meanwhile, in Model II, the result suggests the existence of heterogeneity in Jetty2. Overall, the evidence suggests that the attribute coefficients were very similar across the normal, triangular and uniform distributions; while the lognormal distribution produced results that were very different. The lognormal distribution also differs in terms of the number of significant standard deviations compared to the other distributions.

10.2 Mixed Logit Model with Different Distributional Assumptions Analysis - Unforced Sample (without ASC SQ)

Table 10.2 presents the MXL model estimation results with normal (I), lognormal (II), uniform (III) and triangular distributions (IV) of random parameters for the unforced sample (without the ASC SQ). Model I was statistically significant with a χ^2 statistic of 1032.48 against a critical value 24.996 (with 15 degrees of freedom at alpha level 0.05). Model II was statistically significant with a χ^2 statistic of 1027.066, against a critical value 24.996 (with 15 degrees of freedom at alpha level 0.05). Model III was also statistically significant with a χ^2 statistic of 1035.026 against a critical value 24.996 (with 15 degrees of freedom at alpha level 0.05), and Model IV was statistically significant with a χ^2 statistic of 1033.184, against a critical value 24.996 (with 15 degrees of freedom at alpha level 0.05). All the estimates of the pseudo-R^2 and log-likelihood value are very similar for all distributions. Furthermore, all the significant variables in Model I remain significant in Model III and IV. The statistical significance of the standard deviation reveals the presence of heterogeneity in the model. By referring to the Table 10.2, the results suggest the existence of heterogeneity in all of the attributes in Model I, III and IV.

In Model II, there were six significant random coefficients; Toilet2, Toilet3, Jetty2, CarP100, TIC3 and PlayG2. However, the PlayG2 attribute was negative and significant at a lower level (10% level) in Model II compared to being positive and significant at least at 5% level in Model I, III and IV. Meanwhile, the TIC3 attribute which was not significant in the other models became significant at 10% level in Model II with a negative sign. The negative sign indicates that an additional unit of tourist information attribute will decrease the consumer's willingness to pay for this good. All the standard deviations in Model II were significant, except for the TIC2 attribute. Summarising, all the attribute coefficients and standard deviations were comparable across all the distributions with the exception of the lognormal distribution.

10.3 Mixed Logit Model with Different Distributional Assumptions Analysis - Unforced Sample (with ASC SQ)

Table 10.3 presents the MXL model estimation results with normal (I), lognormal (II), uniform (III) and triangular distributions (IV) of random parameters for the unforced sample (with ASC SQ). Model I was statistically significant with a χ^2 statistic of 1156.468, against a critical value 27.587 (with 17 degrees of freedom at alpha level 0.05). Model II was statistically significant with a χ^2 statistic of 1118.582, against a critical value 27.587 (with 17 degrees of freedom at alpha level 0.05). Model III was also statistically significant with a χ^2 statistic of 1149.38, against a critical value 27.587 (with 17 degrees of freedom at alpha level 0.05) and Model IV was statistically significant with a χ^2 statistic of 1153.892, against a critical value 27.587 (with 17 degrees of freedom at alpha level 0.05).

The estimates of the pseudo-R^2 and log-likelihood value are very comparable in Model I, III and IV. In addition, all the significant variables in Model I remain significant in Model III and IV. In Model II, the estimates of the pseudo-R^2 and log-likelihood value are slightly lower compared to the other models. The number of significant variables in Model II was also lower compared to the other models. The ASC SQ coefficient, which was highly significant at 1% level in Model I, III and IV, became insignificant in Model II. The TIC2 and PlayG2 attributes, which were significant in Model I, III, and IV, became insignificant in Model II. Meanwhile, the TIC3 attribute was not significant in any of the models.

Referring to Table 10.3, the results suggest the existence of heterogeneity in the coefficients of ASC SQ, Jetty2, CarP100, TIC3 and PlayG2 in Model I, III and IV. Meanwhile, in Model II, the results suggest the existence of heterogeneity in all attributes, except for the TIC2 attribute. Summarising, all the attribute coefficients and standard deviations were comparable across all the distributions, except for the lognormal distribution. The results gained from this study are not surprising, as stated by Hensher and Green (2003), most empirical studies obtain the means and measures of variance that are similar and comparable in the normal, triangular and uniforms distributions. However, with the lognormal distribution, the results tend to shift.

Table 10.1: Estimation of the MXL Model with Different Parameter Distributions for the Forced Sample

Attribute	**I - Normal**		**II - Lognormal**		**III - Uniform**		**IV - Triangular**	
Random Coefficients (mean)	**Coeff.**	**tstat.**	**Coeff.**	**tstat.**	**Coeff.**	**tstat.**	**Coeff.**	**tstat.**
Toilet2	0.714	5.434***	-0.4	-2.358**	0.697	5.705***	0.705	5.54***
Toilet3	1.449	8.436***	0.301	2.789***	1.414	9.23***	1.431	8.814***
Jetty2	0.765	6.391***	-0.59	-2.838***	0.738	6.823***	0.752	6.582***
CarP100	0.960	7.759***	-0.16	-1.324	0.932	8.792***	0.946	8.183***
TIC2	0.375	2.954***	-1.032	-2.672***	0.363	2.98***	0.37	2.963***
TIC3	0.084	0.732	-2.754	-1.41	0.08	0.714	0.082	0.721
PlayG2	0.202	2.046**	-1.649	-1.143	0.186	2.085**	0.194	2.059**
Non-random Coefficient								
Fee	-0.198	-8.217***	-0.186	-9.158***	-0.191	-9.704***	-0.195	-8.828***
Standard Deviations								
Toilet2	0.270	0.735	0.216	0.773	1.161	0.176	0.478	0.48
Toilet3	0.270	0.735	0.216	0.773	1.161	0.176	0.478	0.48
Jetty2	0.762	4.45***	0.766	3.386***	1.205	4.895***	1.797	4.631***
CarP100	0.452	2.073**	0.351	1.157	0.688	2.004**	1.034	2.03**
TIC2	0.106	0.338	0.028	0.003	0.093	0.173	0.219	0.282
TIC3	0.031	0.06	0.037	0.001	0.208	0.241	0.164	0.121
PlayG2	0.018	0.067	0.322	0.069	0.057	0.128	0.076	0.117
Summary Statistics								
LL(β_b)	-531.961		-534.18		-532.354		-532.113	
LL(β_0)	-748.599		-748.599		-748.599		-748.599	
Pseudo-R^2	0.289		0.286		0.288		0.289	
Adjusted Pseudo-R^2	0.28		0.277		0.28		0.28	
Number of Observations	1080		1080		1080		1080	

Notes: ***significant at 1%, **significant at 5% and *significant at 10%

Table 10.2: Estimation of the MXL Model with Different Parameter Distributions for the Unforced Sample (without ASC SQ)

Attribute	**I - Normal**		**II - Lognormal**		**III - Uniform**		**IV - Triangular**	
Random Coefficients (mean)	**Coeff.**	**tstat.**	**Coeff.**	**tstat.**	**Coeff.**	**tstat.**	**Coeff.**	**tstat.**
Toilet2	1.672	7.563***	0.27	1.995**	1.728	7.486***	1.676	7.41***
Toilet3	2.74	9.701***	0.811	7.714***	2.828	9.605***	2.746	9.599***
Jetty2	1.907	9.247***	0.302	2.121**	1.979	8.93***	1.922	9.379***
CarP100	1.883	8.638***	0.393	3.114***	1.945	8.755***	1.907	8.523***
TIC2	-0.087	-0.486	-4.255	-0.37	-0.109	-0.587	-0.089	-0.486
TIC3	0.241	1.144	-4.501	-1.672*	0.337	1.544	0.279	1.321
PlayG2	0.455	2.603***	-1.268	-1.945*	0.494	2.725**	0.467	2.649**
Non-random Coefficient								
Fee	-0.421	-9.594***	-0.387	-14.629***	-0.432	-9.827***	-0.423	-9.608***
Standard Deviations								
Toilet2	1.082	2.855***	0.511	4.604***	2.088	4.486***	2.847	3.757***
Toilet3	1.082	2.855***	0.511	4.604***	2.088	4.486***	2.847	3.757***
Jetty2	1.105	2.556**	0.751	5.915***	2.112	4.167***	2.453	2.337***
CarP100	1.457	4.853***	0.7	6.037***	2.257	5.575**	3.546	5.213**
TIC2	0.745	1.986**	1.506	0.243	1.568	2.72***	1.904	2.14**
TIC3	1.419	5.07***	3.531	2.143**	2.527	5.604***	3.505	5.243***
PlayG2	1.059	4.489***	1.273	2.783***	1.763	4.335***	2.551	4.461***
Summary Statistics								
LL(β_b)	-670.261		-672.968		-668.988		-669.909	
LL(β_0)	-1186.501		-1186.501		-1186.501		-1186.501	
Pseudo-R^2	0.435		0.432		0.436		0.435	
Adjusted Pseudo-R^2	0.431		0.429		0.432		0.432	
Number of Observations	1080		1080		1080		1080	

Notes: ***significant at 1%, **significant at 5% and *significant at 10%

Table 10.3: Estimation of the MXL Model with Different Parameter Distributions for the Unforced Sample (with ASC SQ)

Attribute	**I - Normal**		**II - Lognormal**		**III - Uniform**		**IV - Triangular**	
Random Coefficients (mean)	**Coeff.**	**tstat.**	**Coeff.**	**tstat.**	**Coeff.**	**tstat.**	**Coeff.**	**tstat.**
ASC SQ	-3.828	-5.092***	-4.354	-1.638	-6.611	-4.24***	-4.326	-4.902***
Toilet2	1.297	6.277***	0.634	5.925***	1.278	6.31***	1.277	6.428***
Toilet3	2.19	8.255***	1.092	13.287***	2.153	8.393***	2.159	8.513***
Jetty2	1.492	7.947***	0.506	4.367***	1.468	8.221***	1.481	8.135***
CarP100	1.54	8.54***	0.644	6.643***	1.514	8.378***	1.519	8.756***
TIC2	-0.322	-1.977**	-6.041	-0.582	-0.281	-1.747*	-0.313	-1.938*
TIC3	0.163	1.036	-4.699	-1.591	0.154	1.008	0.163	1.049
PlayG2	0.309	2.353**	-0.965	-1.531	0.299	2.314**	0.31	2.4**
Non-random Coefficient								
Fee	-0.377	-9.763***	-0.419	-15.2***	-0.37	-9.574***	-0.372	-10.092***
Standard Deviations								
ASC SQ	4.097	6.587***	3.005	2.223**	10.803	5.58***	10.884	6.633***
Toilet2	0.17	0.45	0.238	2.959***	0.263	0.353	0.262	0.256
Toilet3	0.17	0.452	0.238	2.959***	0.263	0.353	0.262	0.256
Jetty2	0.877	4.086***	0.679	6.674***	1.427	4.04***	2.049	4.103***
CarP100	0.818	3.696***	0.427	4.55***	1.491	4.414***	2.001	3.952***
TIC2	0.157	0.281	3.037	0.701	0.411	0.475	0.211	0.148
TIC3	0.932	3.692***	3.609	2.172**	1.414	3.316***	2.176	3.547***
PlayG2	0.494	1.937*	1.114	1.983**	0.813	1.946**	1.140	1.899*
Summary Statistics								
LL(β_b)	-608.267		-627.21		-611.811		-609.555	
LL(β_0)	-1186.501		-1186.501		-1186.501		-1186.501	
Pseudo-R^2	0.487		0.471		0.484		0.486	
Adjusted Pseudo-R^2	0.484		0.467		0.481		0.482	
Number of Observations	1080		1080		1080		1080	

Notes: ***significant at 1%, **significant at 5% and *significant at 10%

10.4 WTP Estimate

The WTP value for each attribute in each distribution, i.e. normal (I), lognormal (II), uniform (III) and triangular (IV) is calculated as the ratio of the attribute coefficients with the entrance fee coefficient using the Wald procedure (Delta method) in Limdep 8.0.

10.4.1 WTP - Forced Sample

Based on Table 10.4, the comparison between the WTP results from Model I, III and IV, in the forced sample, reveals that the respondents in these models had the same relative importance ranking of WTP estimates. The highest WTP value was Toilet3, followed by CarP100 and Jetty2. In addition, the WTP values for all of the significant attributes in the normal, uniform and triangular distributions were quite comparable. Meanwhile, in the lognormal distribution (Model II), the highest WTP value was also the Toilet3 attribute, similar to that achieved in the other distributions. Even though the respondents express their highest WTP value for the Toilet3 attribute across the distributions, the WTP value for the Toilet3 attribute varied by more than 300% in the lognormal distribution. In addition, the lognormal distribution reveals a negative WTP for most of the attributes. Summarising, the results from this study indicate that the different distributional assumptions of random parameters (normal, uniform and triangular) did not affect the WTP estimates in the forced sample, except for the lognormal distribution.

Table 10.4: WTP Estimates (in RM) for the MXL - Forced Sample

Att.	Willingness-to-pay Value											
	I - Normal			II - Lognormal			III - Uniform			IV - Triangular		
	WTP (t-stat)	95% confidence limits		WTP (t-stat)	95% confidence limits		WTP (t-stat)	95% confidence limits		WTP (t-stat)	95% confidence limits	
Toilet2	3.598 (5.436***)	2.301	4.895	-2.147 (-2.138**)	-4.114	-0.179	3.633 (5.494***)	2.336	4.929	3.611 (5.464***)	2.315	4.906
Toilet3	7.295 (8.325***)	5.578	9.013	1.618 (2.941***)	0.54	2.696	7.373 (8.442***)	5.661	9.084	7.326 (8.377***)	5.612	9.039
Jetty2	3.854 (6.824***)	2.747	4.961	-3.169 (-2.633***)	-5.527	-0.811	3.849 (6.779***)	2.737	4.960	3.853 (6.803***)	2.743	4.962
CarP100	4.835 (9.012***)	3.782	5.887	-0.858 (-1.303)	-2.149	0.432	4.859 (9.012***)	3.802	5.915	4.843 (9.007***)	3.790	5.895
TIC2	1.892 (2.927***)	0.626	3.158	-5.538 (-2.613***)	-9.691	-1.385	1.895 (2.889***)	0.611	3.179	1.895 (2.912***)	0.621	3.169
TIC3	0.427 (0.733)	-0.716	1.571	-14.782 (-1.357)	-36.124	6.56	0.421 (0.716)	-0.731	1.573	0.423 (0.723)	-0.723	1.569
PlayG2	1.019 (2.165**)	0.095	1.942	-8.851 (-1.143)	-24.033	6.331	0.973 (2.116**)	0.072	1.874	0.994 (2.135**)	0.082	1.905

Notes: ***significant at 1%, **significant at 5% and *significant at 10%; t-statistics are in brackets

10.4.2 WTP - Unforced Sample (without ASC SQ)

Based on Table 10.5, the comparison between the WTP results from Model I, III and IV in the unforced sample (without ASC SQ) reveals that the respondents in these models had the same relative importance ranking of WTP estimates. The highest WTP value was Toilet3, followed by Jetty2 and CarP100. In addition, the WTP values for all of the significant attributes in the normal, uniform and triangular distributions were quite similar. For example, the WTP values of Jetty2 attribute were RM 4.535, RM 4.582 and RM 4.536 in the normal, uniform and triangular distributions. The differences between these values were very small.

Meanwhile, in the lognormal distribution (Model II), the highest WTP value was Toilet3 attribute, followed by CarP100 and Jetty2. Even though the respondents with the lognormal distribution express their highest WTP value for the Toilet3 attribute, similar to that achieved in the other distributions, this value varied by more than 200%. Also, the WTP values for the other significant attributes in the lognormal distribution were much lower compared to the other distributions. For example, the WTP values for the Jetty2 attribute in Model I and II were RM 4.535 and RM 0.781 respectively. The difference between these two WTP values is large; RM 4.535 - RM 0.781 = RM 3.754. Thus, the results from this study reveal that the different distributional assumptions of random parameters (normal, triangular and uniform) did not affect the WTP estimates in the unforced sample without ASC SQ, except for the lognormal distribution.

Table 10.5: WTP Estimates (in RM) for the MXL - Unforced Sample (without ASC SQ)

Att.	Willingness-to-pay Value											
	I - Normal			II - Lognormal			III – Uniform			IV - Triangular		
	WTP (t-stat)	95% confidence limits		WTP (t-stat)	95% confidence limits		WTP (t-stat)	95% confidence limits		WTP (t-stat)	95% confidence limits	
Toilet2	3.978 (8.238***)	3.033	4.922	0.699 (2.093**)	0.044	1.353	4 (8.266***)	3.051	4.948	3.956 (8.201***)	3.011	4.900
Toilet3	6.516 (11.45***)	5.400	7.631	2.093 (7.98***)	1.579	2.606	6.546 (11.73***)	5.452	7.639	6.481 (11.463***)	5.373	7.588
Jetty2	4.535 (11.271***)	3.747	5.322	0.781 (2.187**)	0.081	1.481	4.582 (11.145***)	3.776	5.387	4.536 (11.532***)	3.765	5.306
CarP100	4.478 (11.026***)	3.682	5.273	1.015 (3.314***)	0.415	1.614	4.502 (11.437***)	3.731	5.272	4.501 (11.002***)	3.699	5.302
TIC2	-0.208 (-0.489)	-1.042	0.626	-10.983 (-0.371)	-69.063	47.097	-0.254 (-0.594)	-1.092	0.584	-0.210 (-0.49)	-1.053	0.632
TIC3	0.575 (1.162)	-0.395	1.545	-11.616 (-1.645*)	-25.379	2.147	0.780 (1.582)	-0.185	1.746	0.658 (1.343)	-0.302	1.618
PlayG2	1.082 (2.659***)	0.284	1.879	-3.273 (-1.922*)	-6.61	0.064	1.144 (2.84***)	0.356	1.931	1.104 (2.713***)	0.307	1.901

Notes: ***significant at 1%, **significant at 5% and *significant at 10%; t-statistics are in brackets

10.4.3 WTP - Unforced Sample (with ASC SQ)

Based on Table 10.6, the comparison between the WTP results from Model I, III and IV in the unforced sample (with ASC SQ) reveals that the respondents in these models had the same relative importance ranking of WTP estimates. The highest WTP value was Toilet3, followed by CarP100 and Jetty2. Moreover, the WTP values for all of the significant attributes in the normal, uniform and triangular distributions were quite similar. For instance, the WTP values of Toilet2 attribute were RM 3.439, RM 3.447 and RM 3.432 in the normal, uniform and triangular distributions. Obviously, the differences between these values were very small.

Meanwhile, in the lognormal distribution (Model II), the highest WTP value was Toilet3, followed by CarP100 and Toilet2. Even though the respondents with the lognormal distribution express their highest WTP value for the Toilet3 attribute similar to that achieved in the other distributions, this value varied by more than 100%. Besides, the WTP values for the other significant attributes in the lognormal distribution were much lower compared to the other distributions. For example, the WTP values for CarP100 attribute in Model I and II were RM 4.084 and RM 1.535 respectively. The difference between these two WTP values is large; RM 4.084 – RM 1.535 = RM 2.549. Therefore, the results from this study reveal that the different distributional assumptions of random parameters (normal, uniform and triangular) did not affect the WTP estimates in the unforced sample with ASC SQ, except for the lognormal distribution.

Table 10.6: WTP Estimates (in RM) for the MXL - Unforced Sample (with ASC SQ)

Att.	Willingness-to-pay Value											
	I - Normal			II - Lognormal			III – Uniform			IV - Triangular		
	WTP (t-stat)	95% confidence limits		WTP (t-stat)	95% confidence limits		WTP (t-stat)	95% confidence limits		WTP (t-stat)	95% confidence limits	
Toilet2	3.439 (7.237***)	2.508	4.370	1.512 (6.492***)	1.055	1.968	3.447 (7.252***)	2.516	4.378	3.432 (7.229***)	2.502	4.361
Toilet3	5.806 (10.835***)	4.757	6.854	2.602 (13.722***)	2.231	2.972	5.807 (10.82***)	4.756	6.857	5.803 (10.813***)	4.752	6.853
Jetty2	3.956 (10.37***)	3.209	4.703	1.207 (4.569***)	0.689	1.724	3.961 (10.328***)	3.210	4.711	3.981 (10.439***)	3.234	4.727
CarP100	4.084 (11.724***)	3.401	4.766	1.535 (7.276***)	1.121	1.948	4.083 (11.369***)	3.379	5.786	4.082 (11.599***)	3.392	4.771
TIC2	-0.854 (-2.012**)	-1.685	0.808	-14.395 (-0.585)	-62.597	33.807	-0.759 (-1.765*)	-1.601	0.083	-0.841 (-1.976*)	-1.675	-0.007
TIC3	0.433 (1.038)	-0.384	1.251	-11.197 (-1.591)	-24.969	2.593	0.417 (1.012)	-0.392	1.226	0.439 (1.053)	-0.378	1.256
PlayG2	0.821 (2.404**)	0.151	1.490	-2.3 (-1.514)	-5.277	0.677	0.808 (2.358**)	0.138	1.478	0.833 (2.463**)	0.171	1.495

***significant at 1%, **significant at 5% and *significant at 10%; t-statistics are in brackets

10.5 Conclusion

A key issue when analysing the stated preference data using the MXL model specification is to determine the suitable distributional assumptions of random parameters. In the CE literature, analysts commonly specified the random parameters as normally distributed. The other distributions are the lognormal, triangular, uniform, and Johnson's S_B distributions. However, lack of attention is often given to the choice of the functional form of preference distributions. There has been an ongoing debate that the different functional form chosen can have a major impact on WTP estimates. Therefore, a comparison of various MXL models has been carried out in this study with four types of random distributions; normal, lognormal, uniform and triangular. Variation of the goodness-of-fit statistics and the WTP estimates were observed across different mixed logit models.

In the MXL model - forced sample, the goodness-of-fit statistics of models with the normal, uniform and triangular distributions were quite comparable. Meanwhile, the goodness-of-fit of the lognormal distribution was slightly lower compared to the other distributions. The three highest WTP values were Toilet3, CarP100 and Jetty2 for the normal (RM 7.295, RM 4.835, RM 3.854), uniform (RM 7.373, RM 4.859, RM 3.849) and triangular (RM 7.326, RM 4.843, RM 3.853) distributions. However, for the lognormal distribution, the only positive WTP value was Toilet3 (RM 1.618).

In the MXL model – unforced sample (without ASC SQ) with the normal, lognormal, uniform and triangular distributions, the goodness-of-fit statistics of models were quite comparable even though the pseudo-R^2 in the lognormal was slightly lower. The three highest WTP values were Toilet3, Jetty2 and CarP100 for the normal (RM 6.516, RM 4.535, RM 4.478), uniform (RM 6.546, RM 4.582, RM 4.502) and triangular (RM 6.481, RM 4.536, RM 4.501) distributions. In contrast, for the lognormal distribution, the three highest WTP values were Toilet3 (RM 2.093), CarP100 (RM 1.015) and Jetty2 (RM 0.781).

Meanwhile, in the MXL model – unforced sample (with ASC SQ), the model fit for the lognormal distribution was slightly lower compared to the other distributions. The three highest WTP values were Toilet3, CarP100 and Jetty2 for the normal (RM 5.806, RM 4.084, RM 3.956), uniform (RM 5.807, RM 4.083, RM 3.961) and triangular (RM 5.803, RM 4.082, RM 3.981) distributions. In contrast, for the lognormal distribution, the three highest WTP values were Toilet3 (RM 2.602), CarP100 (RM 1.535) and Toilet2 (RM 1.512).

Briefly, the specification of normal, uniform and triangular distributions is not found to have a prominent effect on WTP values of any attributes in the forced and unforced samples. Meanwhile, the lognormal distribution is found to produce a much lower WTP value compared to the other distribution. The most likely reason is the attributes were logged, whereas the price attribute remained as the fixed variable across distribution. Thus, the attribute price ratio is likely to be smaller when variables are lognormal. A literature search failed to reveal why the lognormal distribution make such a big difference to WTP values in the MXL model. Summarising, from the methodological stand point, the analysis of this study is intended to serve as a guideline for future research in choosing the most appropriate random distribution, and the recommendation for future research is to avoid the use of the lognormal distribution.

The empirical results of this chapter provide some key policy messages for the responsible policy makers. The key result of Table 10.4, Table 10.5 and Table 10.6 was that with the proposed entrance fees ranged from RM 1 to RM 10, the respondents were willing to pay for improvements to most of the tourist facilities attributes presented in this study, regardless of the different distributional assumption employed (except for the lognormal distribution). Meanwhile, the highest WTP estimate was for the Toilet3 attribute, regardless of the different distributional assumption of random parameters employed in the MXL model (forced and unforced samples). This implies that the Toilet3 attribute is the most important facility that should be upgraded by policy makers. In addition, this result is also in line with the results presented in Chapter 8 and Chapter 9, whereby the respondents were willing to pay a higher amount for the Toilet3 attribute compared to the other attributes. This is a very useful finding for the policy maker to take a further action for improving the basic facilities, based on the main preferences of visitors.

Chapter 11: Conclusion

This study addressed two research gaps in the environmental economics field. The first is the need to improve the accuracy of the choice experiment models by exploring the methodological issues in this method. The second is the lack of valuation estimates regarding the recreational site attributes in Malaysia particularly in Kenyir Lake, Terengganu; and therefore the inability of policy makers to deliver a more effective strategy for the improvement of the recreational facilities. Summarising, this study is concerned about the methodological issues in a choice experiment as the validity and reliability of the choice experiment results are vital for the policy recommendations which may be applied at Kenyir Lake in the future. Four research objectives were defined in this study to address these gaps. This chapter concludes by summarising the contributions made in this study and how they fulfil these objectives. Limitations of the study and directions for future research are also discussed. Lastly, a brief note on the key message of this study concludes this thesis.

11.0 Summary of Key Contributions

This section highlights the contributions made in this study to achieve the four research objectives.

Objective 1: To examine the effect of offering and not offering the status quo option in discrete choice experiment question on visitors' trade-offs and values for attributes.

The effect of offering and not offering the SQ option in discrete choice experiment question on visitors' trade-offs and values for attributes was presented in Chapter 8. Examining the effect of offering and not offering the SQ option could provide a better understanding regarding the relevance of offering the SQ option in the CE choice card. A split sample design of a CE questionnaire (forced and unforced) was employed to examine this effect. The respondents were randomly assigned to the forced (without SQ option) or unforced (with SQ option) CE question. Realizing that providing two different designs of CE question may cause bias in responses, this study introduce a supplementary question at the end of the choice card to elicit the respondents' opinion regarding the choice card design.

The empirical results indicated that there was little difference in the attribute coefficients and welfare estimates between the forced and unforced CE questions in both the CL and MXL models. However, in the LCM, much larger differences in WTP results were observed between the forced and unforced samples. Offering the SQ option seems unimportant in this study, based on the fact that a very small group of respondents (8.1%) in the unforced sample chose to remain with this option. This also means that the majority of the respondents in the unforced sample chose the hypothetical options and they wanted a change from the current situation. In addition, based on the responses from the supplementary question, a small amount of respondent in the forced sample would have a tendency to choose the SQ option if this option was available on the choice card. This adds to the justification of why the SQ is not relevant to be included in the choice card.

The responses from the supplementary question also reveal that both forced and unforced CE questions have a tendency to induce bias in responses. However, the bias responses are likely to be higher in the unforced CE due to the choice difficulty of having three alternatives (2 hypothetical alternatives + SQ). Summarising, the forced choice design is found to be better compared to the unforced choice design for the case study conducted in this research.

Objective 2: To examine the effect of attribute non-attendance on attribute values.

There is evidence of some individuals ignoring attributes in the choice experiment. Chapter 9 presented some analysis to empirically examine whether attribute relevance is a contributor to this incidence. The main advantage of this investigation was that it helped to determine whether the non-compensatory behaviour in the choice experiment had an impact on the values of attributes. This was done by comparing three different specifications of MXL models (Model 2, 3 and 4) that account for the ANA, with the benchmark model (Model 1) that did not account for ANA. The analysis of three different specifications of MXL models to account for the ANA also allow the researcher to reveal how various methods of dealing with ANA, other than the standard way (Model 2), can impact on the results.

The results of the analysis presented in Chapter 9 revealed that there were no significant differences in WTP estimates derived from Model 1 and Model 2 (the model that restricted the coefficient of the ignored attributes to zero) for both forced and unforced samples. Meanwhile, the comparison between Model 1 and the other models (Model 3 and 4) revealed that the WTP results were varied for both forced and unforced samples. For example, the results showed that there were significant differences in WTP estimates derived from Model 1 and Model 4 (the model that excluded the respondents who ignored any attribute presented in the choice cards) in the forced sample. Summarising, it is important to account for the effect of ANA on attribute values. Besides, it is also important to consider the alternative method beyond Model 2.

Objective 3: To examine the different distributional assumptions of random parameters on attributes values and to determine which assumption produces the best model estimate.

The importance of developing several MXL models with different distributional assumptions of random parameters has been highlighted in the choice experiment literature. Thus, Chapter 10 presented the model estimation results with four different distributional assumptions, i.e. normal, lognormal, uniform and triangular distributions. Overall, the specification of different distributional assumptions is not found to have a prominent effect on the goodness-of-fit of the model and WTP values of the attributes, except for the lognormal distribution. Specifically, in both forced and unforced samples, the lognormal distribution produces a slightly lower pseudo-R^2 value compared to the other distributions and some of the attributes turn to be negative in sign. In addition, the WTP values of the attributes in the lognormal distribution were far lower than the WTP values of the other distributions. Summarising, the attribute coefficients and welfare estimates were found to be identical for the normal, uniform and triangular distributions.

Objective 4: To evaluate the visitors' preferences for the tourist facilities attributes and, on the basis of these, to develop policy recommendations about the facilities and amenities to those involved in the management of recreational lake.

The empirical results of Chapters 8, 9 and 10 had implications for recommending policy actions to improve the provision of tourist facilities attributes at Kenyir Lake. In Chapter 8, the results in the CL, MXL and LCM models showed that there were three most preferred attributes by the respondents in both forced and unforced samples, i.e. Toilet3, CarP100 and Jetty2, except for the respondents in segment 2 of the LCM in the forced sample. The respondents in segment 2 in the forced sample preferred Toilet3, PlayG2 and Toilet2 attributes. In Chapter 9, generally, the three most preferred attributes were also Toilet3, CarP100 and Jetty2 in both forced and unforced samples for most of the models presented. Similar results were also achieved in Chapter 10 whereby the Toilet3, CarP100 and Jetty2 were the three most preferred attributes, regardless of the different random distributions applied, except for the lognormal distribution. Therefore, it is recommended that future development at Kenyir Lake improves existing toilet services, car park and jetty at the Gawi Jetty to enhance the quality of experience of the visitors.

11.1 Methodological Implications

The results of this study provide several methodological recommendations to the future application of CE which relate to the three issues explored in this study, i.e. the status quo, the non-attendance attribute and the different distributional assumptions of random parameters.

For the status quo issue, the results presented in Chapter 8 suggest that the inclusion of the status quo option in the CE choice cards is not important for this study, based on several points; (1) the inclusion of the status quo option in the choice cards increases the complexity of the CE questions, creating difficulty in making a choice between three alternatives and inducing higher bias responses compared to the choice card without the status quo option, (2) the status quo is not a preferred option for most of the respondents compared to the hypothetical options, and (3) the implicit prices reveal no significant differences between the forced (no SQ) and unforced (with SQ) samples in all models applied in this study (except for the LCM model). The implication drawn from the results concerns the need to undertake a significant pilot study to assess the pros and cons of applying the forced choice and unforced choice cards, so that the decision whether to include or exclude the status quo option can be determined empirically at the initial stage of the research. The relevance of the status quo option as an alternative in the choice cards is dependent on the case study. For example, even though the status quo option is found not to be a relevant alternative in this study, since the majority of respondents wanted a change from the current situation, it might be a relevant alternative for another case study. Another suggestion for future research which can be drawn from this study is that, if a CE study wants to apply a forced choice question, it is beneficial to investigate the bias responses that might occur due to not presenting the status quo option in the choice card. This can be done by providing a supplementary question that can elicit the bias responses that may occur, as applied in this study. Subsequently, the bias responses can be excluded from the analysis to obtain a more reliable estimate.

Regarding the ANA issue, the results presented in Chapter 9 suggest that; (1) respondents in both forced and unforced samples still ignore the attributes even if they are already familiar with the attributes presented, (2) there is no significant difference between the proportion of the respondents who ignored the attribute in both forced and unforced samples, (3) respondents do indeed put different emphasis on the different attributes, (4) the characteristics of the respondents and the relevancy of the attributes are the sources of heterogeneity in inducing attribute processing strategy, and (5) the standard way of setting the coefficient of the ignored attribute to zero in the analysis might be inappropriate when in fact the respondents do not ignore the whole attribute entirely. This may be one reason which caused no significant differences in the implicit prices between the model which assumed full attribute attendance and the model which restricted the coefficient of the ignored attributes to zero, for both forced and unforced samples.

Thus, the implication drawn from the ANA issue investigated in this study concerns the importance of investigating the attribute processing strategy which might be employed by the respondents in any choice experiment study, and to consider this behaviour when estimating a stated preference model. It is also important to differentiate the degree of consideration (e.g. between ignored and less emphasis) being given to an attribute. In addition, the ANA responses should be examined, not only at the attribute levels but also at the different levels of the attributes. Finally, this study also proposes and compares other appropriate methods that can be applied by future CE study to account for the stated ANA in the analysis.

In Chapter 10, a number of MXL models were evaluated with different distributional assumptions of random parameters, i.e. normal, lognormal, triangular and uniform. Overall, the results suggested that, in all MXL models, the goodness of fit statistics and WTP values were quite comparable, except for the lognormal distribution. In addition, the lognormal distribution tends to produce the negative coefficients for the attributes compared to the other distributions. Even though the results presented in this study are case specific, the methodological implications that can be drawn concern; (1) the importance of developing several MXL models with different distributional assumptions and comparing the results, and (2) if possible, avoid the use of the lognormal distribution, except in the cases or for attribute where restriction to the sign of the parameter is needed.

11.2 Policy Implications

The results of this study provide several policy recommendations for the responsible policy makers. The key result of Chapters 8, 9 and 10 was that, with the proposed entrance fees ranged from RM 1 to RM 10, the respondents were willing to pay for improvements to most of the tourist facilities attributes presented in this study. This means that the respondents agree with the proposed entrance fees and they realise the benefit that they will get from the introduction of the entrance fee system. Thus, the first implication drawn from the study concerns the imposition of entrance fee to enhance the quantity and quality of visitors' facilities surrounding the jetty. At this moment (2017), no entrance fee is charged to the visitors who enter the lake. This means that the budget, or funds for managing the lake, come solely from the government source. Competition with other government funded programmes often results in the receipt of limited funds, insufficient to cover the maintenance and development of the lake. As a result of limited government funds, it is reasonable that receipts from the future imposition of an entrance fee at Kenyir Lake be used for re-investment into the park.

The second implication concerns the need for improvement of the current service of tourist facilities provided at the lake. The study provides evidence that the majority of the respondents have negative preferences for the current situation and they want change at the prices offered. Respondents are conscious of the quality of tourist facilities provided, and they are willing to pay for better services and facilities. This information is crucial to the policy maker because if the current situation continues, visitors' experience and satisfaction will decrease and it will affect the tourism industry at that lake. Therefore, the responsible policy maker should consider urgent action to improve the facilities at the lake according to the needs of the majority of the visitors.

The other policy implication that can be drawn from this study concerns how budget allocated for the lake can be more effectively spent. Commonly, it is argued that budgets should be invested in the attributes facilities that were mostly preferred by the respondents. For example, in this study, the three most preferred attributes were Toilet3, CarP100 and Jetty2. Nevertheless, the decision to improve these facilities might be inaccurate without considering the cost of providing it. Even though the respondents in both forced and unforced samples mostly preferred the Toilet3, CarP100 and Jetty2 attributes, this does not necessarily specify that the budget should be allocated to these attributes. The other attributes such as the tourist information centre which involves smaller costs, might need to be considered based on the benefit-cost analysis, although they offer minor benefits to the visitors.

The final implication concerns the different provision of facilities to the different categories of visitors to the lake. The study provides evidence that the tourist information centre attribute is not important to the repeat visitors compared to the first time visitors. This means that different types of visitor exhibit different preferences for improvement to the tourist facilities attributes. Thus, it becomes a challenge for the policy maker to carefully consider the different needs of the two types of visitors.

11.3 Limitations and Future Research

This section highlights limitations and suggestions for future research. Several limitations were identified. The first is concerning the attributes used in this study. Some of the attributes were found not to be significant or not important to the particular group of respondents. Therefore, a further choice experiment study should consider other potential tourist facilities attributes based on the different categories of visitors who come to the lake. Determination of the attributes should be explored through two different focus groups, i.e. repeat visitors and first time visitors. This may result in different attributes of preferences based on the different categories of visitors; the analysis of which could provide a richer set of information to the policy maker.

The second limitation concerns the analysis which currently only focuses on the respondents who have visited the lake. The involvement of non-users (those who have not currently visited the lake but might do so in the future) as respondents in valuing the improvement to tourist facilities attributes should be considered important. Therefore, it is suggested for future research to perform a separate analysis for respondents who have visited the lake and those who have not. The comparison of the results from this analysis could explain the difference in the attributes preferred by visitors (users) and their implicit prices compared to non-visitors (non-users).

The third limitation concerns the analysis which is limited to the main effects of the attributes, without considering the interaction effects between attributes. Thus, it is recommended for future research to analyse the interactions among attributes (two-way, three-way, or higher-order interactions). The results of the interaction effects could possibly inform the responsible policy maker about how changes to one particular attribute could influence preferences for the other attributes.

The next limitation relates to the distributional assumptions of random parameters in the MXL model. Most of the researchers in CE (e.g. Revelt and Train, 1998; Hensher and Green, 2003) generally fix the price coefficient to simplify the interpretation of the WTP value. This indicates that all respondents are equally price sensitive, as applied in this study. Nevertheless, assuming all respondents express equal sensitivity in the price coefficient might be incorrect, as argued by Campbell, Doherty, Hynes and Rensburg (2010a). This is because respondents who are highly sensitive to price attribute may possibly follow a different distribution compared to respondents who are low price sensitive. Therefore, it is suggested for future research to explore heterogeneous price sensitivities in the MXL model by allowing the price coefficient to be random.

The functional form used in this study for the analysis of the CE data was limited to a few well-known estimation models, for example, Conditional Logit Model, Mixed Logit Model and Latent Class Model. Thus, it is suggested that future research could explore the other alternative functional forms to address the issues of interest in CE. For instance, Willis (2009) employed the Heteroscedastic Extreme Value (HEV) model to examine the status quo effect and preference uncertainty between alternatives. Meanwhile, Meyerhoff and Liebe (2009b) and Alemu et al., (2013) applied the Error Component Logit (ECL) to investigate the ANA issue.

There is a potential use of non-nested hypothesis tests that can be applied in future for statistically comparing non-nested models in Chapters 8, 9 and 10. Broadly speaking, non-nested models can arise from differences in the way a specific relationship proposed by economic theory is modelled and/or differences in the underlying theoretical paradigms (Pesaran, 1990). Other examples of non-nested hypotheses arise when the probability distributions under consideration belong to different parametric families, for instance, Poisson versus geometric distributions, or normal versus log-normal distributions, as discussed in Chapter 10 in this study.

There are three common methods in the literature that can be considered to test the non-nested hypotheses. The first method is known as the Cox test (1961, 1962) which involves centring the log-likelihood ratio statistic under the null hypothesis and subsequently deriving its asymptotic null distribution. The second method, also proposed by Cox (1962) and investigated extensively by Atkinson (1970), is grounded on an artificially constructed general model. The other method, known as the encompassing technique concentrates on the ability of one model in explaining one or more features of an alternative model (Mizon and Richard, 1986).

This study is the first attempt to employ discrete CE in assessing the quantity and quality of basic tourist facilities in Malaysia. This technique is capable of being extended to other tourist areas in Malaysia by using different tourist facilities attributes and levels. In addition, other branches of Choice Modelling, for example, Contingent Ranking, Contingent Rating and Paired Comparison could also be applied in this field. The application of other branches of Choice Modelling will not only produce diversity in the method used in the economic valuation study but it could simultaneously aid comparison of results and improve the validity and reliability of the analysis. The validity and reliability of the analysis are important in order to help the policy maker in implementing the right policy.

11.4 Closing Remarks

The accurate determination of valuation estimates for non-market goods and services is essential information for developing appropriate policy recommendations. This study explores three methodological issues in choice experiment method to ensure that the estimates obtained are as reliable as possible, thereby providing more sound information for the policy maker in formulating the tourist facilities improvement at Kenyir Lake. The first issue is an investigation into whether the status quo is relevant or not as one of the alternatives in the choice set. The second and third issues are the investigations into whether non-attendance attribute, and the different distributional assumptions of random parameters, affect welfare estimates. The purpose of investigating these three methodological issues in the application of choice experiment is to better understand and model choice behaviour.

Conducting a choice experiment study is a complex task and complexity is an inherent problem of CE. The results from this study reveal that the inclusion of the status quo option makes the choice decision more complex (in Chapter 8). However, the complexity of the choice experiment question due to the availability of the status quo option does not affect the attribute processing strategies employed by the respondents (in Chapter 9). If the field of economic valuation of non-market goods and services is to benefit from methodological advances, then there is a necessity to integrate these advances in empirical applications of choice experiments as done in this study.

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Appendix A: Set of Choice Sets

SET A

Choice card 1

Facility	Option 1	Option 2	Current Situation
Toilet	Basic	Superior	Basic
Jetty	One	Two	One
Car Park	30 slots	100 slots	30 slots
Tourist Information Centre	Medium	Basic	Basic
Children's Playground	Large	Small	Small
Entrance Fee	RM 7.50	RM 0	RM 0
Your Option			

Choice card 2

Facility	Option 1	Option 2	Current Situation
Toilet	Basic	Superior	Basic
Jetty	One	Two	One
Car Park	100 slots	30 slots	30 slots
Tourist Information Centre	Superior	Basic	Basic
Children's Playground	Small	Large	Small
Entrance Fee	RM 10	RM 7.50	RM 0
Your Option			

Choice card 3

Facilities	Option 1	Option 2	Current Situation
Toilet	Medium	Superior	Basic
Jetty	Two	One	One
Car Park	30 slots	100 slots	30 slots
Tourist Information Centre	Medium	Basic	Basic
Children's Playground	Large	Small	Small
Entrance Fee	RM 5	RM 1	RM 0
Your Option			

Choice card 4

Facilities	Option 1	Option 2	Current Situation
Toilet	Medium	Basic	Basic
Jetty	One	Two	One
Car Park	30 slots	100 slots	30 slots
Tourist Information Centre	Superior	Medium	Basic
Children's Playground	Small	Large	Small
Entrance Fee	RM 1	RM 7.50	RM 0
Your Option			

Choice card 5

Facilities	Option 1	Option 2	Current Situation
Toilet Jetty Car Park Tourist Information Centre Children's Playground Entrance Fee	Medium One 100 slots Superior Large RM 7.50	Basic Two 30 slots Medium Small RM 0	Basic One 30 slots Basic Small RM 0
Your Option			

Choice card 6

Facilities	Option 1	Option 2	Current Condition
Toilet Jetty Car Park Tourist Information Centre Children's Playground Entrance Fee	Superior One 30 slots Medium Large RM 2.50	Basic Two 100 slots Basic Small RM 5	Basic One 30 slots Basic Small RM 0
Your Option			

SET B

Choice card 7

Facilities	Option 1	Option 2	Current Condition
Toilet Jetty Car Park Tourist Information Centre Children's Playground Entrance Fee	Medium Two 100 slots Medium Large RM 2.50	Superior One 30 slots Basic Small RM 7.50	Basic One 30 slots Basic Small RM 0
Your Option			

Choice card 8

Facilities	Option 1	Option 2	Current Condition
Toilet Jetty Car Park Tourist Information Centre Children's Playground Entrance Fee	Superior One 100 slots Superior Large RM 0	Medium Two 30 slots Basic Small RM 2.50	Basic One 30 slots Basic Small RM 0
Your Option			

Choice card 9

Facilities	**Option 1**	**Option 2**	**Current Condition**
Toilet	Superior	Basic	Basic
Jetty	One	Two	One
Car Park	100 slots	30 slots	30 slots
Tourist InformationCentre	Medium	Superior	Basic
Children's Playground	Large	Small	Small
Entrance Fee	RM 10	RM 7.50	RM 0
Your Option			

Choice card 10

Facilities	**Option 1**	**Option 2**	**Current Condition**
Toilet	Superior	Medium	Basic
Jetty	Two	One	One
Car Park	30 slots	100 slots	30 slots
Tourist Information Centre	Basic	Superior	Basic
Children's Playground	Large	Small	Small
Entrance Fee	RM 7.50	RM 2.50	RM 0

Choice card 11

Facilities	**Option 1**	**Option 2**	**Current Situation**
Toilet	Medium	Basic	Basic
Jetty	One	Two	One
Car Park	100 slots	30 slots	30 slots
Tourist Information Centre	Superior	Medium	Basic
Children's Playground	Small	Large	Small
Entrance Fee	RM 2.50	RM 10	RM 0
Your Option			

Choice card 12

Facilities	**Option 1**	**Option 2**	**Current Situation**
Toilet	Basic	Superior	Basic
Jetty	One	Two	One
Car Park	30 slots	100 slots	30 slots
Tourist Information Centre	Superior	Basic	Basic
Children's Playground	Large	Small	Small
Entrance Fee	RM 1	RM 0	RM 0
Your Option			

SET C

Choice card 13

Facilities	**Option 1**	**Option 2**	**Current Situation**
Toilet	Superior	Medium	Basic
Jetty	One	Two	One
Car Park	30 slots	100 slots	30 slots
Tourist Information Centre	Superior	Medium	Basic
Children's Playground	Large	Small	Small
Entrance Fee	RM 5	RM 1	RM 0
Your Option			

Choice card 14

Facilities	**Option 1**	**Option 2**	**Current Situation**
Toilet	Medium	Basic	Basic
Jetty	Two	One	One
Car Park	30 slots	100 slots	30 slots
Tourist Information Centre	Basic	Medium	Basic
Children's Playground	Large	Small	Small
Entrance Fee	RM 1	RM 0	RM 0
Your Option			

Choice card 15

Facilities	**Option 1**	**Option 2**	**Current Situation**
Toilet	Basic	Medium	Basic
Jetty	Two	One	One
Car Park	30 slots	100 slots	30 slots
Tourist Information Centre	Superior	Basic	Basic
Children's Playground	Large	Small	Small
Entrance Fee	RM 2.50	RM 5	RM 0
Your Option			

Choice card 16

Facilities	**Option 1**	**Option 2**	**Current Situation**
Toilet	Basic	Superior	Basic
Jetty	One	Two	One
Car Park	30 slots	100 slots	30 slots
Tourist Information Centre	Basic	Superior	Basic
Children's Playground	Small	Large	Small
Entrance Fee	RM 7.50	RM 5	RM 0
Your Option			

Choice card 17

Facilities	Option 1	Option 2	Current Situation
Toilet	Superior	Basic	Basic
Jetty	One	Two	One
Car Park	100 slots	30 slots	30 slots
Tourist Information Centre	Medium	Superior	Basic
Children's Playground	Small	Large	Small
Entrance Fee	RM 7.50	RM 10	RM 0
Your Option			

Choice card 18

Facilities	Option 1	Option 2	Current Situation
Toilet	Medium	Basic	Basic
Jetty	Two	One	One
Car Park	100 slots	30 slots	30 slots
Tourist Information Centre	Medium	Superior	Basic
Children's Playground	Large	Small	Small
Entrance Fee	RM 2.50	RM 10	RM 0
Your Option			

SET D

Choice card 19

Facilities	Option 1	Option 2	Current Situation
Toilet	Superior	Medium	Basic
Jetty	Two	One	One
Car Park	30 slots	100 slots	30 slots
Tourist Information Centre	Medium	Superior	Basic
Children's Playground	Small	Large	Small
Entrance Fee	RM 5	RM 7.50	RM 0
Your Option			

Choice card 20

Facilities	Option 1	Option 2	Current Situation
Toilet	Medium	Superior	Basic
Jetty	One	Two	One
Car Park	30 slots	100 slots	30 slots
Tourist Information Centre	Basic	Superior	Basic
Children's Playground	Large	Small	Small
Entrance Fee	RM 0	RM 10	RM 0
Your Option			

Choice card 21

Facilities	Option 1	Option 2	Current Situation
Toilet	Basic	Medium	Basic
Jetty	One	Two	One
Car Park	100 slots	30 slots	30 slots
Tourist Information Centre	Medium	Basic	Basic
Children's Playground	Large	Small	Small
Entrance Fee	RM 5	RM 10	RM 0
Your Option			

Choice card 22

Facilities	Option 1	Option 2	Current Situation
Toilet	Medium	Basic	Basic
Jetty	One	Two	One
Car Park	30 slots	100 slots	30 slots
Tourist Information Centre	Medium	Basic	Basic
Children's Playground	Small	Large	Small
Entrance Fee	RM 10	RM 1	RM 0
Your Option			

Choice card 23

Facilities	Option 1	Option 2	Current Situation
Toilet	Medium	Basic	Basic
Jetty	Two	One	One
Car Park	30 slots	100 slots	30 slots
Tourist Information Centre	Superior	Basic	Basic
Children's Playground	Small	Large	Small
Entrance Fee	RM 0	RM 5	RM 0
Your Option			

Choice card 24

Facilities	Option 1	Option 2	Current Situation
Toilet	Superior	Basic	Basic
Jetty	Two	One	One
Car Park	30 slots	100 slots	30 slots
Tourist Information Centre	Superior	Basic	Basic
Children's Playground	Small	Large	Small
Entrance Fee	RM 1	RM 2.50	RM 0
Your Option			

SET E

Choice card 25

Facilities	Option 1	Option 2	Current Situation
Toilet	Superior	Medium	Basic
Jetty	One	Two	One
Car Park	30 slots	100 slots	30 slots
Tourist Information Centre	Superior	Basic	Basic
Children's Playground	Small	Large	Small
Entrance Fee	RM 5	RM 10	RM 0
Your Option			

Choice card 26

Facilities	Option 1	Option 2	Current Situation
Toilet	Medium	Basic	Basic
Jetty	Two	One	One
Car Park	100 slots	30 slots	30 slots
Tourist Information Centre	Medium	Superior	Basic
Children's Playground	Small	Large	Small
Entrance Fee	RM 1	RM 0	RM 0
Your Option			

Choice card 27

Facilities	Option 1	Option 2	Current Situation
Toilet	Superior	Medium	Basic
Jetty	Two	One	One
Car Park	100 slots	30 slots	30 slots
Tourist Information Centre	Superior	Basic	Basic
Children's Playground	Small	Large	Small
Entrance Fee	RM 10	RM 0	RM 0
Your Option			

Choice card 28

Facilities	Option 1	Option 2	Current Situation
Toilet	Superior	Medium	Basic
Jetty	Two	One	One
Car Park	30 slots	100 slots	30 slots
Tourist Information Centre	Basic	Large	Basic
Children's Playground	Small	Medium	Small
Entrance Fee	RM 2.50	RM 1	RM 0
Your Option			

Choice card 29

Facilities	Option 1	Option 2	Current Situation
Toilet Jetty Car Park Tourist Information Centre Children's Playground Entrance Fee	Medium Two 100 slots Superior Large RM 0	Basic One 30 slots Basic Small RM 2.50	Basic One 30 slots Basic Small RM 0
Your Option			

Choice card 30

Facilities	Option 1	Option 2	Current Situation
Toilet Jetty Car Park Tourist Information Centre Children's Playground Entrance Fee	Basic One 100 slots Medium Small RM 1	Medium Two 30 slots Superior Large RM 5	Basic One 30 slots Basic Small RM 0
Your Option			

SET F

Choice card 31

Facilities	Option 1	Option 2	Current Situation
Toilet Jetty Car Park Tourist Information Centre Children's Playground Entrance Fee	Basic Two 30 slots Medium Small RM 0	Superior One 100 slots Basic Large RM 10	Basic One 30 slots Basic Small RM 0
Your Option			

Choice card 32

Facilities	Option 1	Option 2	Current Situation
Toilet Jetty Car Park Tourist Information Centre Children's Playground Entrance Fee	Medium One 30 slots Medium Small RM 5	Basic Two 100 slots Basic Large RM 0	Basic One 30 slots Basic Small RM 0
Your Option			

Choice card 33

Facilities	Option 1	Option 2	Current Situation
Toilet	Basic	Superior	Basic
Jetty	Two	One	One
Car Park	100 slots	30 slots	30 slots
Tourist Information Centre	Basic	Medium	Basic
Children’s Playground	Small	Large	Small
Entrance Fee	RM 5	RM 2.50	RM 0
Your Option			

Choice card 34

Facilities	Option 1	Option 2	Current Situation
Toilet	Superior	Medium	Basic
Jetty	Two	One	One
Car Park	100 slots	30 slots	30 slots
Tourist Information Centre	Superior	Medium	Basic
Children’s Playgrond	Large	Small	Small
Entrance Fee	RM 1	RM 10	RM 0
Your Option			

Choice card 35

Facilities	Option 1	Option 2	Current Situation
Toilet	Medium	Basic	Basic
Jetty	Two	One	One
Car Park	30 slots	100 slots	30 slots
Tourist Information Centre	Superior	Basic	Basic
Children’s Playground	Small	Large	Small
Entrance Fee	RM 0	RM 5	RM 0
Your Option			

Choice card 36

Facilities	Option 1	Option 2	Current Situation
Toilet	Medium	Superior	Basic
Jetty	Two	One	One
Car Park	100 slots	30 slots	30 slots
Tourist Information Centre	Superior	Basic	Basic
Children’s Playground	Small	Large	Small
Entrance Fee	RM 7.50	RM 1	RM 0
Your Option			

Appendix B: Unforced Questionnaire

TOURISM FACILITIES SURVEY MALAYSIA

(photo: www.holidaygogo.com/lake-kenyir-terengganu)

Greetings and welcome to Kenyir Lake, Terengganu. My name is Wan Norhidayah W Mohamad. I am a PhD student at Newcastle University, United Kingdom, and a staff member at the University Putra Malaysia. Currently I am conducting a survey regarding tourists' preferences for tourism facilities provided at Gawi Jetty, Kenyir Lake. This survey is part of my PhD research project. Your opinion is important and results obtained from this research project will contribute towards the management of the tourism facilities here. **Please be assured that the information you provided is strictly confidential and will ONLY be used for the study.** The survey will be conducted by an interviewer and will take about 20 minutes. Please answer all questions in the survey. Should you have any questions on the study, do not hesitate to forward them to me at the address below:

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NEWCASTLE UNIVERSITY
NEWCASTLE UPON TYNE
UNITED KINGDOM
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FACULTY OF ECONOMIS AND MANAGEMENT,
UNIVERSITY PUTRA MALAYSIA
43400, SERDANG, SELANGOR
MALAYSIA
Email: w_norhidayah@upm.edu.my

Thank you in advance for your help and cooperation

Part A: Travel Information

1. Have you previously visited Kenyir Lake?

   a) No, this is my first time. ☐

   b) Yes, I have visited Kenyir Lake _____ times in the last 5 years, including this trip. ☐

2. In what type of group are you visiting Kenyir Lake?

   a) I am alone ☐

   b) Family: _______people ☐

   c) Friend: _________people ☐

   d) Group/Club established: _______people ☐

3. What is the main purpose of your visit to Kenyir Lake?

   a) Vacation/recreation ☐

   b) Work/ Business trip ☐

   c) Educational visit ☐

   d) Others ☐
   Please specify: _______________

4. How far is your residence from Kenyir Lake? __________KM

5. Are you staying overnight?

   a) Yes ☐

   b) No ☐

6. If you are staying overnight, how many days you intend staying here? _____Days

7. If you are staying overnight, where are you staying?

a) Camping site ☐

b) Staying in house boat ☐

c) Staying in resort/hotel/chalet ☐

8. Are you likely to re-visit Kenyir Lake in the next 5 years?

a) Yes ☐ b) No ☐

Part B: Attitudes and Perceptions towards Kenyir Lake

9. Please indicate whether you strongly agree, agree, neutral, disagree, or you strongly disagree, with each statement below (Please choose one by checking √ in the appropriate box)

5 = Strongly agree
4 = Agree
3 = Neutral
2 = Disagree
1 = Strongly disagree

Resource	**5**	**4**	**3**	**2**	**1**
a. Kenyir Lake provides an attractive natural environment for recreation					
b. Kenyir Lake serves as an important water catchment area					
c. Kenyir Lake serves as a home for wildlife habitats					
d. The species of fish should be protected so they will not become extinct in the future					

10. Using the scale given, what do you think about the quality of your experience of these activities? (Please choose one by checking √ in the appropriate box)

5 = Very satisfied
4 = Satisfied
3 = Neither
2 = Dissatisfied
1 = Very dissatisfied

Interesting Activities	**5**	**4**	**3**	**2**	**1**	**Not taken**
a. Fishing						
b. Visiting waterfall area						
c. Staying in House boat						
d. Watersport activities						
e. Camping and jungle trekking						
f. Visiting Kelah Sanctuary						
g. Visiting parks and gardens						
h. Visiting caves						

11. Using the scale given, what do you think about the quality of the facilities at Gawi Jetty? (Please choose one by checking √ in the appropriate box)

5 = Excellent
4 = Good
3 = Average
2 = Poor
1 = Very poor

Facilities	**5**	**4**	**3**	**2**	**1**
a. Toilet					
b. Jetty					
c. Car Park					
d. Tourist Information Centre					
e. Children’s Playground					

Part C: Choice Experiment

Gawi Jetty provides a variety of tourism facilities and services. It is important that the facilities here satisfy visitors' needs. In order to satisfy visitors' requirements, the authorities need to take into consideration their preferences for facilities.

Tourism Facilities Attributes

Toilet

Toilets are an important facility. Toilet services should address the needs of visitors, both in terms of availability and accessibility. Furthermore, variety in the range of provision will assist not only visitors with a disability but also benefit elderly, those with babies or young children. Three levels are assigned for this attributes:

Basic: 10 toilets + 2 disabled toilets.
Medium: Basic + bathrooms.
Superior: Medium + Babies' changing rooms.

Jetty

The current size of the jetty is too small and creates a crowded situation where visitors need to join a long queue while waiting for the boats, especially during peak season. The small size of the jetty makes it quite dangerous, especially for those who bring small children. Therefore, it is worth having another jetty that can separate the visitors into small groups. There are two levels assigned:

One: The current small jetty where the speed boats and houseboats load and unload passengers.
Two: One jetty for speedboats and another one for the houseboats to load and unload passengers.

Car Park

Parking may be severely inadequate at any tourism site, an especially site that received an increasing number of visitors every year. There is only a small car park located at the jetty with a limited number of the parking slots. Adding more slots to the car park can provide more convenience for the visitors because they can simply park their car at a safe place. Two levels are assigned for this attributes:

30 slots	The current slots are limited and cannot accommodate the increasing numbers of visitors' cars.
100 slots	Adding more slots can reduce the congestion problem, and visitors do not have to wait or queue to get space.

Tourist Information Centre (TIC)

The main function of the Tourist Information Centre is to ensure that the tourists get the latest information on the tourism offers and hence are able to optimize their knowledge and experiences while enjoying their trip. However, the TIC here is not functioning well due to the unattractive facilities offered. There are three levels assigned for this attribute:

Basic: Brochures, pamphlets and information boards.
Medium: Basic + video presentation.
Superior: Medium + tourist information counsellor.

Children's Playground

Providing a safe and stimulating children's playground could add more attraction for the visitors to come. Two levels are assigned for this attributes:

Small: The playground is small, old and limited in equipment.
Large: A large playground with a new equipment can provide a plenty of space for children to play.

Entrance Fee

Entrance fee is the money that visitors need to pay (per person) when they enter this lake. This fee is going to be used for the provision and maintenance of the facilities provided at the jetty.

RM 0:	Currently there is no charge for entrance fee
RM 1:	Entrance fee amount is RM1
RM 2.5:	Entrance fee amount is RM2.50
RM 5:	Entrance fee amount is RM5
RM 7.50:	Entrance fee amount is RM7.50
RM10:	Entrance fee amount is RM10

Current Situation

Toilet	**:** Basic
Jetty	**:** One
Car Park	**:** 30 slots
Tourist Information Centre (TIC)	**:** Basic
Children's Playground	**:** Small
Entrance Fee	**:** RM 0

For question 12 to 17, you will be required to **CHOOSE ONE** of three options, according to your preferences. If you choose the current situation box, it means that you prefer current conditions to continue with no extra cost to you but the quality of tourism facilities will not be improved.

Example

An example of a choice card is presented below. Two possible development options for the tourism facilities at Gawi Jetty are presented. If you would like to see an additional jetty, more car parking slots, and superior toilets, but you are happy with the basic Tourist Information Centre and a small children's play area and are willing to pay an entrance fee of RM 10 per person, you should choose Option 1.

If you would like to see a large children's play area, superior Tourist Information Centre, an additional jetty, more car parking slots, but you are happy with the existing toilet conditions, and are willing to pay an entrance fee of RM 7.50 per person, then you should choose Option 2.

Alternatively, if you are happy with the current situation at Gawi Jetty or you do not want to pay an entrance fee then you should choose the Current situation option.

Please tick √ which option you prefer.

Facilities	**Option 1**	**Option 2**	**Current Situation**
Toilet	Superior	Basic	Basic
Jetty	Two	Two	One
Car Park	100 slots	100 slots	30 slots
Tourist Information Centre	Basic	Superior	Basic
Children's Playground	Small	Large	Small
Entrance Fee	RM 10	RM 7.50	RM 0
YOUR OPTION	√		

12. If these are the only possible options for the tourism facilities provided in Gawi Jetty, which option would you like to choose? Please choose one option only.

Facilities	Option 1	Option 2	Current situation

13. If these are the only possible options for the tourism facilities provided in Gawi Jetty, which option would you like to choose? Please choose one option only.

Facilities	Option 1	Option 2	Current situation

14. If these are the only possible options for the tourism facilities provided in Gawi Jetty, which option would you like to choose? Please choose one option only.

Facilities	Option 1	Option 2	Current situation

15. If these are the only possible options for the tourism facilities provided in Gawi Jetty, which option would you like to choose? Please choose one option only.

Facilities	Option 1	Option 2	Current situation

16. If these are the only possible options for the tourism facilities provided in Gawi Jetty, which option would you like to choose? Please choose one option only.

Facilities	Option 1	Option 2	Current situation

17. If these are the only possible options for the tourism facilities provided in Gawi Jetty, which option would you like to choose? Please choose one option only.

Facilities	Option 1	Option 2	Current situation

18. Thinking about the choice cards, please indicate which of the following statements was the most applicable to your responses across the choice cards. Please tick only one answer.

Q	Reason	Tick
1	It was difficult to make a choice because there were three alternatives.	
2	I chose the current situation because I do not want to pay an entrance fee.	
3	Choice was difficult because there were 6 attributes to consider.	
4	Choosing the current situation was easy and it meant I did not have to weigh up the benefits of the other two alternative options.	

For the following questions, please choose one by checking √ in the appropriate box.

19. Toilet

a. Did you ignore this attribute because it is not important to you? ☐
b. Did you put less emphasis on this attribute because there were more important attributes in the choice set? ☐
c. Did you give the same weight as all the other attributes in reaching your choice? ☐
d. Did you put more emphasis on this attribute because it is more important than other attributes? ☐

20. Jetty

a. Did you ignore this attribute because it is not important to you? ☐
b. Did you put less emphasis on this attribute because there were more important attributes in the choice set? ☐
c. Did you give the same weight as all the other attributes in reaching your choice? ☐
d. Did you put more emphasis on this attribute because it is more important than other attributes? ☐

21. Car Park

a. Did you ignore this attribute because it is not important to you? ☐
b. Did you put less emphasis on this attribute because there were more important attributes in the choice set? ☐
b. Did you give the same weight as all the other attributes in reaching your choice? ☐
c. Did you put more emphasis on this attribute because it is more important than other attributes? ☐

22. Tourist Information Centre

a. Did you ignore this attribute because it is not important to you?
b. Did you put less emphasis on this attribute because there were more important attributes in the choice set?
c. Did you give the same weight as all the other attributes in reaching your choice?
d. Did you put more emphasis on this attribute because it is more important than other attributes?

23. Children's Playground

a. Did you ignore this attribute because it is not important to you?
b. Did you put less emphasis on this attribute because there were more important attributes in the choice set?
c. Did you give the same weight as all the other attributes in reaching your choice?
d. Did you put more emphasis on this attribute because it is more important than other attributes?

24. Entrance Fee

a. Did you ignore this attribute because it is not important to you?
b. Did you put less emphasis on this attribute because there were more important attributes in the choice set?
c. Did you give the same weight as all the other attributes in reaching your choice?
d. Did you put more emphasis on this attribute because it is more important than other attributes?

Part D: Background Information

25. Gender

a) Male

b) Female

26. To which age group do you belong to?

a) 18 – 24

b) 25 - 34

c) 35 - 44

d) 45 - 54

e) 54 and above

27. Nationality

a) Malaysia b) Foreign

28. Highest level of education:

a) Primary School d) Diploma

b) Secondary School e) Undergraduate

c) Pre-university f) Postgraduate

29. Occupation:

a) Professional & technician e) Business

b) Administration & management f) Student

c) Services industry g) Housewife

d) Sales h) Retired

30. Numbers of People in your Household: ……………

31. Monthly Gross Household Income in Ringgit Malaysia (RM):

a) Less than 1000

b) 1001 to 2000

c) 2001 to 3000

d) 3001 to 4000

e) More than 4001

Appendix C: Forced Questionnaire

UNIVERSITY OF NEWCASTLE

TOURISM FACILITIES SURVEY MALAYSIA

UPM UNIVERSITI PUTRA MALAYSIA

(photo: www.holidaygogo.com/lake-kenyir-terengganu)

Greetings and welcome to Kenyir Lake, Terengganu. My name is Wan Norhidayah W Mohamad. I am a PhD student at Newcastle University, United Kingdom, and a staff member at the University Putra Malaysia. Currently I am conducting a survey regarding tourists' preferences for tourism facilities provided at Gawi Jetty, Kenyir Lake. This survey is part of my PhD research project. Your opinion is important and results obtained from this research project will contribute towards the management of the tourism facilities here. **Please be assured that the information you provided is strictly confidential and will ONLY be used for the study.** The survey will be conducted by an interviewer and will take about 20 minutes. Please answer all questions in the survey. Should you have any questions on the study, do not hesitate to forward them to me at the address below:

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FACULTY OF ECONOMIS AND MANAGEMENT,
UNIVERSITY PUTRA MALAYSIA
43400, SERDANG, SELANGOR
MALAYSIA
Email: w_norhidayah@upm.edu.my

Thank you in advance for your help and cooperation

Part A: Travel Information

1. Have you previously visited Kenyir Lake?

   a) No, this is my first time. ☐

   b) Yes, I have visited Kenyir Lake _____ times in the last 5 years, including this trip. ☐

2. In what type of group that you visiting Kenyir Lake?

   a) I am alone ☐

   b) Family: _______people ☐

   c) Friend: _________people ☐

   d) Group/Club established: _______people ☐

3. What is the main purpose of your visit to Kenyir Lake?

   a) Vacation/recreation ☐

   b) Work/ Business trip ☐

   c) Educational visit ☐

   d) Others ☐
   Please specify: _______________

4. How far is your residence from Kenyir Lake? __________KM

5. Are you staying overnight?

   a) Yes ☐

   b) No ☐

6. If you are staying overnight, how many days you intend staying here? _____Days

7. If you are staying overnight, where are you staying?

   a) Camping site ☐

   b) Staying in house boat ☐

   c) Staying in resort/hotel/chalet ☐

8. Are you likely to re-visit Kenyir Lake in the next 5 years?

a) Yes ☐ b) No ☐

Part B: Attitudes and Perceptions towards Kenyir Lake

9. Please indicate whether you strongly agree, agree, neutral, disagree, or you strongly disagree, with each statement below (Please choose one by checking √ in the appropriate box)

5 = Strongly Agree
4 = Agree
3 = Neutral
2 = Disagree
1 = Strongly disagree

Resource	**5**	**4**	**3**	**2**	**1**
a. Kenyir Lake provides an attractive natural environment for recreation					
b. Kenyir Lake serves as an important water catchment area					
c. Kenyir Lake serves as a home for wildlife habitats					
d. The species of fish should be protected so they will not become extinct in the future					

10. Using the scale given, what do you think about the quality of your experience of these activities? (Please choose one by checking √ in the appropriate box)

5 = Very satisfied
4 = Satisfied
3 = Neither
2 = Dissatisfied
1 = Very dissatisfied

Interesting Activities	**5**	**4**	**3**	**2**	**1**	**Not taken**
a. Fishing						
b. Visiting waterfall area						
c. Staying in House boat						
d. Watersport activities						
e. Camping and jungle trekking						
f. Visiting Kelah Sanctuary						
g. Visiting parks and gardens						
h. Visiting caves						

11. Using the scale given, what do you think about the quality of the facilities at Gawi Jetty? (Please choose one by checking √ in the appropriate box)

5 = Excellent
4 = Good
3 = Average
2 = Poor
1 = Very poor

Facilities	**5**	**4**	**3**	**2**	**1**
a. Toilet					
b. Jetty					
c. Car Park					
d. Tourist Information Centre					
e. Children's Playground					

Part C: Choice Experiment

Gawi Jetty provides a variety of tourism facilities and services. It is important that the facilities here satisfy visitors' needs. In order to satisfy visitors' requirements, the authorities need to take into consideration their preferences for facilities.

Tourism Facilities Attributes

Toilet

Toilets are an important facility. Toilet services should address the needs of visitors, both in terms of availability and accessibility. Furthermore, variety in the range of provision will assist not only visitors with a disability but also benefit elderly, those with babies or young children. Three levels are assigned for this attributes:

Basic: 10 toilets + 2 disabled toilets
Medium: Basic + bathrooms
Superior: Medium + Babies' changing rooms

Jetty

The current size of the jetty is too small and creates a crowded situation where visitors need to join a long queue while waiting for the boats, especially during peak season. The small size of the jetty makes it quite dangerous, especially for those who bring small children. Therefore, it is worth having another jetty that can separate the visitors into small groups. There are two levels assigned:

One: The current small jetty where the speed boats and houseboats load and unload passengers.
Two: One jetty for speedboats and another one for the houseboats to load and unload passengers

Car Park

Parking may be severely inadequate at any tourism site, an especially site that received an increasing number of visitors every year. There is only a small car park located at the jetty with a limited number of parking slots. Adding more slots to the car park can provide more convenience for the visitors because they can simply park their car at a safe place. Two levels are assigned for this attributes:

30 slots	The current slots are limited and cannot accommodate the increasing numbers of visitors' cars.
100 slots	Adding more slots can reduce the congestion problem, and visitors do not have to wait or queue to get space.

Tourist Information Centre (TIC)

The main function of The Tourist Information Centre is to ensure that the tourists get the latest information on the tourism offer and hence, aid them to optimize their knowledge and experiences while enjoying their trip. However, the TIC here is not functioning well due to the unattractive facilities offered. There are three levels assigned for this attribute:

Basic: Brochures, pamphlets and information boards.
Medium: Basic + video presentation.
Superior: Medium + tourist information counsellor.

Children's Playground

Providing a safe and stimulating children's playground could add more attraction for the visitors to come. Two levels are assigned for this attributes which are:

Small: The playground is small, old and limited in equipment.
Large: A large playground with a new equipment can provide a plenty of space for children to play.

Entrance Fee

Entrance fee is the money that visitors need to pay when they enter this lake. This fee is going to be used for the provision and maintenance of the facilities provided at the jetty.

RM 0:	Currently there is no charge for entrance fee
RM 1:	Entrance fee amount is RM1
RM 2.5:	Entrance fee amount is RM2.50
RM 5:	Entrance fee amount is RM5
RM 7.50:	Entrance fee amount is RM7.50
RM10:	Entrance fee amount is RM10

Current Situation

Toilet	**:** Basic
Jetty	**:** One
Car Park	**:** 30 slots
Tourist Information Centre (TIC)	**:** Basic
Children's Playground	**:** Small
Entrance Fee	**:** RM 0

For question 12 to 17, you will be required to **CHOOSE ONE** of two options, according to your preferences.

Example

An example of a choice card is presented below. Two possible development options for the tourism facilities at Gawi Jetty are presented. If you would like to see an additional jetty, more car parking slots, and superior toilets, but you are happy with the basic Tourist Information Centre and a small children's play area, and are willing to pay an entrance fee of RM 10 per person you should choose Option 1.

If you would like to see a large children's play area, superior Tourist Information Centre, an additional jetty, more car parking slots, but you are happy with the existing toilet conditions, and are willing to pay an entrance fee of RM 7.50 per person, then you should choose Option 2.

Please tick √ which option you prefer.

Facilities	Option 1	Option 2
Toilet	Superior	Basic
Jetty	Two	Two
Car Park	100 slots	100 slots
Tourist Information Centre	Basic	Superior
Children's Playground	Small	Large
Entrance Fee	RM 10	RM 7.50
YOUR OPTION	√	

12. If these are the only possible options for the tourism facilities provided in Gawi Jetty, which option would you like to choose? Please choose one option only.

Facilities	**Option 1**	**Option 2**

13. If these are the only possible options for the tourism facilities provided in Gawi Jetty, which option would you like to choose? Please choose one option only.

Facilities	**Option 1**	**Option 2**

14. If these are the only possible options for the tourism facilities provided in Gawi Jetty, which option would you like to choose? Please choose one option only.

Facilities	**Option 1**	**Option 2**

15. If these are the only possible options for the tourism facilities provided in Gawi Jetty, which option would you like to choose? Please choose one option only.

Facilities	**Option 1**	**Option 2**

16. If these are the only possible options for the tourism facilities provided in Gawi Jetty, which option would you like to choose? Please choose one option only.

Facilities	**Option 1**	**Option 2**

17. If these are the only possible options for the tourism facilities provided in Gawi Jetty, which option would you like to choose? Please choose one option only.

Facilities	**Option 1**	**Option 2**

18. Thinking about the choice cards, please indicate which of the following statements was the most applicable to your responses across the choice cards. Please tick only one answer.

Q	Reason	Tick
1	It was easy to make a choice because there were only two alternatives.	
2	I tended to choose the option with the lowest price increase because there was no option to choose the current situation where there is no entrance fee.	
3	Choice was difficult because there were 6 attributes to consider.	
4	I felt forced to make a choice between Option 1 and Option 2 because I could not vote for "no change".	

For the following questions, please choose one by checking √ in the appropriate box.

19. Toilet

a. Did you ignore this attribute because it is not important to you? ☐
b. Did you put less emphasis on this attribute because there were more important attributes in the choice set? ☐
c. Did you give the same weight as all the other attributes in reaching your choice? ☐
d. Did you put more emphasis on this attribute because it is more important than other attributes? ☐

20. Jetty

a. Did you ignore this attribute because it is not important to you? ☐
b. Did you put less emphasis on this attribute because there were more important attributes in the choice set? ☐
c. Did you give the same weight as all the other attributes in reaching your choice? ☐
d. Did you put more emphasis on this attribute because it is more important than other attributes? ☐

21. Car Park

a. Did you ignore this attribute because it is not important to you? ☐
b. Did you put less emphasis on this attribute because there were more important attributes in the choice set? ☐
c. Did you give the same weight as all the other attributes in reaching your choice? ☐
d. Did you put more emphasis on this attribute because it is more important than other attributes? ☐

22. Tourist Information Centre

a. Did you ignore this attribute because it is not important to you?
b. Did you put less emphasis on this attribute because there were more important attributes in the choice set?
c. Did you give the same weight as all the other attributes in reaching your choice?
d. Did you put more emphasis on this attribute because it is more important than other attributes?

23. Children's Playground

a. Did you ignore this attribute because it is not important to you?
b. Did you put less emphasis on this attribute because there were more important attributes in the choice set?
c. Did you give the same weight as all the other attributes in reaching your choice?
d. Did you put more emphasis on this attribute because it is more important than other attributes?

24. Entrance Fee

a. Did you ignore this attribute because it is not important to you?
b. Did you put less emphasis on this attribute because there were more important attributes in the choice set?
c. Did you give the same weight as all the other attributes in reaching your choice?
d. Did you put more emphasis on this attribute because it is more important than other attributes?

Part D: Background Information

25. Gender

a) Male

b) Female

26. To which age group do you belong to?

a) 18 – 24

b) 25 - 34

c) 35 - 44

d) 45 - 54

e) 54 and above ☐

27. Nationality

a) Malaysia ☐ b) Foreign ☐

28. Highest level of education:

a) Primary School ☐ d) Diploma ☐

b) Secondary School ☐ e) Undergraduate ☐

c) Pre-university ☐ f) Postgraduate ☐

29. Occupation:

a) Professional & technician ☐ e) Business ☐

b) Administration & management ☐ f) Student ☐

c) Services industry ☐ g) Housewife ☐

d) Sales ☐ h) Retired ☐

30. Numbers of Members in your Household: ……………

31. Monthly Gross Household Income in Ringgit Malaysia (RM):

a) Less than 1000 ☐

b) 1001 to 2000 ☐

c) 2001 to 3000 ☐

d) 3001 to 4000 ☐

e) More than 4001 ☐