Advances in Social Sciences Research Journal – Vol. 12, No. 06
Publication Date: June 10, 2025
DOI:10.14738/assrj.1206.18923.
Mohamad, W. N. W., Lee, Y., & Kong, S. (2025). The Effects of Attribute Non-Attendance on Willingness to Pay Estimates in Choice Experiments: Evidence from Visitors Preferences for Tourism Facilities Attributes in Kenyir Lake, Malaysia. *Advances in Social Sciences Research Journal*, 12(06). 102-119.

The Effects of Attribute Non-Attendance on Willingness to Pay Estimates in Choice Experiments: Evidence from Visitors Preferences for Tourism Facilities Attributes in Kenyir Lake, Malaysia

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ABSTRACT

An extensive literature of Choice Experiments (CE) has recognized that it is usual, especially where there are many attributes, for a person to ignore one or more attributes in the alternatives presented on the CE choice cards for many reasons. Yet, there is evidence that persons who declared they have neglected or ignored certain attributes might actually have given them lesser or lower importance. Stemming from this evidence and given the significant implication of not accounting for attribute non-attendance (ANA) in welfare estimates, we apply a supplement question in ANA to investigate how respondents pay attention to the attributes. Different techniques for modelling ANA in a case study investigating preferences of the visitors for the tourist facilities attributes in Malaysia are then compared. A conditional logit (CL) models analysis reveals different willingness-to-pay (WTP) estimates after accounting for ANA, suggesting the importance of considering ANA in the analysis and considering the appropriate method to deal with it. The results also reveal that different categories of visitors influenced the exclusion of a specific attribute. This information provides hints to the policy maker in understanding potentially conflicting preferences between different types of visitors which is useful for the sustainability of the tourism sector in the future.

Keywords: attribute non-attendance, choice experiments, conditional logit model, sustainability, willingness to pay.

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INTRODUCTION

Choice experiments (CE), or conjoint analysis as it is also known, are frequently applied by the researcher to estimate the consumer's value for a product including the value of non-market goods and services. The widespread use of the CE method has been found in various fields (e.g. economics, transport, environment and market research). In a nutshell, CE mimics purchasing decisions in the real world where the consumers have an abundance of choices based on a combination of different attributes and levels and they also have an option not to purchase. In CE consumers are asked to pick their most desired alternatives that will maximize their utility based on hypothetical product scenarios.

A typical assumption of CE is that when consumers are requested to pick their most favored alternative, they are expected to fully contemplate all presented attributes when making the trade-offs. Nevertheless, current research in the fields of transport economics [1-3], health economics [4-7], environmental economics [8-11] and food studies [12-19] have revealed that only a subgroup of the attributes is considered and traded off by individuals during the decision-making procedure. This situation suggests that some of the attributes presented in the CE choice cards are being discounted by the individuals. Consequently, the continuity axiom assumption, which is a basis of the theory in CE is violated.

According to Scarpa et al., (2009), ignoring attributes indicates a non-compensatory strategy on the basis that the given attribute level improvement is unsuccessful in compensating for the reductions of levels of other attributes. As a result, choices from non-compensatory strategies incapable of being represented as valid preferences over respondent's utility function and the accuracy of welfare estimates can be questioned [20]. Recently, a growing number of studies have explored how attribute non-attendance (ANA) has impacted on welfare estimation and how it could be accounted for in the analysis of CE [9,10,17,18,21,22].

Evidence of ANA leading to a decrease in welfare estimates has been found in various fields where CE are used, including environmental economics, health economics, food economics, etc [8,10,15,19,23]. Accounting for ANA has also proven to significantly increase the welfare estimates [22,24,25]. However, it is believed that studies which fail to consider whether individuals have ignored certain attributes when making their choices possibly will give biased welfare estimates. Consequently, this situation may lead to misrepresentative policy implications. If certain attribute levels have no meaning to the respondents, then the proposed improvement will give no benefit or utility to them. This is supported by numerous researchers [9,26,27,28,29].

In a nutshell, ANA can either be 1) stated ANA where individuals are questioned straight away if they discounted any attributes in the study, or, 2) inferred ANA, where the attributes that have been ignored by the individuals are calculated mathematically [30]. For the stated ANA, eliciting evidence can be conducted in two techniques, namely, at the choice task level or the serial level. For the choice task level, individuals are inquired to state any attributes they disregarded after each single choice card. Meanwhile, in the serial approach the questions of ANA are provided in the last part of the whole choice card. In contrast to the serial approach, the conditional logit (CL) model and mixed logit (MXL) model are typically applied in the stated approaches [11,18,19]. Meanwhile, the latent class models are typically used in the inferred approach. Each class in the inferred approach indicates a certain ANA decision rule and the

URL: http://dx.doi.org/10.14738/assrj.1206.18923

parameter for the ignored attributes has been set to zero. The goodness of inferred ANA method is that the supplementary question for ANA is not needed, and indeed which may not have been collected in final survey [31,32,33]. However, there is no clear 'winner' between these two methods as discovered by Scarpa et al. (2013) and Lew and Whitehead (2020) [34,35].

Interestingly, the respondents who declared that they have discounted few attributes may have assigned attributes as of lesser or lower importance as suggested by some scholars [19,36,37]. This finding has driven further investigations within this study to explore if respondents really ignored an attribute by presenting a new follow-up question to elicit ANA responses. Therefore, the first objective of this study is to examine the effect of attributing non-attendance on attribute values and willingness to pay approximations. The second objective of this study is to assess the preferences of the visitors for the tourist facilities service attributes, and subsequently initiate policy recommendations to policy makers that focus on the improvement of amenities and facilities at Kenyir Lake. This is useful for the sustainability of tourism in the future.

To deal with ANA, the coefficient of the attribute that has been ignored by each of the respondents is set to zero in the analysis following the literature [11,18,19]. This approach is called the conventional approach [13]. However, this standard method of dealing with ANA can be challenged. The method of letting the ignored attribute become zero in the analysis has been criticized in the literature because this approach may produce biased model estimates since the marginal utility of specific attribute has been set to zero [14,38]. In response to this, a study by Mohanty et al. (2019) used de-briefing data and implemented a shrinkage coefficient on each attribute compared to the model level [14]. Meanwhile, a study by Hindsley et al. (2020) applied a conventional approach and a validation approach to state ANA. In the validation approach, two parameters were estimated for each attribute used in the study. Specifically, the first parameter accounts for attended attributes and for the non-attended attribute, the coefficients are set to zero. Meanwhile the second parameters account for non-attended attributes and for the attended attribute, the coefficients are set to zero [22]. Moreover, a recent study conducted by Notaro et al. (2022) investigated the influence of ANA through providing respondents with two types of ANA questions, namely the first focusing on asking them which attributes they ignored while the second concentrated on which attributes they considered during their decision making [11].

In addition, to completely obey the consumer choice theory axiom in CE, it could be argued that we should only count those individuals who considered all the attributes in the analysis. As revealed by Lew and Whitehead (2020), when individuals who do not totally contemplate all the attributes that are incorporated in the model analysis, the WTP became approximately 100% higher [35]. Taking this into account, we estimate the model that completely obeys the axiom of consumer choice theory, and we compared it with the model (conventional) that follows the standard analysis of ANA in the literature. Our paper contributes significantly to the methodological discussion regarding the reliable estimation of preferences in CE by examining the ANA methodological issue in the context of tourism research. In addition, our paper adds to the limited amount of non-market valuation studies on tourist facilities in the context of developing countries by means of a CE.

MATERIALS AND METHODS

The empirical data used were based on CE that was constructed to elicit the choice and preferences of the visitors for improvements in tourist facilities provided at Gawi jetty, Kenyir Lake, Malaysia (see Figure 1). Apart from being the main entry point of Kenyir Lake, Gawi jetty also offers visitors with a number of basic facilities such as a jetty, toilets, car park, etc. Nevertheless, the facilities here are observed as inadequate and limited in their services and attractiveness. With no entrance fee being imposed to the visitors, this means that the provision and maintenance of the facilities provided here are solely dependent on government funding. However, the reliance on government funding is not essentially the greatest choice for the upcoming development of the tourism sector here. An alternative would be to consider imposing an entrance or admission fee. The collection of an entrance fee would be hypothecated to provide better facilities for visitors.

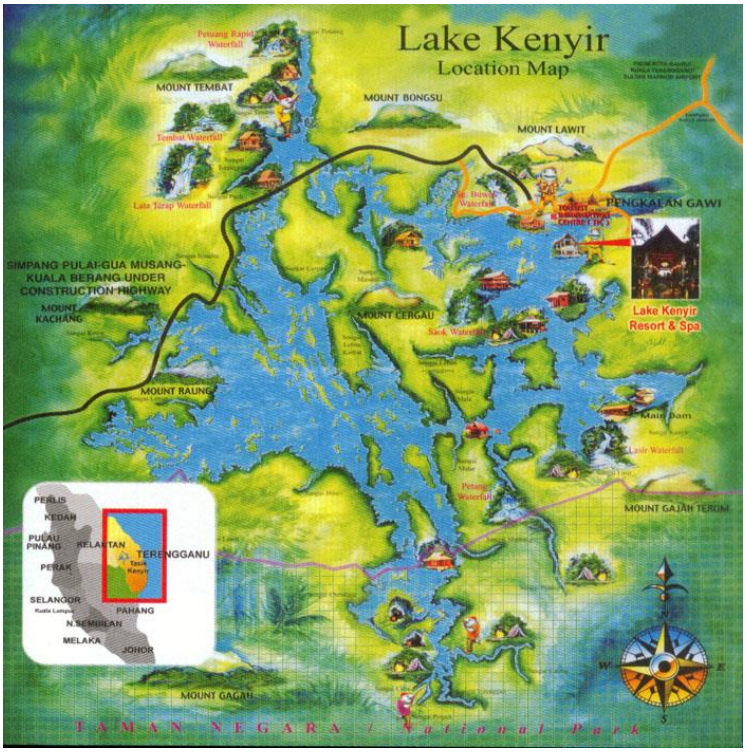

Figure 1: Kenyir lake location map.

Source:https://malaysiahoteldotcc.wordpress.com/2015/12/09/lake-kenyir-resort-taman-negara-lake-kenyir-terengganu-malaysia/[39]

An essential part of the choice experiment method involved the use of questionnaire survey with a total of thirty six choice cards, generated by the D-efficient experimental design of SAS. These thirty six choice cards were then disseminated into six different blocks whereby each respondent received 1 block with six choice cards. The lists of attributes and attributes levels selected in this research are shown in Table 1. There were five attributes used, each with different levels; toilet (3 levels), jetty (2 levels), car park (2 levels), tourist information center (3 levels), playground (2 levels) and entrance fee (6 levels). The attributes listed in Table 1 are significant facilities for visitors and relevant to the lake administration, as specified by respondents in the pilot test, stakeholders and members of focus groups. Specifically, two focus group meetings with volunteer visitors at Kenyir Lake were held to discuss the importance of

facilities at the lake. Besides that, an on-going online discussion and face-to-face interviews with responsible policy maker were held to discuss the attribute levels and improvements which were relevant to the management and policy of the lake, as well as to validate the attributes levels that suitable to be used in the final survey.

The entrance fee attribute, which became the payment vehicle was carefully chosen to allow welfare measures of changes in the improvement of facilities to be estimated. Visitors currently pay nothing as an entrance fee and five additional prices were offered, ranging from RM 2.50 to RM 10. It was explained to the visitors that the introduction of the entrance fee system will be utilized to funding the expansion in visitors facilities proposed in the CE choice alternatives. Figure 2 presents one of the examples of a CE choice card used in this study. It can be seen from Table 2 that there were two hypothetical options and one status quo. Respondents can choose any option that provides the highest utility for them.

To elicit the ANA information, we presents a new supplementary question on how respondents attended to each of the attributes used in the study; as a way of distinguishing between ignored and less important attributes. Previous studies simply asked individuals to express which attribute they ignored [11,13,19]. However, as revealed by Heidenreich et al. (2018) and Yin et al. (2022), persons who asserted to have neglected certain attributes may perhaps only assigned that attribute lesser or lower importance [19,37]. This assertion was basically based on the evidence that the greatest discounted attribute in the choice card located on the last ranking of preferences in the utility model estimation. Therefore, it appears insufficient to solely ask respondents whether some of the attributes has been ignored by them. Based on this issue, there is a need for further research to identify how respondents pay attention to the attributes. Hence, we present four different statements to reveal their attribute processing strategies in the study of tourism choices. These statements as below:

(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 to this attribute 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?

Option (a) was generated based on Carlsson et al. (2010) and Alemu et al. (2013)[28,40]. People may reveal that they have discounted a particular attribute just because the attribute did not give any positive or negative effect to their utility. They might also do not have a willingness to pay for the suggested improvement in that attribute[28]. Option (b) was based on two sources; the input from the focus groups meetings and also from the outcome by Hess and Hensher (2010), Quan et al. (2017) and Yin et al. (2022) [19,41,42]. They that claimed persons who asserted to have neglected certain attributes may perhaps only assigned that attributes lesser or lower importance. Meanwhile, option (c) and option (d) were chosen based on the inputs received during the focus group meetings. Using this structure, individuals have the freedom to set apart the attributes they discounted, and the attributes that were of lesser importance for them, during the decision making process.

Analysts have been discovering reasons as to why people employ attribute processing strategies [40]. One factor is related to the socioeconomic backgrounds of the individuals; this influences the inclusion or exclusion of specific attributes during the decision-making process [28,43]. Thus, a cross-tabulation analysis can be conducted for the attribute responses and socioeconomic information of the individuals for the attribute. By conducting this analysis, we are able to examine the impact of the characteristics of individuals towards the attribute responses.

Face-to-face interviews with the visitors were conducted on-site started from the second week of March 2016 to May 2016. The simple random sampling was applied. In particular, the targeted visitors were those who aged eighteen years old and above, who showed up at the Gawi jetty. It is worth highlighting here that as soon as the interview ended, the following visitors to pass was approached and interviewed. Hence, we systematically sampled the following person to pass to avoid any bias in the selection of respondents. To minimize refusal to participate and avoid sampling bias, we provided respondents with a token of RM10 if they willing to take part and contribute to the survey. The payment of this token was not to influence their answers, but to compensate the time they spent in answering all the questions.

Before the final survey, we also conduct a pilot survey during the first week of March 2016, comprising 48 responses. The purposes of this pilot survey were to estimate the average time taken by each participant to answer all the questions, check the choice of wording, check whether the questionnaires are properly translated, understandable and also the clarity of questions. The results from pilot survey showed that all the attributes had a correct sign according to expectations.

Overall, 196 respondents were interviewed by the enumerators during the final survey. The number in the sample that had to be discarded because respondents failed to complete all parts in the questionnaire was 16 or 8.16%. Therefore, for the final sample we managed to collect 180 (91.84%) usable responses to be used in the analysis. Jones (1996) stated that in a real situation, the goal of a 80% to 90% useful response rate was very challenging to achieve[44]. Nevertheless, the total useful response rate in our study was more than 90%. Therefore, the proportion of non-responses was very small, and it was not expected to influence results. Following Pearmain et al.'s rule of thumb[45], a sample size of more than hundred can offer the basis for modelling choice data in a choice experiment. Thus, the sample size in our study is enough to provide reliable results.

Table 1: Attributes and levels used in the study.

Attribute	Level	Description
Toilet	Basic Medium Superior	Ten toilets and two disabled toilets are available Basic toilet services and add with bathrooms Medium toilet service and add with changing rooms for babies
Jetty	One Two	Only one small size jetty for the boats to load and unload visitors. One jetty specifically for speedboats and another one jetty specifically for the houseboats to load and unload visitors

Car Park	30 parking slots 100 parking slots	Limited parking slot, unable to cater the massive numbers of car at one time Adding more car park can cater to the massive numbers of car at one time
Tourist Information Center(TIC)	Basic Medium Superior	Pamphlets, brochure and information boards Basic TIC service and add with video presentation Medium TIC service and add tourist information counsellor
Playground	Small Large	Old and dangerous. The equipment is restricted and inadequate Providing new equipment can secure children's safety, as well as big space for them to enjoy their activities
Entrance Fee per person in Ringgit Malaysia	RM 0 (SQ) RM 1 ($0.23) RM 2.50 ($0.58) RM 5 ($1.16) RM 7.50 ($1.74) RM 10 ($2.33)	

Note: The word in italic is the status quo or current situation. USD ($)1 = RM 4.30 (in 2016).

Table 2: An example of CE choice card.

Facility	Choice A	Choice B	Status Quo
Jetty	One	Two	One
Toilet	Medium	Superior	Basic
Car Park	100 slots	30 slots	30 slots
Playground	Small	Large	Small
Tourist Information Center	Basic	Medium	Basic
Entrance Fee	RM 2.50	RM 5.00	RM 0
Your Option			

ECONOMETRIC SPECIFICATION

The commonly applied CL model can be used if it is expected to have independently and identically distributed (IID) error term with a Weibull distribution which implies that the error terms are logistically distributed [46]. It is also known as the Type I extreme value or Gumbel distribution. This model relays the choice probability among two or more hypothetical options to the attribute levels characteristics of the describing those options [47]. In a nutshell, the probability of choosing among two recreational parks is related to the characteristics of the attributes levels describing those parks. The attributes of the park are such accessibility, safety, recreational facilities and so on. Consumers will consider these characteristics during the decision making process before they decide to go to which park. A CL model is appropriate for our study when the choice among two or more alternatives option is established as a function of the characteristics of the alternatives.

The likelihood of individual n selects alternative i as follow:

$$P_{ni} = \frac{\exp(\mu V_{ni})}{\sum_{j}^{i} \exp(\mu V_{nj})} \quad (1)$$

where μ is the scale parameter and assumed to be equal to 1. By supposing that V_{ni} is linear in coefficients, the practical equation of the individual systematic component of the utility function can be expressed as follow:

$$V_{ni} = \beta_1 X_{ni} + \beta_2 X_{2ni} + \beta_3 X_{3ni} + \cdots \ldots \beta_k X_{kni} \quad (2)$$

where:

- X_s= variables in the utility function, and
- β_s = estimated parameters

If a sole vector of parametersβ_s that spread over to all the utility functions related to entirely of the alternatives is well-defined, the equation (1) can be modified equally:

$$P_{ni} = \frac{\exp(\beta' V_{ni})}{\sum_j^i \exp(\beta' V_{nj})} \quad (3)$$

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

The following step is used to approximate the choice probability and welfare measure by estimating the coefficient value of β in equation 3. The typical method to determine the value of β is through maximum likelihood (ML) procedure [48] as shown in equation 4 below:

$$LL = \sum_{n=1}^{N} \sum_{j=1}^{J} y_{ni} \log P_{ni} \quad (4)$$

where:

- LL = Log likelihood function
- y_{ni} = indicator variable defines as y_{ni} = 1 if respondent n chooses alternative i and zero otherwise

To account for ANA, we compare three different CL models. Model I is the model that does not account for ANA. Following Paffarini et al. (2021), Yin et al. (2022) and Notaro et al. (2022) [11,18,19], Model II takes account of ANA in the analysis by setting the discounted attributes parameters become zero. If a respondent n declares that he/she neglected an attribute i in the presented hypothetical situation, then in the utility function the attribute coefficient β_{ni} will be setting to equal zero. The last model which is Model III omits those individuals who discounted any attribute offered in the CE choice cards. The justification of Model III is based on the fundamental assumptions in discrete choice theory whereby respondents should consider all attributes and alternatives given to them. Hence, Model III only includes those respondents who fulfilled this fundamental assumption.

WTP values or implicit prices for attributes were then estimated by apportioning the non-price attribute parameter by the value of the cost attribute parameter [49]. Particularly, the WTP value specify how much people are willing to pay to get the advantage from the enhancement

of the attribute [50]. As shown in equation 5, the WTP for a unit change in non-price attribute i is equal to the negative of the ratio of i's β coefficient divided by the parameter of cost attribute β_{cost}. In our case, we use an entrance fee as a payment vehicle. The inclusion of price attribute is important in any CE research as it allows the estimation of WTP for the other non-price attribute [51].

$$WTP = -\frac{\beta_i}{\beta_{cost}} \quad (5)$$

RESULTS AND DISCUSSION

Descriptive Analysis

Table 3 presents the socio-demographic characteristics of respondents. Based on Table 3, the sample comprised of 61.7% male and 38.3% female respondents. Majority of the them fell into the 25-34 age group and the average age was 30 years old. Of the 180 respondents, 66.2% were 3 to 5 person households. Meanwhile, 6 to 8 person households and 2 person or fewer households were 28.8% and 4.4% respectively.

The proportion of households consisting of more than 8 individuals was 0.6%. Respondents mostly had attained a higher education qualification whereby the diploma holders account for 37.2% and an undergraduate and postgraduate degree account for 34.4% from the total respondents. Merely a very small percentage (3.4%) of respondents were households with a minimum primary education level. In conclusion, the majority of the visitors have a high level of education. As shown in Table 3, most of the respondents (68.9%) fell into the medium income category.

Table 3: Socio-demographic characteristics of respondents.

Characteristic	Frequency	Percent (%)	Mean	Standard Deviation
Gender				
Male	111	61.7		
Female	69	38.3		
Age (years)				
18-24	26	14.4		
25-34	73	40.6	30.4	9.2
35-44	51	28.3		
45-54	19	10.6		
55 and above	11	6.1		
Household Size (people)				
2 or fewer	8	4.4		
3-5	119	66.2	4.86	1.63
6-8	52	28.8		
> 8	1	0.6		
Education Level				
Primary school	6	3.4		
Secondary school	26	14.4		
Pre-University	19	10.6		
Diploma	67	37.2		

Undergraduate & Postgraduate	62	34.4		
Household Income (monthly)				
Low (RM 2000 and less)	19	10.5		
Medium (RM 2001 – RM 4000)	124	68.9	RM 3544	2502.14
High (more than RM 4001)	37	20.6		

Incidence of Stated ANA

For the attribute responses, we present a new follow-up question regarding how individuals respond to each of the attributes offered in the CE option card. By doing this, we can reveal which attributes respondents ignored the most and we can further examine the reasons related to this non-compensatory strategy. Table 4 presents responses towards attributes listed on the choice card. Based on Table 4, the most ignored attribute was the tourist information Centre (41.6%), followed by playground (15%) and jetty (1.7%). Most of the respondents revealed that they give the same weight as all the other attributes in reaching their choice for toilet (76.15), jetty (76.7%) and car park (86.1%) attributes. Meanwhile, more than half of the respondents put more emphasis on the fee attributes (51.1%) which denotes that they were concerned about the payment vehicle value.

Table 4: Responses towards attributes.

Response	Answer (%)					
	Toilet	**Jetty**	**Car Park**	**TIC**	**Playground**	**Fee**
(a) Did you ignore this attribute because it is not important to you?	-	1.7	-	41.6	15	0.6
(b) 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
(c) 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
(d) 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

Choice Experiment Results

Simple Conditional Logit Model:

We estimated and compared three different CL models (Table 5) to account for ANA using NLOGIT 4 software.

- Model I: the parameters of the attributes were not restricted.
- Model II: the parameters of the ignored attributes were restricted to zero.
- Model III: omitted the individuals who ignored any attribute offered in the choice cards.

Model I is discussed as a reference point and compared to Model II and Model III. Based on Table 5, all models were statistically significant. Model I, II and III were statistically significant

with the χ2 statistics of 509.91, 507.32 and 288.78 respectively, against a critical value 15.507 (with 8 degrees of freedom at alpha level 0.05). It is worth mentioning here that we dropped the status quo attribute for simplicity since our focus is on the ANA issue. We also want to avoid dummy variable traps if all dummy variables are used in data regression.

The goodness-of-fits of Model I and Model II were comparable; however, the goodness-of-fits of Model III was slightly lower than Model I and Model II. In contrast to the finding of Kosenius (2013) and Rose et al. (2012) [25,52], including ANA into the analysis did not increase the performance of the assessed model. Comparison of the results achieved between Model II which is the standard model of dealing with ANA, and Model I, which is the benchmark model reveals that TIC3 becomes insignificant in Model II, in contrast to being significant at 1% level in Model I. This result can be linked with the attribute responses presented in Table 4 whereby the TIC attribute was mostly ignored by many of the respondents. In other words, many respondents did not care about the TIC attribute and this behavior led to the insignificant coefficient estimate of the TIC attribute in Model II.

Model III was used to account for the respondents who attended to all the attributes presented in the CE choice sets. All attributes were significant at least at 5% level in Model III, except for the TIC2 attribute. Surprisingly, this result reveals that even when the individuals stated they considered all presented attributes in Model III, it does not reflect that they essentially prefer all attributes. Nor does it not mean that all attributes in the study will be statistically significant even when the individual stated they considered everything given on the choice cards.

The analysis in Model II and Model III involved different techniques for dealing with ANA. Therefore, the comparison between these two models is considered interesting. Though the technique used in Model II is widely used in literature, several scholars [37,41,42,53] argued about the relevancy of this technique to account for ANA in CE. Thus, it is worth comparing Model II and Model III to see whether these models produce different outcomes. The result from Table 5 shows that TIC3 becomes significant in Model III in comparison to being insignificant in Model II. The size of the coefficients is also smaller in Model III in comparison to Model II for most of the significant variables.

Table 5: Parameter estimate from the simple conditional logit models with different specifications for the ANA issue.

Attribute	Simple Conditional Logit					
	Model I		Model II		Model III	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Toilet2	1.059	9.536***	1.117	10.16***	0.929	6.33***
Toilet3	1.749	13.698***	1.794	14.19***	1.479	9.13***
Jetty2	1.216	13.394***	1.241	13.76***	1.015	8.53***
CarP100	1.251	12.680***	1.264	13.20***	1.135	8.93***
TIC2	-0.035	-0.315	-0.071	-0.50	0.09	0.60
TIC3	0.236	2.181**	0.075	0.54	0.287	1.96**
PlayG2	0.318	3.633***	0.275	2.94***	0.270	2.26**
Fee	-0.252	-12.978***	-0.248	-13.06***	-0.268	10.67***
Summary Statistics						

Log-likelihood function: LL(βb)	-716.582	-717.87	-422.17
Log-likelihood: LL(β0)	-971.537	-971.53	-566.56
Pseudo-R2	0.262	0.261	0.25
Adjusted Pseudo-R2	0.26	0.26	0.24
Number of observations	1080	1080	588

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

Model I: parameters of the attributes were not restricted.
Model II: ignored attributes parameters become 0.
Model III: omitted the individuals who ignored any attribute offered in the choice cards.

Estimation of Willingness-to-pay Values

Table 6 presents the WTP values from the CL models. The Delta method in NLOGIT 4 was used to estimate all these WTP values. Referring to Table 6, the comparison between the willingness to pay estimates from Model I, Model II and Model III exposes that the individuals exhibit the similar significance level of WTP estimates. In details, the highest WTP value was Toilet3, and this is followed by CarP100 and Jetty2 attributes. Moreover, the WTP values for all the similar significant attributes in both Model I and Model II are relatively equivalent and their confidence intervals values are overlap. Implicit prices that overlap with the confidence intervals are supposed to be alike [54]. However, accounting for ANA reveal that one attribute turns out to be insignificant; the respondents in Model II were unwilling to pay for the TIC3 attribute since this attribute was not significant in comparison to being significant at 5% level in Model I. Meanwhile, the comparison between the results in Model I and Model III revealed that the WTP values are higher in Model I compared to Model III and some of the WTP values do not overlap. Overall, accounting for ANA either by using Model II or Model III significantly affects the WTP estimate.

Meanwhile, the comparison between Model II and Model III reveals that the WTP values are much lower in Model III compared to Model II for all the significant attributes. For example, the WTP values of the Toilet3 attribute in Model II and Model III were RM 7.22 and RM 5.51 respectively. The difference between these two WTP values was large; RM 7.22 - RM 5.51 = RM 1.71. Also, the WTP values of most of the attributes in Model II and Model III do not significantly overlap. Overall, the evidence recommends that there is a significant difference between accounting for stated ANA by confining the coefficient of the ignored attribute to zero and accounting for stated ANA by excluding all the individuals who ignored any of the attributes from the analysis.

Table 6: WTP estimates (in RM) from the conditional logit models.

Attribute	**Model I**			**Model II**			**Model III**		
	WTP (t-stat)	**95% confidence intervals**		**WTP (t-stat)**	**95% confidence intervals**		**WTP (t-stat)**	**95% confidence intervals**	
Toilet2	4.19 (8.56***)	3.23	5.15	4.49 (9.16***)	3.53	5.45	3.46 (5.75***)	2.28	4.64
Toilet3	6.93 (12.69***)	5.86	7.99	7.22 (13.02***)	6.14	8.31	5.51 (8.65***)	4.26	6.76
Jetty2	4.81	4.09	5.53	5.00	4.26	5.73	3.78	2.96	4.60

	(13.15***)			(13.35***)			(9.02***)		
CarP100	4.95 (13.9***)	4.25	5.65	5.09 (14.05***)	4.38	5.8	4.23 (9.72***)	3.4	5.08
TIC2	-0.14 (-0.317)	-	-	-0.288 (-0.504)	-	-	0.33 (0.60)	-	-
TIC3	0.93 (2.17**)	0.09	1.78	0.304 (0.546)	-	-	1.07 (1.97**)	0.01	2.13
PlayG2	1.25 (3.73***)	0.59	1.92	1.108 (2.996***)	0.38	1.83	1.01 (2.34**)	0.16	1.85

Notes: ***significant at 1%, **significant at 5% and *significant at 10%; t-statistics are in brackets. $1 = RM 4.30 (2016).

CONCLUSION AND FUTURE DIRECTION

This study contributes to the increasing interest in CE studies of the issue of heuristic rules [13,15,37,55] mainly ANA by presenting a new follow-up question to judge the validity of ANA responses. The study compares two methods of dealing with ANA; firstly, by confining the coefficients of the attributes that have been ignored to be equal to zero and secondly, by dropping the individuals who do not fully consider all presented attributes in the CE choice cards.

Overall, accounting for ANA impacts on welfare estimates, our results are in line with the previous research such as Scarpa et al. (2010), Kosenius (2013) and Lagarde (2013) [25,56,57]. Thus, not accounting for ANA may lead to bias WTP results. Since the results from valuation studies are commonly used to formulate and design management plans by policy makers, it is crucial to examine the factors that could affect the consistency and reliability of the estimates, such as ANA. It has been suggested by a few scholars such as Hess (2014) and Yin et al. (2022) that individuals may actually just place less weight on the 'ignored attribute' rather than completely ignoring it, and the results of this study confirm this [19,41]. Based on the attribute responses analysis presented in Table 4, those individuals who declared that they ignored certain attributes on the choice card can indeed be identified as genuine and differentiated from those who consciously stated that they put less emphasis on certain attributes.

A comparison between the ordinary approach of accounting for ANA by confining the disregarded attribute to zero and dropping those individuals who do not completely contemplate all attributes, reveals a significant dissimilarity in WTP estimates in CL models. To our knowledge, there is no research on the effect of deleting irrational responses such as lexicographic preferences or ANA in CE analysis. This might be because the exclusion of respondents also removes other possible factors affecting the coefficient and WTP estimates; not only ANA [58]. However, we do not find evidence that those respondents who considered all attributes and those respondents who were dropped from the data because of ANA were different in terms of socio-demographic characteristics based on the hypothesis test for the difference between two sample proportions. Therefore, we suggest that future studies should consider Model III when accounting for the ANA in a CE analysis. The justification is that Model III only includes respondents who make trade-off between all attributes presented on the choice card. This follows the continuity axiom assumption that is the basis of the theory in CE. Overall, it is important to account for ANA in CE. Our findings add to the methodological discussion in CE by examining the ANA issue in the context of tourism research.

The CE analysis in this study might be improved by estimating a latent class model (LCM). The LCM for example can classify and distinguish numerous preference groups. Thus, LCM can accommodate the limitation in the CL model which assumes homogeneity in preferences. The other limitation concerns the analysis which currently only focuses on those 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.

Based on the WTP results, the three highest WTP values in all Models I, II and III are Toilet3, Jetty2 and CarP100 attributes. These results reveal the three main visitor preferences for the tourist facility attributes at Kenyir Lake. Particularly, visitors prefer to pay a higher amount to have toilet services with bathrooms and baby changing room facilities, instead of having basic toilets only. Visitors prefer the provision of two jetties; one for the speedboats service and another one for the houseboats service to load and unload visitors, instead of having only one jetty that combine both services. They also prefer to have more parking slots compared to the limited available slots. Overall, based on these preferences, visitors are conscious of the quality of facilities provided, and they are keen to pay for better services.

The results of our study also provide policy recommendations that would bring benefits in the future. Through the recommended level of entrance fees ranging from RM 1 to RM 10, the visitors to Kenyir Lake were eager to spend money to get the benefits of basic facilities attributes improvement. This suggests that the visitors agree and approve the recommended entrance fees. They are also aware of the advantage that they will receive in return of the entrance fee that they have to pay. Therefore, it is reasonable to impose the entrance fee to future visitors. Most importantly, the receipts from the obligation of an entrance fee can be used for re-investment into lake facilities in the future. 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 respondents demand change at the prices offered. For that reason, the responsible policy maker could deliberate prompt act to upgrade the basic tourist facilities at the lake for sustainability of the tourism sector in future.

The other implication concerns the different provision of facilities to the different categories of visitors to the lake. The ANA results revealed that the tourist information attribute is unimportant to repeat visitors as opposed to first time visitors. The finding indicates that dissimilar categories of visitor express dissimilar choices for the tourist facilities expansion. Consequently, this finding is beneficial for the responsible policy maker in determining which attributes are important, less important or not important at all to visitors, and thus the provision of financial plan for the expansion of facilities can take this into account. In addition, a set of attributes based on the different categories of visitors can be developed in the future. This will provide more detailed information to the policy maker regarding the conflicting preferences between different types of visitors and enrich any management plan for the lake.

Ethical Considerations

Respondent anonymity was used in this study. Respondents have been asked and is declared that their answers can be used as research material.

Conflict of Interest

The authors declare no conflicts of interest.

Funding

This research did not receive any financial support.

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