

# Valuation of South China tiger conservation in Wangcheng Park, China: A discrete choice experiment accounting for attribute nonattendance



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Abstract The South China tiger is endemic to China and has been evaluated as critically endangered (possible extinct in the wild) by IUCN since 2008, which resulted in distributing them zoos in China to conserve its species before finding a suitable area in the wild and bringing them back to the roar. Economic valuations of endangered species can help policymakers develop more efficient conservation strategies. Discrete choice experiment is becoming more appropriate, allowing the valuation of specific attributes of environmental goods and services. However, ignoring the attribute nonattendance issue in the DCE analysis yields biased estimates and erroneous potential recommendations. In this study, multinomial logit and mixed logit models are estimated to explore visitors' preferences and the implications of attribute nonattendance issues by using supplementary questions. The results indicate that the number of SCT is the most preferred attribute, followed by size of the natural habitat, frequency of the conservation campaigns, and level of the conservation institutions. Moreover, the results also show that accounting for attribute nonattendance does not change the relative ranking order of visitors' preferences in both multinomial and mixed logit models, while yielding higher WTP estimates in both models. These results shed more light on the importance of attribute nonattendance in future DCE analyses.

Keywords: preferences, willingness to pay, stated attribute nonattendance

# 1. Introduction

Biodiversity, known as the common contraction of the term "biological diversity", was first officially defined by the Convention on Biological Diversity (CBD) in 1992, and it was described as "the variability among living organisms from all sources including inter alia, terrestrial, marine and other aquatic ecosystems and the ecological complexes of which they are part: includes diversity within species, between species and of ecosystems" (United Nations, 1992). According to this definition, biodiversity holds significant importance for the existence of human beings. However, biodiversity is currently under threat from many causes, such as climate change, habitat fragmentation and loss, and environmental pollution (Newbold et al., 2015). According to the Living Planet Index 2022 by the World Wildlife Fund (WWF), the average population of globally monitored wildlife, including mammals, fish, reptiles, birds and amphibians, plummeted by 69% from 1970 to 2018 (WWF, 2022). Worse, human beings, as the top species and ultimate beneficiaries, are now in a precarious position due to biodiversity loss and its significant value. Therefore, there is increasing interest in the conservation of animals such as turtles (Azlina et al., 2019), wolves (Estifanos et al., 2020), elephants (Wang et al., 2020), monkeys (Lima et al., 2022), and tigers (Mzek et al., 2022).

Tigers (*Panthera tigris*), as one of the largest mammals and at the top of the food chain in the ecosystem, are key species that are crucial for the integrity of ecosystems, and three of nine subspecies have been completely extinct in the world (Goodrich et al., 2022). The South China tiger (SCT), as one of the remaining tiger subspecies and indigenous species to China, was thought to be the common ancestor of all tiger subspecies by Herrington (Herrington, 1987) and considered the rarest living subspecies and "critically endangered (possibly extinct in the wild)", as evaluated by the IUCN (Nyhus, 2008). In an attempt to save it from extinction, major efforts were made by specialized institutions at home and abroad. Consequently, the population of SCTs increased from 18 to more than 240 in 2022, and all the remaining SCTs were distributed in zoos to restore their species before they would be reintroduced to nature (Xinhua News Agency, 2022). However, there is still a long way to go before these plants can be reintroduced to the wild. The situation portrays an alarming picture of SCT conservation. The current endangered situation requires immediate attention. As a nonmarket product or service provider, the tiger cannot be traded in the market as usual, but conservation of the tiger and its habitat not only increases its population but also generates direct and indirect economic value. In such a context, it is crucial to estimate the potential economic value of SCT and help

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policymakers invest appropriately in conservation actions. To the best of our knowledge, there is a lack of research that focuses on valuing SCT to elicit its hidden value.

As a result, economic valuations of endangered species are gaining popularity as an efficient way to measure the benefits people derive from them, and nonmarket valuation techniques are useful tools for quantifying their specific economic value. With respect to nonmarket valuation techniques, the discrete choice experiment (DCE) method has become increasingly popular for determining the implicit price of endangered or threatened species. Compared with the contingent valuation method (CVM), the stated preference method can estimate multiple attributes simultaneously and evaluate the marginal value of changes in different attributes of an environmental product or service (Hanley et al., 1998). To date, many studies have been conducted on various species across many countries using DCE techniques over the past few years to estimate the economic value of endangered or threatened species (Kamaludin et al., 2023; Moreaux et al., 2023; Mzek et al., 2022; Bhatta et al., 2022; Estifanos et al., 2020; Imamura et al., 2020; Wang et al., 2020; Subroy et al., 2018; Steven et al., 2017; Lee & Du Preez, 2016; Zander et al., 2014; Hanley et al., 2003).

In general, DCEs assume that individuals have the ability to consider all the attributes presented to them and select the optimal option that maximizes their utility (Nguyen et al., 2015). However, this assumption was violated because individuals might ignore one or more attributes during their trade-off process because of the limited cognitive ability and complexity of choice tasks (Notaro et al., 2022). This simplifying heuristic is commonly acknowledged as attribute nonattendance (ANA). Ignoring one or more attributes indicates that a noncompensatory attribute processing strategy fails to compensate for the attended attributes (Scarpa et al., 2009). As a result, the issue of ANA in DCE methods has received much attention in recent years. Based on the DCE literature, many researchers have proven that not considering ANA in the DCE method might produce biased welfare estimates and lead to potentially incorrect policy recommendations (Jourdain & Vivithkeyoonvong, 2017; Kragt, 2013; Scarpa et al., 2013; Hensher & Greene, 2010; Hensher & Rose, 2009). Thus, there is a consensus that ANA does matter in DCE and that the ANA issue needs to be taken into account.

In terms of addressing ANA issues, there are three methods for identifying and quantifying ANA issues in the literature, namely, stated ANA, inferred ANA and visual ANA (Notaro et al., 2022). The first approach can be achieved by additional self-reported information, such as follow-up questions involving asking respondents directly whether they ignore one or more attributes during their trade-off process (Hensher et al., 2005). The second approach refers to the use of some analytical models to infer ANA rather than respondents' self-reported statements (Campbell, 2008). The latter approach is relatively new in economics and uses eye-tracking technology to examine visual ANA (Balcombe et al., 2015).

Typically, techniques for identifying stated ANA are categorized into two types based on the location of the follow-up questions in conjunction with DCE questions. The former approach, called serial ANA, refers to presenting the debriefing questions after the whole choice cards (Campbell et al., 2008). Compared to the serial ANA approach, in the choice task ANA, the debriefing questions are asked after each choice task to report whether they ignored one or more attributes (Scarpa et al., 2010). Furthermore, a significant cognitive burden might be produced by asking the ANA questions after each choice card (Nguyen et al., 2015). In addition, a series of questions at the end of each choice card could influence respondents' choices (Carlsson et al., 2010). Thus, the serial ANA approach seems more appropriate for ANA. Generally, the ignored attribute parameter is assigned a value of 0 in the utility function (Hensher et al., 2005).

Most previous studies have chosen the mixed logit model to estimate ANA (Hua et al., 2021; Su & Li, 2020; Mohamad et al., 2019; Kragt, 2013; Carlsson et al., 2010; Hensher & Rose, 2009; Hensher et al., 2005). In contrast, the combination and comparison of multinomial logit and mixed logit models has received insufficient attention in the related literature, especially for DCE analysis using different attribute processing strategies. In such a context, the aim of this study is to investigate visitors' preferences for SCT conservation attributes, estimate the economic value of SCT and explore the impact of ANA issues on visitors' willingness to pay (WTP) in different model specifications.

The remainder of the paper is structured as follows. Section 2 provides details of the study area and presents the survey design and implementation. Section 3 is devoted to the econometric specification. Section 4 reports the visitors' preferences and WTP based on the DCE results and compares the differences between the MNL and MXL models with and without ANA. Section 5 concludes the findings.

#### 2. Materials and Methods

## 2.1. Study area

Wangcheng Park (WCP) is located in the central part of Luoyang city (34°40′27.9″N, 112°25′37.6″E), Henan Province, China. It is well known for its ability to perform captive breeding and artificial rearing of SCTs in China, and for eight years, its SCT population has been the largest among zoos. According to the latest report from the China Biodiversity Conservation and Green Development Foundation (CBCGDF) released in 2022, approximately 99% of tigers in China are distributed in zoos, breeding bases and circuses, including the Siberian tiger, Bengal tiger, Indochinese tiger and SCT (CBCGDF, 2022). Worst of all, among these tiger subspecies, SCTs are captive in zoos. This means that visitors can only see one SCT at a zoo. Thus, to better understand visitors' preferences and WTP for SCT, the WCP was selected as the target region in this study.



## 2.2. Development of an attribute level list

Identifying and developing a list of attributes and their levels is the first and crucial step in employing a DCE approach. Reviewing the related literature, holding some focus group discussions with experts and the target population is widely accepted as the best way to develop an appropriate attribute level list (Bhat et al., 2020). In the present study, a potential attribute level list for SCT conservation was first proposed based on a number of DCE studies focused on endangered or threatened species conservation. It was then developed and finalized through online discussions with two experts from the SCT conservation research base, focus groups with eight target visitors, and two individual interviews with policymakers and management of the WCP from mid-May to early September 2022. As a result, five attributes were selected, and their levels were assigned in the study (see Table 1).

Table 1         Attribute levels for the DCE survey.			
Attributes Levels (Coding)			
Number of SCT (NUMB)	250 (NUMB1)		
	350 (NUMB2)		
	450 (NUMB3)		
Size of Natural Habitat (HABT)	Small (HABT1): less than 1000 km <sup>2</sup>		
	Medium (HABT2): approximately 1000 km <sup>2</sup>		
	High (HABT3): more than 1000 km <sup>2</sup>		
Frequency of Conservation Campaign (CAMP)	Low (CAMP1): not much		
	Medium (CAMP2): more often		
	High (CAMP3): very often		
Level of SCT Conservation Institutions (LTCI)	Local (LTCI1)		
	Provincial (LTCI2)		
	National (LTCI3)		
Conservation Fee (PRICE)	¥0, ¥5, ¥10, ¥15, ¥20		

Note: The underlined attribute level denotes the current status.

# 2.3. Development of an experimental design

Once the attribute level list for SCT conservation was determined, an appropriate experimental design was used to generate the combination of choice tasks. Therefore, the full factorial design will produce 405 ( $3\times3\times3\times3\times5$ ) hypothetical scenarios, resulting in 81810 combinations of choice sets that hinder the ability of researchers to complete sample collection. Thus, this paper employed a D-efficient experimental design because of its ability to capture the largest amount of information and sufficiently low D-errors to generate 45 choice tasks by using Statistical Analysis System (SAS) software. To reduce the cognitive burden on the respondents due to the complexity of the choice sets, the 45 choice tasks were randomly distributed into 9 blocks in the questionnaire, with 5 choice cards presented to each respondent. In each questionnaire, the respondent was required to choose the preferred option from three options, including two hypothetical alternatives plus a current situation. An example of a DCE choice task is shown in Figure 1.

### 2.4. Development of the questionnaire

The final questionnaire was adjusted based on feedback from a pretest and pilot study. It consists of four sections. The first section is related to the prior knowledge and attitudes of the visitor toward SCT and its conservation. The second section is devoted DCE, which first introduces the details of the hypothetical scenario and then asks the visitor to select their preferred option in each choice task. After completing the five-choice tasks, five follow-up questions were presented to the participants to explore whether one or more of the attributes were ignored in their decision-making process. Visitors ticked the attribute(s) they ignored. The last section was designed to collect information on visitors' social characteristics (e.g., age, gender, marital status, education, monthly income and so on).

## 2.5. Data collection

A one-week pilot test was conducted from the 2nd to the 3rd week of March 2023 with a total of 63 randomly selected visitors at the WCP to check visitors' understandability of the questionnaire. The final survey was then carried out on-site from late June to mid-September 2023, using convenience sampling near the SCT area in the WCP to ensure that respondents did know and see an SCT. The target population was WCP visitors aged 18 years and over. According to Orme (2010), the rule of thumb for determining the minimum sample size for a DCE survey was as follows:

$$N = 500 \times \frac{L}{A \times C}$$
(1)

where N denotes the minimum sample size needed for each version of the questionnaire, L indicates the highest number of attribute levels among all attributes, A is the number of options in each choice task (without the status situation), and C represents the number of choice tasks in each version of the questionnaire. Based on the computation, each version of the questionnaire required a minimum of 250 ( $500 \times 5/[2 \times 5]$ ) surveys. Finally, 412 samples were collected for the survey. After excluding 52 invalid questionnaires, 360 valid questionnaires were retained for analysis, for an efficient response rate of 87.38%.

SCT Conservation Attribute	Option 1	Option 2	Current Status
Number of the SCT	350	450	250
Size of natural habitat	Medium	Large	Small
Frequency of conservation campaign		Medium	Low
Level of the SCT conservation institutions	Provincial Network Provincial Load	National Network Provided Load	Local Neuron Invested Local
Conservation fee	¥ 10	¥5	¥0
Your Option		1	

Figure 1 A DCE choice task example.

# 3. Econometric specification

The DCE data of this study were analyzed using the estimation of the multinomial logit model (MNL) and mixed logit (MXL) models. These two models were built on two main underlying theories, namely, the Lancasterian theory of consumer behavior (Lancaster, 1966) and random utility theory (RUT), which were extended by McFadden (1974). The first theory was proposed in 1966 by Lancaster, who stated that a good consisted of several characteristics (attributes) from which individuals obtained utility rather than from the good itself. The second RUT was developed in 1974 by McFadden, who derived a discrete choice model to explain the choice behavior of respondents. Under the RUT, respondents' utility was assumed to be continuous, and they weighted the trade-offs associated with each attribute (Jourdain & Vivithkeyoonvong, 2017). Normally, in the MNL model, the utility function can be formulated as follows.

$$U = V + \varepsilon \tag{2}$$

where the whole utility U obtained from each option is made up of an observable or deterministic part V and an unobservable or random term  $\varepsilon$ . Regarding the deterministic part, Train (2003) assumed linear, and it can be rewritten in another way as follows:

$$V_{ij} = \beta_1 X_{1ij} + \beta_2 X_{2ij} + \beta_3 X_{3ij} + \dots + \beta_m X_{mij}$$
(3)

where  $\beta$  is the estimated coefficient and X represents the attribute variable of a product or service.

In the MNL model, the error terms are assumed to be independently and identically distributed (IID) in the choice set with a Gumbel distribution, which is the basis for the MNL model (Train, 2003). The probability that the respondent selects the optimal option to maximize his or her utility can be calculated via the following equation:

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$$P_{ij} = \frac{\exp\left(\mu V_{ij}\right)}{\sum_{k}^{j} \exp\left(\mu V_{ik}\right)} \tag{4}$$

where  $\mu$  is a scale parameter that cannot be observed in any model and is expected to be 1 (Hanley et al., 2001).

Traditionally, another important assumption in the MNL model is the property of independence from irrelevant alternatives (IIA), which means that adding or eliminating one option will not change the relative ratio of the probability of selecting between any two options (Louviere et al., 2000). In addition, the MNL model also assumes that preferences (tastes) are homogeneous among individuals and that these assumptions are normally violated in practice (Train, 2003). Consequently, if these assumptions are violated, the MNL model may generate biased estimates. Correspondingly, the MXL model is becoming more popular because it relaxes these assumptions and is able to capture the heterogeneity of preferences among respondents. The utility function in the MXL model can be presented in the following form:

$$U_{ik} = \beta'_i x_{ik} + \varepsilon_{ik}$$
(5)

where  $\beta'$  describes an unobserved vector of the coefficients for each i and the tastes that differ in the population with density f( $\beta$ ),  $x_{ik}$  is the vector of observed variables associated with option k and individual i, and  $\varepsilon_{ik}$  indicates an unobserved error term that follows the IID extreme value and is independent from  $\beta'_i$  and  $x_{ik}$ . Finally, the probability of selecting alternative j by the respondents in the MXL model can be written as:

$$P_{ij} = \int \left( \frac{e^{\beta' x_{ij}}}{\sum_{k} e^{\beta' x_{ij}}} \right) f(\beta) d\beta$$
 (6)

Therefore, the WTP or welfare value can be estimated using DCE models with collected data. The Marginal WTP (MWTP) value for each attribute is considered the ratio between the coefficients of a specific attribute and the price attribute (Bennett and Adamowicz, 2001). The specific equation is as follows:

$$WTP = -\frac{\beta_i}{\beta_{\text{price}}}$$
(7)

where  $\beta_i$  denotes the coefficient of attributes,  $\beta_{price}$  represents the coefficient of costs or payment, and the negative sign is used to eliminate the negative sign of the parameter of price (Hasan-Basri, 2015).

Based on the above general equations 4 and 6, the MNL and MXL models were specified and estimated in this study to compare and explore the effect of ANA on model performance, visitors' preferences and their WTP. Specifically, the MXL was chosen because it accounts for heterogeneity in preferences, assuming a normal distribution for the nonmonetary parameters and a fixed monetary parameter using 100 Halton draws.

In this paper, four models are estimated and compared to determine the best model specification to accommodate the stated ANA. The MNL model is the benchmark model for DCE analysis. Therefore, the paper starts with the estimation of MNL models. The two models differ as follows:

MNL-1 (with full attribute attendance): All attributes are considered during the respondents' decision in the MNL model estimation.

MNL-2 (with ANA restricted to 0): one or more attributes are not attended or ignored by respondents, and the coefficients of the ignored attribute (attributes) are restricted to 0 in the utility function. This model was estimated based on MNL models following Hess and Hensher (2010).

The results of the IIA test after the MNL model was estimated show that the MXL model is more flexible and suitable. Then, two MXL models were developed to produce more reliable estimations compared to the biased results of MNL models:

MXL-1 (with full attribute attendance): All attributes are attended to during respondents' decisions in the MXL model estimation.

MXL-2 (with ANA restricted to 0): one or more attributes are not attended or ignored by respondents and are restricted to 0 in the utility function. This model was estimated based on MXL models following Hensher et al. (2005).

# 4. Results and Discussion

# 4.1. Incidence of Stated ANA

To capture whether respondents ignored one or more attributes, this survey required visitors to answer the follow-up question at the end of the choice tasks: "Did you ignore any attributes in the choice cards? If yes, please tick the box." Table 2 and Table 3 provide an overview of the answers to the follow-up stated ANA questions.

As shown in Table 2, the factor "Conservation Fee" ranked first among all the attributes, with 42.22% of the responses, followed by the factors "Frequency of Conservation Campaign" and "Level of SCT Conservation Institutions", with 19.72% and 19.17% of the responses, respectively. The factors "Size of Natural Habitat" and "Number of SCTs" were the least common, with 13.61% and 5.83%, respectively. According to this finding, it seems that visitors' decisions were least influenced by the

"Conservation Fee" factor, which indicates that visitors place more emphasis on nonmonetary SCT conservation attributes than on monetary attributes. Approximately two-tenths of all visitors said they did not care about the factors "Frequency of Conservation Campaign" and "Level of SCT Conservation Institutions", suggesting that there were no trade-offs between these two factors and improvements in SCT conservation attributes. Fewer than 15% of all visitors stated that they ignored both the factors "Size of Natural Habitat" and "Number of SCTs". This implies that most visitors believe that these two factors are crucial for improving SCT conservation.

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Attributes	Frequency	Share (%)
Number of SCT	21	5.83
Size of Natural Habitat	49	13.61
Frequency of Conservation Campaign	71	19.72
Level of SCT Conservation Institutions	69	19.17
Conservation Fee	152	42.22

Table 2	Responses	to the state	d ANA questions.
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In addition, Table 3 presents the incidence of ANA using a specific attribute processing strategy (APS). The APS is categorized into four types: all-attribute attendance (AAA), one-attribute nonattendance (1-ANA), two-attribute nonattendance (2-ANA) and three-attribute nonattendance (3-ANA). As shown in Table 3, only a smaller percentage of visitors (21.11%) said they took all factors into account while making their decisions. In other words, approximately eight-tenths of visitors ignored one or more attributes that violated the basic assumption of the DCE method, and this behavior is consistent with practice in real markets. Four and three attributes were identified by 58.33% and 19.72% of the visitors, respectively. A total of 0.83% of the visitors stated that they considered only two attributes. These statistical results show the importance of taking the ANA issue into account when analyzing DCE models.

Table 5 incluence of ANA under a specific Ars.		
APS	Frequency	Share (%)
AAA	76	21.11
1-ANA	210	58.33
Ignored NUMB only	15	4.17
Ignored HABT only	33	9.17
Ignored CAMP only	37	10.28
Ignored LTCI only	44	12.22
Ignored PRICE only	81	22.50
2-ANA	71	19.72
Ignored NUMB & CAMP	1	0.28
Ignored NUMB & LTCI	2	0.56
Ignored NUMB & PRICE	3	0.83
Ignored HABT & LTCI	1	0.28
Ignored HABT & PRICE	13	3.61
Ignored CAMP & PRICE	30	8.33
Ignored LTCI & PRICE	21	5.83
3-ANA	3	0.83
Ignored HABT & CAMP & PRICE	2	0.56
Ignored CAMP & LTCI & PRICE	1	0.28
Total	360	100

Table 3 Incidence of ANA under a specific APS

## 4.2. Results of the MNL models

Two MNL models are used to estimate the DCE data collected. Table 4 shows the results of the two MNL models. A detailed comparison of the two models is described in the following sections.

All attributes are statistically significant at the 1% level in both model specifications. Moreover, the sign of the coefficient with respect to the conservation fee is negative, as expected, implying that the marginal utility obtained from the SCT conservation attribute decreases when the conservation fee increases. Regarding the relative importance of SCT conservation attributes, NUMB3 (increasing the number of SCTs to 450 in the future) is the most favored among all attributes in both models, and the LTCI ranks the least. Overall, the order of the attributes in both models is NUMB-HABT-CAMP-LTCI. There does not seem to be much difference between the two models.

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Moreover, in terms of the estimated parameters of the two models, the results show some slight variations when comparing MNL-2 to MNL-1, but the differences are quite small, and the majority of the attribute parameters tend to decrease at the same time (i.e., 1.645 and 1.523), while NUMB2 tends to increase slightly. This finding is in line with the findings of Hess and Hensher (2010), Rose et al. (2012), Kragt (2013) and Scarpa et al. (2013). This indicates that the failure to take the ANA issue into account does produce biased estimates.

The overall performances of the two models vary. Comparing MNL-2 with MNL-1, the pseudo-R<sup>2</sup> in the model decreased from 0.259 to 0.188. This finding implies that by restricting the parameters of ANA to 0, the performance of the estimated MNL-2 is not enhanced. This finding stands in stark contrast to prior studies, which focused on estimating MNL models employing attribute nonattendance restricted to 0 and reported better model fit (Scarpa et al., 2010; Rose et al., 2012). This finding is new and interesting for exploring the significance of ANA in DCE analyses and deserves more in-depth investigations to increase its robustness.

In summary, considering ANA in the MNL model does not affect the ranking of visitors' preferences for SCT conservation, but it does have an effect on the estimated coefficients of attributes. NUMB received the most preference from visitors, indicating that visitors are likely to increase the population of SCT in the future. This finding is in line with the goals of the current SCT conservation program (Reintroduce SCT to the Roar) to save SCT from its critically endangered situation. Interestingly, the effect of ANA on MNL model performance is different from that in previous studies. These findings shed light on the importance and necessity of considering ANA in DCE analysis.

	Table 4 Estimation for	or two MNL model	S.	
	MNL-1		MNL-2	
Variable	Coefficient	SE	Coefficient	SE
NUMB2	1.161***	0.093	1.163***	0.086
NUMB3	1.645***	0.095	1.523***	0.089
HABT2	0.786***	0.087	0.722***	0.087
НАВТЗ	1.357***	0.098	1.260***	0.093
CAMP2	0.640***	0.087	0.580***	0.089
CAMP3	1.070***	0.089	0.984***	0.091
LTCI2	0.771***	0.088	0.726***	0.090
LTCI3	0.594***	0.093	0.507***	0.091
PRICE	-0.144***	0.007	-0.116***	0.006
Summary Statistics				
Log-likelihood function	-1198.989		-1314.639	
Log-likelihood	-1619.627		-1619.627	
Pseudo-R <sup>2</sup>	0.259		0.188	
Observation	1800		1800	

Note: \*\*\*, \*\* and \* denote 1%, 5% and 10% significance levels, respectively; SE: standard error.

# 4.3. Results of the MXL models

As mentioned above, the MNL model has some limitations in capturing the preference homogeneity among respondents. However, the MXL model is more flexible and can overcome the limitations of the MNL model in terms of its ability to capture random heterogeneity among respondents. As a consequence, this study uses MXL models to investigate the heterogeneity of preferences and explores the implications of ANA. Typically, the standard treatment for ANA is to restrict the parameter of ANA in the utility function to zero (Hensher et al., 2005). Hence, two MXL models are used to estimate visitors' preferences and WTP by using the collected data of 360 visitors: the MXL model with full attribute attendance and restricting the ANA parameter to zero. Table 5 displays the results of the ANA analysis for the MXL model with two different specifications.

Overall, all SCT conservation attributes are statistically significant at the 1% level. Similar to the MNL model above, the negative sign of the Price attribute is in line with expectations. Considering the importance of different SCT conservation attributes, NUMB3 receives the most preference in both MXL models, while LTCI obtains the least. The ranking order of visitors' preferences for SCT conservation attributes in both models is consistent with that in the MNL model. The findings suggest that visitors are more willing to increase SCT population than to increase other SCT conservation attributes. Moreover, even if visitors ignore one or more attributes during their decision-making process, their preference for SCT conservation remains the same, indicating that the ANA did not affect their preference in MXL models.

More importantly, the standard deviations (SDs) in the two models are statistically significant, indicating that visitors' preferences for nonmonetary attributes are heterogeneous. Thus, it seems that the MXL model is more appropriate for explaining ANA issues in DCE analysis. Concerning the SD estimates, visitors' preferences differ across the specifications of the two MXL models. The SD value of NUMB3 is statistically significant at the 1% level in both models. HABT3, CAMP2 and LTCI2

were significantly different in MXL-1 at the 1%, 10% and 5% levels, respectively, while they became nonsignificant in MXL-2. This phenomenon also demonstrates that ANA issues influence preference heterogeneity for nonmonetary conservation attributes, suggesting the importance of considering ANA in DCE analysis. In addition, the results also show that the MXL model outperforms the MNL model due to the detection of preference heterogeneity and is more appropriate.

For the coefficient values in the two MXL models, there is a slight decrease in all attributes from MXL-1 to MXL-2. This finding is relatively similar to a prior study that focused on the stated ANA issue in the valuation of Kenyir Lake in Malaysia, where the MXL models were estimated by restricting the coefficients of attribute nonattendance to 0 (Hess & Hensher, 2010; Mohamad et al., 2019). These findings are different from those of Kragt (2013) and Notaro et al. (2022). Based on the comparison of the MXL results with those of previous studies, the effect of ANA on the estimated values is still unclear.

With respect to the goodness measures of model fit, McFadden's pseudo-R<sup>2</sup> values ranging from 0.2 to 0.4 are considered the rule of thumb (Bennett & Blamey, 2001). The pseudo-R<sup>2</sup> values in the two MXL models are 0.397 and 0.336, respectively. In addition, the information criteria, namely, the Akaike information criterion (AIC) and Bayesian information criterion (BIC), can help to determine which model represents the data best, following the rule that the lower the AIC and BIC are, the better the model fit (Boxall & Adamowicz, 2002). According to the AIC and BIC, MXL-2 seems to have a better fit. Taken together, the results show that MXL-2 yields the best data and has a better fit than MXL-1. These findings are consistent with the ANA literature, which demonstrates that accounting for ANA improves model performance (Hua et al., 2021; Kragt, 2013; Scarpa et al., 2013; Hess & Hensher, 2010; Scarpa et al., 2010; Campbell et al., 2008). As a result, addressing the ANA issue in DCE model estimation leads to a significantly better fit to the data, and it is necessary to consider ANA in practice.

In summary, accounting for ANA yields lower parameter estimates and improves model performance, but the relative importance ranking of visitors' preferences remains unchanged in the estimation of the MXL model. In addition, the results also indicate the existence of preference heterogeneity among visitors. However, the underlying driver of preference heterogeneity could be visitors' socioeconomic factors or other unobservable factors that need to be explored in future research.

Table 5 Results for two MXL models.						
	М	MXL-1		XL-2		
Variable	Coefficient	SE	Coefficient	SE		
NUMB2	1.291***	0.117	1.181***	0.091		
NUMB3	1.857***	0.142	1.550***	0.101		
HABT2	0.863***	0.103	0.760***	0.094		
HABT3	1.421***	0.119	1.286***	0.098		
CAMP2	0.741***	0.106	0.610***	0.094		
CAMP3	1.227***	0.115	1.022***	0.097		
LTCI2	0.958***	0.121	0.772***	0.102		
LTCI3	0.669***	0.106	0.539***	0.096		
PRICE	-0.166***	0.011	-0.120***	0.007		
SD						
NUMB2	0.158	0.362	0.086	0.400		
NUMB3	0.783***	0.179	0.535***	0.180		
HABT2	0.261	0.310	0.016	0.384		
HABT3	0.764***	0.194	0.106	0.268		
CAMP2	0.355*	0.209	0.191	0.384		
CAMP3	0.215	0.216	0.107	0.240		
LTCI2	0.479**	0.197	0.339	0.273		
LTCI3	0.088	0.169	0.018	0.162		
Summary Statistics						
Log-likelihood function	-1191.769		-1312.855			
Log-likelihood	-1977.502		-1977.502			
Pseudo-R <sup>2</sup>	0.397		0.336			
Observation	1800		1800			
AIC	4001.004		3989.004			
BIC	4127.401		4082.428			

Note: \*\*\*, \*\* and \* denote 1%, 5% and 10% significance levels, respectively; SE: standard error.

### 4.4. Comparison of WTP estimates

The final step in the DCE analysis is the welfare measure. In this paper, the welfare measure will be achieved by computing the MWTP. Table 6 summarizes the MWTP estimates. A comparison of the MNL and MXL models revealed significant differences in the WTP values. A description of the details is provided in the following section.

In the MNL model, the values of the WTP estimated in MNL-2 with the ANA issue taken into account show higher values than those in MNL-1 among all SCT conservation attributes. This implies that ignoring ANA produced potentially biased and erroneous welfare estimates. This finding is similar to that of a previous study that utilized the MNL model to explore the differences in terms of MWTP estimates when accounting for choice task ANA and serial ANA and revealed that considering serial ANA in the MNL model yielded better model fit and a greater WTP (Scarpa et al., 2010). Moreover, the results reveal the same ranking of the WTP values in both models. Visitors prefer NUMB3 the most and are likely to pay for the increase in the number of SCTs to 450, with estimated MWTP values of CNY13.096 and CNY11.409, respectively, in both models. This finding is in accordance with a previous study on Malayan tiger conservation (Mzek et al., 2022). Thus, ANA significantly affects welfare estimates, while it does not have any effect on preferences in MNL models.

Similar to the MNL model above, MXL-2 considering ANA produces a greater WTP than does MXL-1 without accounting for ANA. This finding corresponds well with those of several previous studies (Puckett & Hensher, 2008; Hensher et al., 2007; Rose et al., 2005). Moreover, the visitors in both models share the same ranking of the WTP estimates. Accounting for ANA in MXL-2, visitors are willing to pay an estimated value of CNY12.866 for improving the number of SCTs to 450, followed by increasing the natural habitat size of SCTs to a large value of CNY10.677 and improving the level of SCT conservation institution to the national level to rank last, with an estimated WTP of CNY4.470. The difference between the two MXL models suggests that the ANA issue needs to be taken into account in DCE analysis to generate more reliable estimates. Reviewing the related literature, we find that there is no agreement on the impact on WTP estimation when accounting for the stated ANA issue by estimating the MXL model, which includes three main results, namely, higher WTP (Puckett & Hensher, 2008; Hensher et al., 2007; Rose et al., 2005), lower WTP (Hua et al., 2021; Hensher et al., 2005) and no impacts (Su & Li, 2020; Carlsson et al., 2010).

Overall, the findings imply that accounting for ANA in both the MNL and MXL models may yield a greater MWTP than in both models with all attribute attendance. However, it seems that this does not affect the relative importance ranking of the MWTP estimates with and without ANA. Therefore, it is necessary to account for ANA in DCE analysis to obtain more accurate welfare estimates.

Variables	MNL-1	MNL-2	MXL-1	MXL-2
	Coefficient	Coefficient	Coefficient	Coefficient
	(SE)	(SE)	(SE)	(SE)
NUMB2	8.049***	10.001***	7.795***	9.801***
	0.688	0.817	0.652	0.815
NUMB3	11.409***	13.096***	11.209***	12.866***
	0.683	0.831	0.714	0.873
HABT2	5.452***	6.210***	5.207***	6.308***
	0.590	0.747	0.598	0.758
HABT3	9.408***	10.831***	8.576***	10.677***
	0.673	0.844	0.726	0.844
CAMP2	4.442***	5.065***	4.471***	5.064***
	0.579	0.751	0.594	0.773
CAMP3	7.429***	8.462***	7.408***	8.484***
	0.612	0.799	0.588	0.799
LTCI2	5.347***	6.244***	5.781***	6.407***
	0.598	0.768	0.616	0.797
LTCI3	4.118***	4.357***	4.038***	4.470***
	0.614	0.768	0.587	0.764

Table 6 MWTP estimates for the MNL and MXL models.

Note: \*\*\*, \*\* and \* denote 1%, 5% and 10% significance levels, respectively; SE: standard error.

# 5. Conclusion

This study develops a DCE to explore visitors' preferences and estimate the benefit of a specific SCT conservation attribute as well as to explore the effect of the stated ANA issue. The results of this study confirmed that visitors are, on average, prepared to make monetary contributions to improve SCT conservation. Increasing the number of SCTs to 450 in the future proved to be the most preferred attribute, with high amounts of CNY11.209 to CNY13.096. The attribute HABT is the least valued attribute, followed by CAMP, and LTCI receives the least preference ranking. Therefore, creating efficient conservation programs and appropriate budget allocations to increase SCT population, such as providing education tours with

specific institutions to raise awareness of SCT conservation and placing conservation fees at the zoo, seems to be the most important and urgent issue for policymakers. In addition, finding an appropriate wildlife and nature reserve for the SCT should also be considered, as well as restoring wildlife and ecosystems for the SCT to help them return to nature rather than being kept in captivity.

Moreover, this study also explored the impact of the stated ANA issue on both the MNL and MXL models by using a specific attribute processing strategy. Consistent with previous studies, restricting the ANA parameter to zero does not affect the relative ranking of visitors' preferences for SCT in either the MNL or MXL models. Nonetheless, the MWTP estimates for all nonmonetary attributes show an increasing trend in both the MNL and MXL models, suggesting that ignoring the ANA issue underestimates the welfare estimates for SCT conservation. Furthermore, the results of the MXL models with and without ANA prove the existence of preference heterogeneity among visitors and the superiority of the MXL model over the MNL model. However, the underlying drivers of preference heterogeneity remain ambiguous and need to be investigated in future research.

Overall, the results show that visitors ignore some attributes in their decision-making process. This study asked the visitors directly whether they ignored any attribute with a simple follow-up question. However, there is evidence that those who stated that they ignored some attributes might have given them a lower priority (Hess and Hensher, 2010; Hess, 2014; Espinosa-Goded et al., 2021). Hence, identifying the reasons behind ANA through follow-up questions and qualitative interviews could enhance the reliability of DCE analysis in future studies. In addition, this study only focuses on a serial stated ANA, and it is necessary to consider the choice task ANA and compare the results to produce more information on the implications of the ANA issue for future research. Moreover, there is a debate on the existence of potential endogeneity bias from the stated ANA (Hess & Hensher, 2013; Alemu et al., 2012). Therefore, further research on ANA treatment could strengthen and enhance the robustness of DCE analysis, such as by adding more detailed follow-up questions and semistructured interviews, applying different attribute processing strategies (i.e., restricting the ANA parameter to zero, excluding respondents who ignored some attributes, following up on ANA questions with positive and negative versions, etc.), and conducting comparative studies.

# **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.

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