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Research article

# Has COVID-19 changed tourist destination choice?

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ABSTRACT

This study investigates changes in tourists' preferences for destination choice in the context of the COVID-19 pandemic using a scenario-based intertemporal hybrid choice model. The empirical results indicate that tourists emphasized medical services, hygiene conditions, and smart tourism when selecting tourist destinations during the pandemic but were more concerned with attractions and service quality when the pandemic eased. The preference structure at various stages of the pandemic differed greatly for tourists who strongly engaged in counterfactual thinking. Individuals who perceived increased risks tended to select alternative destinations to those they had previously visited. The results also show that tourist choice behavior in this context can be explained by reference dependence and loss aversion as underlined by prospect theory.


## Introduction

Tourism is bracing the “new normal” post-pandemic situation. Although confirmed cases of COVID-19 continue to occur globally, the negative impacts of the pandemic have come under control in almost every country. The COVID-19 pandemic has greatly affected the entire world, from the national to the individual level. As a vulnerable industry, tourism has suffered particularly substantial losses due to the pandemic (Qiu et al., 2021; Zhang & Lu, 2021). Although the number of domestic tourists in China grew considerably from 0.695 billion to 6.006 billion from 1998 to 2019, the COVID-19 pandemic hit domestic tourism hard, with the number of domestic tourists shrinking to 2.879 billion in 2020. Since the easing of the pandemic in 2021, tourist arrivals have gradually recovered to 3.246 billion, reaching approximately 54 % of the 2019 level (China Economic Information Center, 2022). With the complete elimination of pandemic prevention and control measures since the last quarter of 2022, China has entered into a “new normal” situation. Furthermore, because of the sudden, unprecedented, uncertain, and severe nature of the COVID-19 pandemic, policymakers and tourism practitioners have learned much and accumulated substantial experience in managing and responding to the crisis.

With over two years having passed since the outbreak of the pandemic in China, researchers have identified changes to Chinese tourist behavior regarding destination choice, which deserve attention for the future development of the domestic industry in the post-pandemic “new normal” (Bayrsaikhan et al., 2021; Qiu et al., 2020). Before the outbreak of the COVID-19 pandemic, tourists tended to base their decision-making process on primary tourism attributes, such as tourism attractions, service quality, and the tourism expenditure. However, according to a report published by the Pacific Asia Travel Association (2020), travelers increasingly

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emphasized the health, cleanliness, and safety of destinations after the outbreak of COVID-19. Tourists preferred destinations that had better managed the pandemic. Weltman et al. (2020) found that high levels of health and safety positively affected destination competitiveness after the outbreak of the pandemic. Thus, the COVID-19 pandemic has reshaped the map of the most popular travel destinations. Although some studies have examined the impacts of the pandemic on tourist preference for destination types, very few have explored tourist preference for destination choice post-pandemic or compared during- and post-pandemic tourist behaviors.

Given the unpredictability of uncertainties such as extreme weather events, pandemics, and financial crises that can significantly impact tourism, comprehending shifts in tourists' behavior, especially in terms of destination selection, becomes imperative for destination policymakers. This understanding equips them to proactively mitigate and address the potential repercussions of such crises in the future. To help tourism practitioners and policymakers understand and satisfy tourists' needs in the post-pandemic "new normal," this study aims to investigate the changes to Chinese domestic tourist preferences for destinations at different stages of the pandemic with consideration of both the destination attributes and psychological antecedents. This study proposes scenario-based intertemporal hybrid choice models to address the research questions and explain the tourist destination choice mechanisms.

This study makes three main contributions. First, no prior study has attempted to compare the differences in tourist preferences for destination choice during and after the pandemic. We formulate a unique theoretical framework to illustrate the choice behavior in the context of the crisis in contrast to that in a normal situation. Second, the study develops scenario-based intertemporal hybrid choice models to generate estimates and verify the hypotheses. This method is useful to examine tourist behavioral changes in times of the crisis. Third, the study contributes to the revitalization of domestic tourism by suggesting the most effective post-pandemic improvements to destination attributes.

The remainder of the study is structured as follows. The Literature review section reviews the literature on the factors influencing destination choice and the preference change for destination attributes across stages of the pandemic. The hypotheses are then formulated based on this literature. The Methodology section discusses the experimental design and methods of the study. The Results and discussions section provides the empirical results. The Implications and conclusion section concludes the paper.

## Literature review

### *Alternative-specific factors and the effects of the COVID-19 pandemic*

Tourists' destination choices are commonly influenced by three categories of factors: decision maker-specific factors, alternative-specific factors, and situational factors (Wu et al., 2011). Decision maker-specific factors are those associated with individual socio-demographic information, such as gender, age, income, and education, as well as psychological factors, such as individual perceptions and travel motivation (Lepp & Gibson, 2008). Alternative-specific factors are the attributes of destinations, such as tourism attractions, service quality, travel fares, destination image (Pan et al., 2021), and accessibility (e.g., travel distance, available travel modes). Situational factors include weather conditions, cultural differences, and social status (Seddighi et al., 2001).

Although the abovementioned factors continued to greatly influence tourists' decision-making processes after the outbreak of the COVID-19 pandemic, tourists were also more likely to pay attention to factors such as health and safety attributes and the availability of contactless services (Hao et al., 2023). Wen et al. (2020) highlighted the ways in which the pandemic reshaped tourism patterns as tourists increasingly preferred health and wellness tourism and smart tourism, as well as destinations with high-quality medical facilities. Rasoolimanesh et al. (2021) emphasized the importance of the healthcare system in affecting travel intention and tourists' willingness to support a destination. Nair and Sinha (2020) investigated the heterogeneities of destination-choice-based motivators among tourists and found that accessibility and discounting, health and hygiene, and low COVID-19 incidence were three major motivators for choosing a destination. Li, Zhang, et al. (2021) found that tourists in China emphasized the importance of clean, sanitary, and safe travel and added that local and surrounding tours became the primary tourism markets during the National Day holiday amid the pandemic.

In addition, Li, Gong, et al. (2021) identified two main phenomena related to tourist destination choice: regional bias and spatial distance preference. They found that tourists were inclined to travel to destinations with fewer confirmed COVID-19 cases relative to their places of origin (regional bias) and short-distance destinations, and a particular emphasis on local trips after the end of lockdown (spatial distance preference). Jin et al. (2022) found that tourists preferred to travel to destinations that promoted comfort and escape, such as beach destinations. Huang et al. (2021) concluded that the majority of Chinese tourists preferred nature-based, cultural and historical heritages, and rural areas for the outbound tourism during the pandemic. Miao et al. (2022) investigated post-pandemic and post-traumatic tourism behavior and found that tourists were likely to select less-popular destinations to ensure social distancing from other travelers.

Considering the literature on the impacts of the COVID-19 pandemic on destination choice, we formulated Hypothesis 1 as follows:

**Hypothesis 1.** Domestic leisure tourists prioritize factors related to health and safety when selecting destinations during the pandemic.

Although the COVID-19 pandemic severely hindered the overall development of the tourism industry, smart tourism has been developed and promoted during the crisis (Yang et al., 2021). Prior to the pandemic, the intelligent and digital transformation of the tourism industry led to the replacement of various traditional travel modes by online smart modes, including information searching, booking, and sharing (Wen et al., 2020). This transformation has been particularly accelerated amid the pandemic. For example, numerous smart tourism modes, such as artificial intelligence services and face swiping systems, have become mainstream. Creative modes of tourism have boomed, including cloud tourism and virtual reality parks, which enable tourists to become familiar with destinations before departure. To guarantee travel safety, smart body temperature monitoring was deployed in scenic spots, hotels, and restaurants to check tourists' temperatures in real time and thus mitigate COVID-19 risk.

Contactless services are commonly defined as service behaviors that minimize human face-to-face contact, including self-service fare collection, electronic payments, intelligent parking, code scanning, and service robots (Bae & Chang, 2020). Due to their substantial reduction of interpersonal interactions (Gaur et al., 2021) amid the spread of disease, contactless services have become increasingly popular (Bae & Chang, 2020) and have therefore received extensive attention from scholars. For instance, Parvez and Cobanoglu (2021) observed that the COVID-19 pandemic boosted the utilization of service robots in the service industry as they are convenient to access, provide alternative communication options, and improve operation safety. Gaur et al. (2021) highlighted the importance of artificial intelligence and robotics to provide customers with contactless services. They mentioned that robots are useful to perform repetitive, routine, and dangerous tasks, including cleaning and disinfection, which minimizes the physical contact between hotel staff and guests to prevent the spread of disease. In addition, self-driving vehicles such as drones became popular during and after the COVID-19 pandemic. Zeng et al. (2020) stated that drones were used during the pandemic to remind people to maintain social distance in public areas. Individuals' behavioral intentions to use drones for food delivery services were reinforced under the influence of the pandemic (Kim et al., 2021). Overall, to enhance hotels' competitive advantages amid the pandemic, artificial intelligence and robotics were used to provide protective service delivery that would rebuild guests' confidence and create a technological shield based on the contactless services (Gaur et al., 2021).

Artificial intelligence and robotics are not only widely used in tourism-related sectors to support the development of smart tourism amid the pandemic but also very helpful in maintaining daily business operations and recovering from the crisis in the post-pandemic era. Gaur et al. (2021) found that individuals' fear of infection was reduced with the adoption of AI and robotics, which rekindled tourism demand. Messori and Escobar (2021) mentioned that smart tourism technologies mitigated tourists' perceived risk of infection and improved consumer experience or promote post-pandemic destination rebranding. In addition, robots play a role in ensuring the availability of human resources in tourism-related sectors. For example, many hotels in Japan have replaced frontline employees with communication robots; restaurants and the broader food service sector in the UK have increased their interest and investment in robots (Tuomi et al., 2021); and many airports have implemented service robots to ensure safety and social distance (Ivkov et al., 2020).

In consideration of these prior studies on the impacts of smart tourism on destination choice amid the COVID-19 pandemic, we formulated Hypothesis 2 as follows:

**Hypothesis 2.** Domestic leisure tourists prioritize factors related to smart tourism when selecting destinations during the pandemic.

*Decision maker-specific factors and the effects of the COVID-19 pandemic*

Tourists' experience and psychology, including past travel and risk perception, also determine destination choice. Past travel experience is a useful reference for tourist decision-making, such as destination choice. Crouch et al. (2014) asserted that past travel experience was a key driver of future destination preferences. The economic perspective of prospect theory, proposed by Kahneman and Tversky (1979), provides a solid foundation to investigate the relationship between experience and choice. According to prospect theory, individuals evaluate alternatives according to their deviation from a certain reference level rather than from an absolute level (reference dependence). Negative deviations (losses) have more influence than positive deviations of equivalent magnitudes (gains) because most individuals are loss-averse (Tversky & Kahneman, 1991). Many studies have found that prior experiences serve as good reference points in reference-dependent models. For example, Masiero and Qiu (2018) applied prospect theory to verify and explain reference-dependent behaviors in a long-haul destination choice context in which respondents evaluated potential travel destinations by comparison to their typical travel experience.

Román and Martín (2016) applied prospect theory to clarify asymmetric customer preference for hotels valued by gains and losses in terms of willingness to pay for and willingness to accept the quality of hotel attributes. Masiero et al. (2016) found that hotel guests selected rooms based on the characteristics of rooms that they had stayed in before. Guests perceived the losses from a downgrade of room attributes in comparison with the reference room much more negatively than equivalent gains from an upgrade. Nicolau (2012) found that tourists in Spain compared the magnitude of the difference between the reference price and actual price when they selected destinations. They reacted more strongly to price rises than to price reductions relative to the reference price, which revealed significant loss aversion. Given the crucial role of prospect theory in analyzing tourists' choices, we proposed Hypotheses 3 and 4 as follows:

**Hypothesis 3.** Domestic leisure tourists assess destination attributes based on attributes that they experienced before the pandemic (reference dependence).

**Hypothesis 4.** Domestic leisure tourists select destinations by asymmetrically evaluating the gains and losses of destination attributes and experience losses more severely than equivalent gains (loss aversion).

Studies have also emphasized the importance of risk perception in tourists' decision-making processes. Karl and Schmude (2017) thoroughly reviewed the literature on the role of risk perception in destination choice and concluded that risk perception affects tourists' decision-making processes in terms of travel mode, organization, time, style, costs, and destination. Sönmez and Graefe (1998) examined the relationship between risk perception and destination choice in terms of uncertainty, worry, and fear and found that tourists with higher risk perception were less likely to travel to risky destinations. Huang et al. (2020) stated that perceived health risk was one of the most critical determinants of travel activities.

Risks induced by the COVID-19 pandemic have greatly affected tourist choice and consumption behaviors. Tourists with higher risk perception have been shown to prefer domestic tourism to international tourism, thus displaying a “home-is-safer-than-abroad” bias (Matiza, 2020). Chen et al. (2022) identified that travel choices during the crisis were considerably influenced by latent factors such as risk perception, fear of infection, travel anxiety, attitudes, and social responsibility, as well as traditional attributes that prevail in normal situations such as travel time and cost. Perić et al. (2021) found that Serbian tourists' perceived risks in relation to health, psychological, financial, and destination aspects negatively affected their travel intentions during the pandemic. Bayrsaikhan et al. (2021) confirmed the role of risk perception in the choice of leisure destinations during the pandemic. Risk perception was positively correlated with the choice of natural destinations, disinfected areas, and socially distanced places, and negatively correlated with the choice of crowded destinations.

Risk perception also influences tourist choice in terms of revisit intention. Rather (2021) stated that both fear of COVID-19 and perceived risk negatively affected tourists' attitudes towards traveling, but these attitudes promoted revisit intention to destinations to which they had previously traveled. Repeat visitors rated risk factors lower than first-time visitors, as their knowledge based on familiarity, expertise, and consumption experiences in previously visited destinations reduced the risks (Kerstetter & Cho, 2004). In contrast, Chew and Jahari (2014) confirmed a negative relationship between physical risk and revisit intention, mediated by destination image. Osti and Nava (2020) found that COVID-19-related risk perception did not reduce tourists' loyalty to previous destinations but did shift their preferences from destinations on the coast to those in the mountains.

Although many studies have explored the effects of risk perception on destination choice, none have conclusively determined which types of destination tourists with higher/lower risk perception chose amid the pandemic. To address this issue, we proposed Hypothesis 5 as follows:

**Hypothesis 5.** Domestic leisure tourists with higher risk perception tend to select alternative destinations during the COVID-19 pandemic to those they had visited before the outbreak of the pandemic.

*Counterfactual thinking and the effects of the COVID-19 pandemic*

Counterfactual thinking is defined as the cognitive process of thinking about alternatives to reality (Roese, 1997). As a mental simulation, counterfactual thinking incorporates three stages: activation, construction, and evaluation (Roese & Olson, 1995). It can be activated by a real or imagined stimulus internal to the person or in the external environment (Kasimatis & Wells, 1995). It then follows the causal means-end framework of a logical statement that stipulates the cause (or antecedent) and the effect (or consequent) of the scenario (Roese, 1994). Counterfactual thinking can take an automatic form or an elaborative form, with the latter being intentional and consciously directed and pertaining to surprising and unexpected events (Wells & Gavanski, 1989). Kahneman (1995) explained that individuals engaging in elaborative counterfactual thinking intentionally construct and assess alternative sequences of actions and corresponding outcomes.

Counterfactual thinking has been applied to numerous aspects of tourism studies. Thai and Yuksel (2017) applied it to choice overload effects in destination choice. They found that tourists more willingly selected destinations from a small (vs. large) portfolio, which also resulted in more satisfaction and less regret. Yilmaz et al. (2022) found that counterfactual thinking was one of the psychological determinants of individual intentions, feelings, and behaviors related to a destination's environmental protection and sustainable development. Wang et al. (2017) highlighted the role of counterfactual thinking in reversing tourists' negative impressions of and experiences in a destination and thus their recommendation intention based on marketing messages. Park and Jang (2018) investigated the impacts of discount rates and temporal distance on the perceived regret level induced by counterfactual thinking. They found a positive relationship between counterfactual thinking and perceived regret caused by a change of discount rates.

Considering that counterfactual thinking can involve tourists in imagined alternative scenarios, we formulated Hypothesis 6 as follows:

**Hypothesis 6.** Domestic leisure tourists who are strongly engaged in counterfactual thinking display preference structure changes at different stages of the COVID-19 pandemic.

On the basis of our literature review, we designed a theoretical framework to illustrate destination choice in the context of the COVID-19 pandemic, as shown in Fig. 1. First, the pandemic induced a unique behavioral mechanism of destination choice relative to that in a normal situation, and different stages of the pandemic featured different preferences for tourism attributes (H1 and H2). Second, tourists selected destinations during the crisis with reference to previously visited destinations and exhibited loss aversion (H3 and H4). Third, COVID-19-related risk perception influenced tourists' choices between alternative destinations (status quo specific; H5). Finally, counterfactual thinking was useful to involve tourists into the hypothetical scenario (H6).

## Methodology

The complete discrete choice modeling process incorporate three major stages: experimental design, data collection, and model estimation (Kemperman, 2021). In the first stage, the choice experiment is designed via the following steps: (a) identifying influential attributes, (b) assigning attribute levels, (c) constructing choice sets, and (d) designing the questionnaire survey (Hensher et al., 2015). In the second stage, the pilot study and main survey are conducted for data collection. The stated choice experiments are used to obtain information regarding individuals' preferences in different situations. In the third stage, the model with the best performance is selected for further analysis.

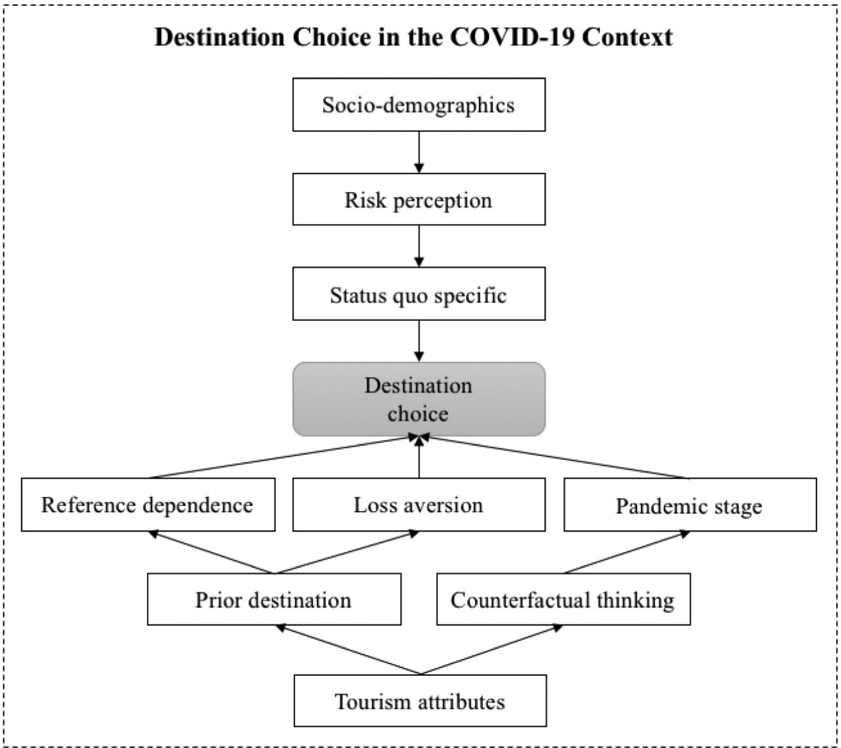


**Fig. 1.** Theoretical framework.

*Stage 1: discrete choice experiment design*

The primary step of designing a choice experiment is to identify the influential attributes and corresponding attribute levels. Tourism attractions, service quality, and the tourism expenditure were chosen as three destination attributes typically used in destination choice studies (Masiero & Qiu, 2018), while smart tourism, medical quality, and hygiene conditions were added as attributes with particular relevance to the COVID-19 pandemic period (Pacific Asia Travel Association, 2020). Since the pandemic-related factors are the major focus of our study, we operate under the assumption that the rest of the factors remain constant across all alternative destinations. In the questionnaire survey, we provided the respondents with the introductory statement before the choice experiment: "Except for the tourism attributes listed below, all the other attributes of the destination are the same." Hence, we proceeded with the assumption of their uniformity across all alternative destination options. A mix-and-match design was adopted in the choice experiment, which resulted in 50 choice sets with three options per set. This mix-and-match method preserved the orthogonality of the choice sets, implying uncorrelated attribute levels across choice profiles. The 50 choice sets were further divided into 10 blocks, which were randomly assigned to the respondents.

The final questionnaire consisted of four sections. The first comprised several screening questions on age, gender, place of residence, and household monthly income. In the second section, we asked the respondents to identify a "prior destination," which referred to a domestic tourism destination that they had visited for leisure purposes before the outbreak of the pandemic. The respondents were then asked to answer questions associated with this destination in light of their past travel experience. The second section also collected information about individual perceptions of pandemic risks.

In the third and fourth sections, the stated choice experiments were conducted by asking the respondents to select one destination from three options in two scenarios: post-pandemic (Scenario A) and during the pandemic (Scenario B). Each scenario provided the respondents with five choice sets. In the third section, the experiment was set in a post-pandemic context under the assumption that the pandemic was under control (Scenario A). This scenario was in line with the real situation when the questionnaire was conducted. In the fourth section, the choice experiment was set during the pandemic, with the pandemic considered at a medium strength and not completely contained (Scenario B). This scenario was similar to the real situation in the second quarter of 2020 when there were confirmed cases in some cities but tourists were free to travel around the whole country. We designed questions based on counterfactual thinking theory to help the respondents to mentally revisit the scenario amid the pandemic. In the final part of the questionnaire, we collected socio-demographic information. Two attention check questions were inserted into the questionnaire to screen out unreasonable responses.

*Stage 2: data collection and analysis*

Three rounds of the pilot study and preliminary test were conducted to verify the clarity and applicability of the stated choice experiments and questionnaire. The main survey aimed at domestic Chinese tourists was conducted online by a professional data collection company. The company utilized in this study is internationally renowned for its expertise in data analysis, insights, and consultancy services. Concerning the sampling process, the company employed stratified sampling approach with the strata designed to maintain a balanced sample mix and maximize socio-demographic diversity.

There were 820 completed responses. After the elimination of invalid responses, such as those completed too quickly and straight-line responses, 796 acceptable questionnaires were used for the data analyses and model estimations. The respondents' socio-demographic information is presented in Table 1. They had a nearly even gender distribution, as 50.88 % were men and 49.12 % were women. Most of the respondents (62.81 %) were aged between 30 and 50 years old, and 72.87 % were married with children. The majority (84.55 %) held a bachelor's degree or above. More than half of the respondents (58.79 %) had a monthly household income of less than RMB35,000.

The main survey was conducted in November 2021 when China entered into the post-pandemic era. To compare tourist preference structure changes at different stages of the COVID-19 pandemic, this study utilized counterfactual thinking to guide tourists back into the scenario during the relatively severe period of the pandemic. Five items were used to measure counterfactual thinking, such as, "If only I went back to the during pandemic era (i.e., the second quarter of 2020) when COVID-19 was not completely contained and some cities still had confirmed cases, then I would select a destination different to that I would have chosen without the pandemic." The respondents' degree of engagement in counterfactual thinking was tested with a set of items rated on a 5-point Likert scale (Wang et al., 2017). The mean response to the five questions was taken as a counterfactual thinking index score. Higher scores indicate a stronger degree of engagement. The overall mean of the sample (3.88) was used to classify the respondents into two groups (Thai & Yuksel, 2017; Yilmaz et al., 2022). Almost half of the respondents (49.12 %) scored higher than the mean (3.88) and were classified as strongly engaged in counterfactual thinking (above average), while the remaining 405 respondents were categorized as weakly engaged (50.88 %).

In terms of respondents' risk perceptions, the questionnaire featured eight items related to the pandemic, such as "I feel worried and anxious when I see news about the COVID-19 pandemic on social media." According to the overall measurement of risk perception and taking the mean (3.21) of the sample as the classification level, 53.52 % of the respondents had higher risk perception and fear of the severity of the pandemic.

**Table 1**
Respondents' socio-demographic information.

| Socio-demographics | Number | Percentage |
|---|---|---|
| *Gender* | | |
| Male | 405 | 50.88 % |
| Female | 391 | 49.12 % |
| *Age* | | |
| ≤29 | 201 | 25.25 % |
| 30–50 | 500 | 62.81 % |
| ≥51 | 95 | 11.94 % |
| *Income* | | |
| Below ¥5001 | 16 | 2.01 % |
| ¥5001–15,000 | 144 | 18.09 % |
| ¥15,001–25,000 | 172 | 21.61 % |
| ¥25,001–35,000 | 136 | 17.09 % |
| ¥35,001–45,000 | 47 | 5.90 % |
| ¥45,001–55,000 | 48 | 6.03 % |
| ¥55,001–65,000 | 66 | 8.29 % |
| ¥65,001–75,000 | 24 | 3.02 % |
| ¥75,001–85,000 | 49 | 6.16 % |
| ¥85,001–95,000 | 15 | 1.88 % |
| ¥95,001–105,000 | 30 | 3.77 % |
| Above ¥105,000 | 49 | 6.16 % |
| *Marital status* | | |
| Single | 134 | 16.83 % |
| Married without children | 66 | 8.29 % |
| Married with children | 580 | 72.87 % |
| Separated | 12 | 1.51 % |
| Others | 4 | 0.50 % |
| *Tourism companions* | | |
| Spouse | 582 | / |
| Children | 364 | / |
| Other relatives | 93 | / |
| Friends | 225 | / |
| Others | 9 | / |
| Sole traveler | 64 | / |
| *Education* | | |
| High school | 24 | 3.01 % |
| Junior college | 99 | 12.44 % |
| Bachelor | 598 | 75.13 % |
| Postgraduate | 75 | 9.42 % |

*Stage 3: specification of the scenario-based intertemporal hybrid choice models*

Discrete choice modeling is playing increasingly critical roles in analyzing and identifying the major attributes of human behavior in relation to tourism (Chen et al., 2018; Grigolon et al., 2014), hospitality (Karlsson et al., 2017), and leisure (Grigolon et al., 2013).

A hybrid choice model is an extension of the multinomial logit model, which integrates the standard discrete choice model with latent constructs (Ben-Akiva et al., 2002). The hybrid choice model bridges the gap between discrete choice models and behavioral theories by incorporating psychometrically unobserved elements (e.g., attitudes, feelings, and perceptions) (Abou-Zeid & Ben-Akiva, 2014).

The hybrid choice model adopts the multinomial logit model and the multiple indicators multiple causes models as the discrete choice component and latent variable component, respectively. Both the discrete choice and latent variable components include a structural element and a measurement element. The structural relationship of the discrete choice component is indicated by the effects of the observed explanatory variables and latent variables on the utility function of the choice alternatives, while the measurement relationship is determined by the utility maximization assumption (Kim et al., 2014). The two equations in the discrete choice component are specified as follows:

$$U_{in} = \beta_n^M X_i^M + \lambda_i^L X_n^L + \varepsilon_{in} \tag{1}$$

$$y_{in} = \begin{cases} 1, & \text{if } U_{in} \geq U_{jn} \forall j \in C_n \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

where $U_{in}$ indicates the random utility of alternative $i$ for individual $n$; $X_i^M$ represents a set of destination attribute variables associated with alternative $i$; $X_n^L$ denotes the individual specific latent variables; $\varepsilon_{in}$ is an extreme value error term; $\beta_n^M$ is a set of individual specific parameters governing the individual preference on destination attributes and follows the distribution $f_\beta\left(\beta_n^M\right)$; $\lambda_i^L$ is an alternative specific parameter linking the latent variable with the utility of each alternative; $y_{in}$ is a choice indicator equal to 1 if individual $n$ selected alternative $i$ and 0 otherwise; and $C_n$ represents the choice set of individual $n$.

In terms of the latent variable component, the structural equation identifies the causal relationship between the observable exogenous variables and the latent variable, while the measurement element links the item responses with the latent variable. The two equations are as follows:

$$X_n^L = \alpha X_n^E + \eta_n \tag{3}$$

$$I_{nq} = \begin{cases} 1 & \tau_{q0} \leq \zeta_q X_n^L < \tau_{q1} \\ 2 & \tau_{q1} \leq \zeta_q X_n^L < \tau_{q2} \\ \vdots & \vdots \\ S & \tau_{q(S-1)} \leq \zeta_q X_n^L < \tau_{qS} \end{cases} \tag{4}$$

where $X_n^L$ indicates the latent variables of individual $n$; $X_n^E$ denotes the observable exogenous characteristics of individual $n$; $I_{nq}$ represents the item responses to attitudinal questions related to the latent variable; $\eta_n$ is a normal error term with a density function $f_\eta(\eta_n)$; $\alpha$ describes the formation procedure of latent variables from individual characteristics; and $\tau_{q\#}$ and $\zeta_q$ are model parameters that regulate item responses.

The joint likelihood function of the hybrid choice model was expressed as the product of the conditional choice probability and the conditional density function of the indicators, and was integrated over the density of the latent variables, given as:

$$\mathbb{L}_n\left(y_n, I_{nq} | X_i^M, X_n^E; \beta^M, \lambda^L, \zeta, \alpha, \tau\right) = \int_\eta \int_\beta P\left(y_n \middle| X_n^M, X_n^L; \beta^M, \lambda^L\right) \mathcal{L}_{I_{nq}}\left(I_{nq} | X_n^L; \tau, \zeta\right) f_\beta\left(\beta_n^M\right) f_\eta(\eta_n) d\beta d\eta$$

with

$$\mathcal{L}_{I_{nq}}\left(I_{nq} | X_n^L; \tau, \zeta\right) = \sum_{s=1}^{S}\left(I_{nq} = s\right)\left[\frac{1}{1 + \exp\left(\tau_{qs} - \zeta_q X_n^L\right)} - \frac{1}{1 + \exp\left(\tau_{q,s-1} - \zeta_q X_n^L\right)}\right] \tag{5}$$

where $P(\cdot)$ represents the choice probability conditional on the destination attributes and latent variables; $\mathcal{L}_{I_{nq}}$ is the likelihood of obtaining a certain set of item responses from the attitudinal questions; $f_\beta(\cdot)$ indicates the joint density function of the individual specific attribute preferences; and $f_\eta(\cdot)$ denotes the joint density function of the latent variables.

Based on the basic form of the hybrid choice model, we proposed two scenario-based intertemporal hybrid choice models to generate the estimations: the benchmark model (Model 1) and the reference-dependent model (Model 2). Model 1 follows the random utility model, which measures the utility of travel to a destination by summing the attribute values of the destination weighted by preference coefficients. Model 1 considers the intertemporal scenarios in relation to the pandemic and counterfactual thinking, expressed by:

$$V_{AD,n} = \sum_{k=1}^{K} \left[\beta_{a,k} X_{AD,k} D_a + \beta_{bs,k} X_{AD,k} (1 - D_a) D_{bs} + \beta_{bw,k} X_{AD,k} (1 - D_a)(1 - D_{bs})\right] \tag{6}$$

$$V_{PD,n} = ASC_{PD,n} + \sum_{k=1}^{K} \left[\beta_{a,k} X_{PD,k} D_a + \beta_{bs,k} X_{PD,k} (1 - D_a) D_{bs} + \beta_{bw,k} X_{PD,k} (1 - D_a)(1 - D_{bs})\right] \tag{7}$$

where $X_{AD,k}$ ($X_{PD,k}$) denotes the level of attribute $k$ in the alternative destination (prior destination); $D_a$ is a scenario-specific indicator that equals 1 in Scenario A (post-pandemic scenario) and 0 in Scenario B (during-pandemic scenario); $D_{bs}$ is a dummy variable that equals 1 if the individual was strongly engaged in counterfactual thinking (above average) and 0 otherwise; $ASC_{PD,n}$ is the alternative specific constant indicating the overall preference for the prior destination, which is related to respondents' biases towards familiar destinations and their risk perceptions regarding COVID-19 ($ASC_{PD,n} = ASC_{PD} + \gamma X_n^L$); and $\beta_{a,k}$, $\beta_{bs,k}$, and $\beta_{bw,k}$ are parameters to be estimated by the model.

Furthermore, Model 2 integrates Model 1 with a reference-dependent specification to measure the marginal effect of the attribute level relative to the reference level. Apart from the new components of intertemporal scenarios, risk perception, and counterfactual thinking added in Model 1, Model 2 specifies the utility function of the hybrid choice model according to prospect theory, as follows:

$$V_{AD,n} = \sum_{k=1}^{K} \left[(\beta_{a,G} G_k + \beta_{a,L} L_k) D_a + (\beta_{bs,G} G_k + \beta_{bs,L} L_k)(1 - D_a) D_{bs} + (\beta_{bw,G} G_k + \beta_{bw,L} L_k)(1 - D_a)(1 - D_{bs})\right] \tag{8}$$

$$V_{PD,n} = ASC_{PD,n} \tag{9}$$

where $G_k$ and $L_k$ denote, respectively, the gain and loss valued by the deviations of the attribute level from the reference level of the prior destination ($G_k = |X_{AD,k} - X_{PD,k}|$ if $X_{AD,k} - X_{PD,k} > 0$; $L_k = |X_{AD,k} - X_{PD,k}|$ if $X_{AD,k} - X_{PD,k} < 0$); $ASC_{PD,n}$ is the alternative specific constant indicating the overall preference for the prior destination; and $\beta_{a,G}$, $\beta_{a,L}$, $\beta_{bs,G}$, $\beta_{bs,L}$, $\beta_{bw,G}$, and $\beta_{bw,L}$ are unknown parameters related to the gains and losses. The value function of the prior destination is also generally specified as a function of the gains and losses of attribute levels. However, because its own values are used as the reference, all of the terms other than $ASC_{PD,n}$ are equal to 0. In Model 2, loss aversion was verified if $\left|\frac{\beta_{s,L}}{\beta_{s,G}}\right| > 1$, where $s$ indicates the scenario ($a$ = Scenario A, $bs$ = Scenario B-1 with strong counterfactual engagement, and $bw$ = Scenario B-2 with weak counterfactual engagement).

The methodological framework is shown in Fig. 2. First, we investigated the changes in tourist preference for the major destination attributes at different stages of the pandemic. Second, counterfactual thinking was embedded into the scenarios to help respondents

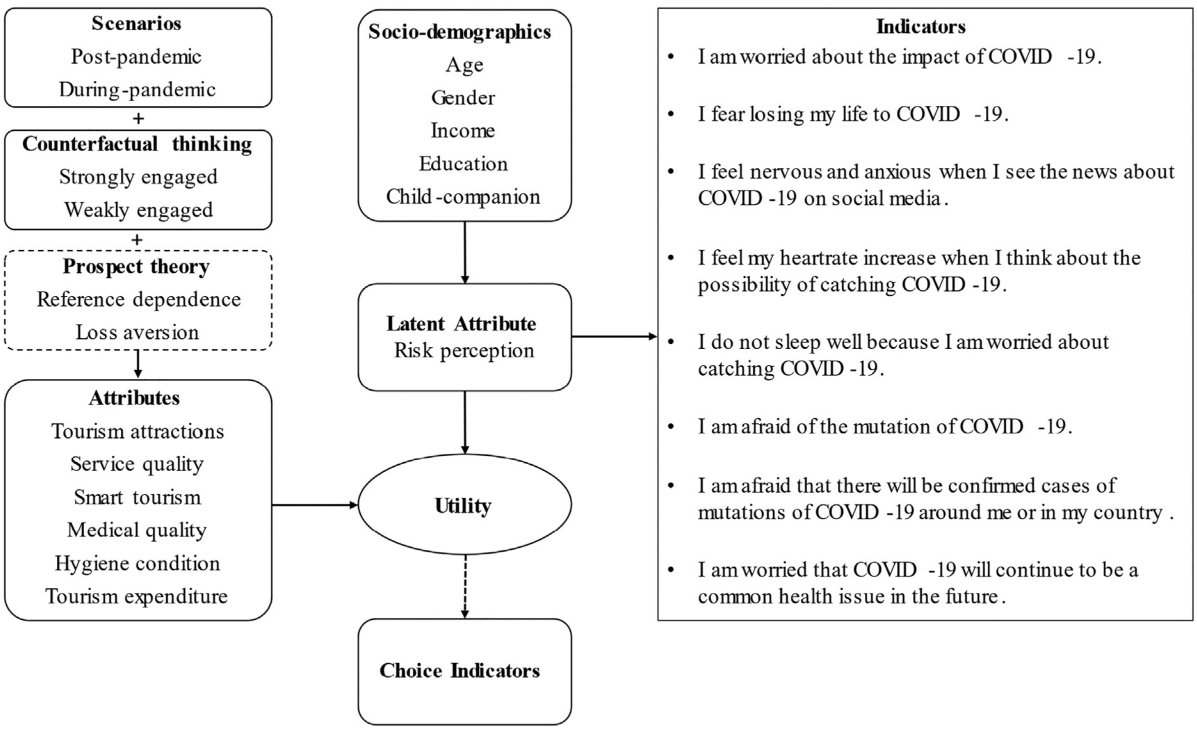


**Fig. 2.** Methodological framework.

place themselves in the during-pandemic scenario. Third, the value functions in the model were specified according to prospect theory to further investigate reference dependence and loss aversion behavior in the respondents' choice processes. Fourth, the respondents' preferences were influenced by their risk perceptions, which was specified as a function of their socio-demographic characteristics and indicated by attitudinal questions.

## Results and discussions

### *Goodness-of-fit and prediction ability*

The estimation performance of the hybrid choice model was benchmarked with the multinomial logit model and mixed multinomial logit models, and their goodness-of-fit and model prediction accuracy are shown in Table 2. The indicators overwhelmingly suggest the superior performance of the hybrid choice model over the multinomial logit model and mixed multinomial logit models. This can be attributed to the better specification of preference heterogeneity in the hybrid choice model.

### *Estimation results*

We estimated the benchmark model and reference-dependent model using the simulated maximum likelihood method with 100 Halton random draws on each random component. The scenario-based intertemporal hybrid choice model was run using the *apollo* package in R (Hess & Palma, 2019). To further verify the relationship between the coefficients, we applied the Delta method to assess the standard errors of the derived ratios of parameters across scenarios as well as the loss aversion ratios (Daly et al., 2012). The estimation results of the benchmark model and reference-dependent model are shown in Tables 3 and 4, respectively. Most of the major coefficients were significant and had the expected signs.

According to the model fit criteria (i.e., log-likelihood, Akaike information criterion, and predictive accuracy), the reference-dependent model overwhelmingly outperformed the benchmark model. This illustrates that tourists selected destinations by assessing attribute levels based on their past travel experiences, which supported Hypothesis 3. Furthermore, the loss aversion ratios measured by $\left|\frac{\beta_{s,L}}{\beta_{s,G}}\right|$ are reported in Table 5. In all of the scenarios, most of the ratios >1 fell within the certain confidence bands. This shows that the respondents were more likely to reject destinations with downgraded tourism attributes than to accept destinations with equivalent upgraded attributes compared with the prior destinations. These results supported Hypothesis 4.

Because of the superior performance of the reference-dependent model, we used the results generated by this model for further analyses. In light of the estimates presented in Table 4, we explored the preference change of the destination attributes across stages of the pandemic by comparing the corresponding coefficients in the two scenarios. When the pandemic threat was relatively severe, medical quality and hygiene conditions played significant roles in tourist choice, as indicated by the higher values of the significant mean estimates. Tourists believed that advanced medical services and good hygiene conditions would safeguard their travel, and these factors therefore reduced the fear associated with tourism during the pandemic. In addition, in the gain domain, smart tourism was estimated to have a significant positive mean (0.160) and a non-significant standard deviation (0.198). This indicates that when threatened by the pandemic, tourists had a homogenous preference regarding smart tourism, as those who disliked smart tourism would change their minds and pursue elements such as contactless services in their choices (Train, 2003). Because the prevention and protection measures in the destinations were immature and deficient during the pandemic, tourists had not built strong confidence in the safety of human contact. Therefore, they preferred destinations that provided smart tourism, particularly contactless services.

With the pandemic under control, smart, medical, and hygiene facilities were no longer imperative for tourist demand because of improved prevention measures and widespread vaccination. This is shown by the non-significant low mean estimate of smart tourism and the reduced coefficients of medical quality and hygiene condition. In the post-pandemic era, tourists had higher confidence in human contact and diverted their attention from contactless services, medical facilities, and hygiene conditions back to primary tourism attributes such as tourism attractions and service quality. Additionally, in accordance with demand theory, budget was negatively

**Table 2**
Goodness-of-fit results.

| Model | Log-likelihood (choice) | AIC (choice) | Predictive accuracy |
|---|---|---|---|
| *Benchmark model (M1)* | | | |
| MNL | −8742.290 | 17,522.580 | 48.56 % |
| MMNL | −8742.290 | 17,558.580 | 48.78 % |
| Scenario-based intertemporal HCM | −7748.797 | 15,573.594 | 49.12 % |
| *Reference-dependent model (M2)* | | | |
| MNL | −8742.290 | 17,558.580 | 53.92 % |
| MMNL | −8742.292 | 17,630.584 | 53.92 % |
| Scenario-based intertemporal HCM | −7185.674 | 14,519.348 | 54.16 % |

Note: AIC = Akaike information criteria; MNL = multinomial logit; MMNL = mixed multinomial logit; HCM = hybrid choice model.

**Table 3**
Estimation results for the benchmark model.

| | Coeff. | (Std. err.) | Std. dev. | (Std. err.) |
|---|---|---|---|---|
| Alternative specific constant | 0.018 | 0.035 | | |
| Scenario A: Post-pandemic | | | | |
| Tourism attractions | 0.532*** | 0.039 | 0.668*** | 0.050 |
| Service quality | 0.380*** | 0.032 | 0.471*** | 0.049 |
| Smart tourism | 0.045 | 0.027 | 0.246*** | 0.055 |
| Medical quality | 0.267*** | 0.030 | 0.413*** | 0.053 |
| Hygiene condition | 0.361*** | 0.031 | 0.410*** | 0.051 |
| Tourism expenditure | −0.481 | 0.518 | 8.151*** | 0.800 |
| Scenario B-1: During pandemic with strong engagement in counterfactual thinking | | | | |
| Tourism attractions | 0.135*** | 0.041 | 0.383*** | 0.060 |
| Service quality | 0.189*** | 0.039 | 0.389*** | 0.058 |
| Smart tourism | 0.112*** | 0.032 | 0.091 | 0.073 |
| Medical quality | 0.303*** | 0.042 | 0.472*** | 0.064 |
| Hygiene condition | 0.237*** | 0.040 | 0.401*** | 0.060 |
| Tourism expenditure | −2.116*** | 0.563 | 2.080 | 1.645 |
| Scenario B-2: During pandemic with weak engagement in counterfactual thinking | | | | |
| Tourism attractions | 0.137*** | 0.033 | 0.219** | 0.079 |
| Service quality | 0.137*** | 0.033 | 0.323*** | 0.054 |
| Smart tourism | 0.059* | 0.027 | 0.009 | 0.060 |
| Medical quality | 0.134*** | 0.031 | 0.204** | 0.077 |
| Hygiene condition | 0.146*** | 0.030 | 0.175** | 0.063 |
| Tourism expenditure | −0.708 | 0.525 | 3.984*** | 0.976 |
| Effects of latent variable on utility | | | | |
| Risk perception | 0.111** | 0.035 | | |
| Effects of socio-demographic information on latent variable | | | | |
| Age: Young | −0.179** | 0.063 | | |
| Age: Old | 0.268*** | 0.082 | | |
| Education: University | −0.016 | 0.073 | | |
| Gender: Female | −0.241*** | 0.051 | | |
| Income: Low | 0.154* | 0.071 | | |
| Income: Middle | −0.127 | 0.084 | | |
| Married with children | 0.021 | 0.068 | | |
| Risk perception indicated by attitudinal questions | | | | |
| Risk perception indicator 1 | −2.474*** | 0.108 | | |
| Risk perception indicator 2 | −2.403*** | 0.104 | | |
| Risk perception indicator 3 | −2.564*** | 0.112 | | |
| Risk perception indicator 4 | −2.315*** | 0.100 | | |
| Risk perception indicator 5 | −1.648*** | 0.078 | | |
| Risk perception indicator 6 | −2.910*** | 0.128 | | |
| Risk perception indicator 7 | −2.055*** | 0.091 | | |
| Risk perception indicator 8 | −1.386*** | 0.072 | | |
| Log-likelihood (choice) | −7748.797 | | | |
| Log-likelihood (whole) | −22,397.830 | | | |
| AIC | 44,965.670 | | | |

Note: AIC = Akaike information criterion.
*** 1 % significance level.
** 5 % significance level.
* 10 % significance level.

associated with tourism demand. The results of the Delta methods reflected the confidence of the determined relationships between parameters in the population (see Table 6). The significant ratios of the coefficients across Scenarios A and B-1 further confirmed the importance of smart tourism, medical facilities, and hygiene conditions during the pandemic. Thus, Hypotheses 1 and 2 were supported.

Given that the utilities of alternatives were at an arbitrary scale and only their relative relationships determined the choices of tourists, the relative magnitudes of the preference coefficients formed a preference structure that revealed tourists' tradeoffs among the destination attributes. The ratios shown in Table 6 were further standardized with the coefficient ratio of the tourism expenditure. The preference structures of the different scenarios are presented in Table 7. In the gain domain, the preference structures were distinct in the two stages of the COVID-19 pandemic for individuals strongly engaged in counterfactual thinking. For example, when the pandemic was under control, tourists placed more weight on tourism attractions (3.899) and service quality (2.277) but reduced the weightings of smart tourism (0.760) and medical quality (0.842), respectively. This shows that tourists substituted their emphasis on enhanced smart tourism features and medical facilities with improvements in tourism attractions and service quality. However, the desire for good hygiene conditions changed little (1.034) between the two stages. These changes in the preference structure supported Hypothesis 6. Among respondents who were weakly engaged in counterfactual thinking, the preference weights on all of the destination attributes were <1, which implies that this group of respondents put slightly more emphasis on the tourism expenditure. The preference weightings for tourism attractions, service quality, smart tourism,

**Table 4**
Estimation results for the reference-dependent model.

| | Coeff. | (Std. err.) | Std. dev. | (Std. err.) |
|---|---|---|---|---|
| Alternative specific constant | −0.329*** | 0.084 | | |
| Scenario A: Post-pandemic (gain) | | | | |
| Tourism attractions | 0.541*** | 0.059 | 0.491*** | 0.108 |
| Service quality | 0.322*** | 0.049 | 0.443*** | 0.087 |
| Smart tourism | 0.053 | 0.039 | 0.026 | 0.161 |
| Medical quality | 0.214*** | 0.047 | 0.311*** | 0.085 |
| Hygiene condition | 0.363*** | 0.048 | 0.420*** | 0.074 |
| Tourism expenditure | −0.991 | 0.847 | 6.282** | 2.039 |
| Scenario A: Post-pandemic (loss) | | | | |
| Tourism attractions | −0.573*** | 0.062 | 0.807*** | 0.086 |
| Service quality | −0.458*** | 0.059 | 0.432*** | 0.089 |
| Smart tourism | −0.148** | 0.056 | 0.426*** | 0.079 |
| Medical quality | −0.378*** | 0.057 | 0.467*** | 0.105 |
| Hygiene condition | −0.382*** | 0.061 | 0.495*** | 0.093 |
| Tourism expenditure | −3.153** | 1.078 | 15.650*** | 1.440 |
| Scenario B-1: During pandemic with strong engagement in counterfactual thinking (gain) | | | | |
| Tourism attractions | 0.317*** | 0.089 | 0.138 | 0.211 |
| Service quality | 0.324*** | 0.068 | 0.285* | 0.124 |
| Smart tourism | 0.160** | 0.062 | 0.198 | 0.114 |
| Medical quality | 0.582*** | 0.079 | 0.500*** | 0.115 |
| Hygiene condition | 0.803*** | 0.088 | 0.783*** | 0.108 |
| Tourism expenditure | −2.267 | 1.227 | 4.345 | 2.846 |
| Scenario B-1: During pandemic with strong engagement in counterfactual thinking (loss) | | | | |
| Tourism attractions | −0.423*** | 0.077 | 0.576*** | 0.106 |
| Service quality | −0.422*** | 0.071 | 0.251* | 0.127 |
| Smart tourism | −0.308*** | 0.077 | 0.457*** | 0.097 |
| Medical quality | −0.586*** | 0.086 | 0.615*** | 0.108 |
| Hygiene condition | −0.451*** | 0.085 | 0.657*** | 0.120 |
| Tourism expenditure | −6.118*** | 1.615 | 15.671*** | 1.846 |
| Scenario B-2: During pandemic with weak engagement in counterfactual thinking (gain) | | | | |
| Tourism attractions | 0.339*** | 0.063 | 0.263 | 0.138 |
| Service quality | 0.178** | 0.059 | 0.328*** | 0.096 |
| Smart tourism | 0.030 | 0.048 | 0.033 | 0.219 |
| Medical quality | 0.429*** | 0.070 | 0.594*** | 0.105 |
| Hygiene condition | 0.280*** | 0.063 | 0.523*** | 0.094 |
| Tourism expenditure | −0.491 | 0.980 | 0.769 | 3.479 |
| Scenario B-2: During pandemic with weak engagement in counterfactual thinking (loss) | | | | |
| Tourism attractions | −0.429*** | 0.080 | 0.614*** | 0.096 |
| Service quality | −0.267*** | 0.061 | 0.117 | 0.118 |
| Smart tourism | −0.009 | 0.067 | 0.183 | 0.131 |
| Medical quality | −0.430*** | 0.069 | 0.243* | 0.120 |
| Hygiene condition | −0.356*** | 0.075 | 0.598*** | 0.110 |
| Tourism expenditure | −2.303 | 1.197 | 6.616*** | 1.492 |
| Effects of latent variable on utility | | | | |
| Risk perception | 0.135** | 0.045 | | |
| Effects of socio-demographic information on latent variable | | | | |
| Age: Young | −0.146* | 0.065 | | |
| Age: Old | 0.243** | 0.084 | | |
| Education: University | 0.001 | 0.066 | | |
| Gender: Female | −0.268*** | 0.050 | | |
| Income: Low | 0.096 | 0.066 | | |
| Income: Middle | −0.121 | 0.078 | | |
| Married with children | 0.001 | 0.066 | | |
| Risk perception indicated by attitudinal questions | | | | |
| Risk perception indicator 1 | −2.556*** | 0.113 | | |
| Risk perception indicator 2 | −2.439*** | 0.106 | | |
| Risk perception indicator 3 | −2.632*** | 0.117 | | |
| Risk perception indicator 4 | −2.357*** | 0.104 | | |
| Risk perception indicator 5 | −1.660*** | 0.079 | | |
| Risk perception indicator 6 | −2.994*** | 0.133 | | |
| Risk perception indicator 7 | −2.112*** | 0.095 | | |
| Risk perception indicator 8 | −1.432*** | 0.074 | | |
| Log-likelihood (choice) | −7185.674 | | | |
| Log-likelihood (whole) | −21,839.400 | | | |
| AIC | 43,920.800 | | | |

Note: AIC = Akaike information criterion.
*** 1 % significance level.
** 5 % significance level.
* 10 % significance level.

**Table 5**
Loss aversion ratio.

| Measurement | Value | Robust std. err. |
|---|---|---|
| *Loss aversion ratio in Scenario A* | | |
| Tourism attractions | 1.059*** | 0.198 |
| Service quality | 1.423*** | 0.337 |
| Smart tourism | 2.771 | 2.546 |
| Medical quality | 1.767*** | 0.544 |
| Hygiene condition | 1.051*** | 0.258 |
| Tourism expenditure | 3.182** | 0.268 |
| *Loss aversion ratio in Scenario B-1* | | |
| Tourism attractions | 1.332*** | 0.564 |
| Service quality | 1.303*** | 0.405 |
| Smart tourism | 1.918*** | 0.946 |
| Medical quality | 1.007*** | 0.234 |
| Hygiene condition | 0.561*** | 0.151 |
| Tourism expenditure | 2.699*** | 0.237 |
| *Loss aversion ratio in Scenario B-2* | | |
| Tourism attractions | 1.267*** | 0.418 |
| Service quality | 1.501*** | 0.771 |
| Smart tourism | 0.306 | 2.938 |
| Medical quality | 1.002*** | 0.333 |
| Hygiene condition | 1.272*** | 0.495 |
| Tourism expenditure | 4.690* | 0.465 |

Notes: Scenario A = post-pandemic; Scenario B-1 = during pandemic with strong engagement in counterfactual thinking; Scenario B-2 = during pandemic with weak engagement in counterfactual thinking; ***, **, and * represent the significance levels of the mean ratios statistically different from one at 1 %, 5 %, and 10 %, respectively

and hygiene conditions did not noticeably change between the two stages of the pandemic. In the loss domain, similar results can be identified.

Apart from the destination-specific attributes, the findings confirm that risk perception as an unobserved psychological factor had a significant influence on destination choice during the COVID-19 pandemic. The parameter of risk perception in the utility functions of the prior destination was significant and positive in the reference-dependent model (0.135). In contrast, the coefficients of the measurement equations in the latent variable model indicated that risk perception was negatively linked with its indicators. Considering the overall effects, tourists with higher risk perception were inclined to select alternative destinations rather than revisit prior destinations (status quo specific). This is an intriguing finding that differs from those of some prior studies (Kerstetter & Cho, 2004; Rather, 2021), which have supported a positive relationship between risk perception and revisit intention. Although past experiences might lower cognitive risks in certain destinations, this does not appear to be the case in relation to the perceived risks surrounding COVID-19. Under the influence of the pandemic, tourists tended to avoid crowded and highly populated destinations to minimize COVID-19-related risks. Typically, the prior destinations in tourists' minds are well-known and popular. As these popular destinations have a

**Table 6**
Delta method results for the reference-dependent model.

| Measurement | Value | Robust std. err. | Value | Robust std. err. |
|---|---|---|---|---|
| | Gain domain | | Loss domain | |
| *Ratio of coefficients across Scenario A and Scenario B-1* | | | | |
| Tourism attractions | 1.704 | 0.535 | 1.354 | 0.336 |
| Service quality | 0.995 | 0.263 | 1.087 | 0.253 |
| Smart tourism | 0.332** | 0.277 | 0.480** | 0.215 |
| Medical quality | 0.368*** | 0.100 | 0.645** | 0.145 |
| Hygiene condition | 0.452*** | 0.082 | 0.848 | 0.235 |
| Tourism expenditure | 0.437 | 0.485 | 0.515** | 0.224 |
| *Ratio of coefficients across Scenario A and Scenario B-2* | | | | |
| Tourism attractions | 1.597* | 0.361 | 1.335 | 0.328 |
| Service quality | 1.809 | 0.724 | 1.715 | 0.478 |
| Smart tourism | 1.762 | 3.498 | 15.965 | 139.497 |
| Medical quality | 0.498*** | 0.152 | 0.878 | 0.223 |
| Hygiene condition | 1.300 | 0.370 | 1.074 | 0.322 |
| Tourism expenditure | 2.017 | 4.949 | 1.369 | 0.909 |

Notes: Scenario A = post-pandemic; Scenario B-1 = during pandemic with strong engagement in counterfactual thinking; Scenario B-2 = during pandemic with weak engagement in counterfactual thinking; ***, **, and * represent the significance levels of the mean ratios statistically different from one at 1 %, 5 %, and 10 %, respectively.

**Table 7**
Preference structure change across scenarios.

| Measurement | Value in gain domain | Value in loss domain |
|---|---|---|
| *Preference structure change across Scenario A and Scenario B-1 anchoring tourism expenditure* | | |
| Tourism attractions | 3.899 | 2.629 |
| Service quality | 2.277 | 2.111 |
| Smart tourism | 0.760 | 0.932 |
| Medical quality | 0.842 | 1.252 |
| Hygiene condition | 1.034 | 1.647 |
| Tourism expenditure | 1 | 1 |
| *Preference structure change across Scenario A and Scenario B-2 anchoring tourism expenditure* | | |
| Tourism attractions | 0.792 | 0.975 |
| Service quality | 0.897 | 1.253 |
| Smart tourism | 0.874 | 11.662 |
| Medical quality | 0.247 | 0.641 |
| Hygiene condition | 0.645 | 0.785 |
| Tourism expenditure | 1 | 1 |

Notes: Scenario A = post-pandemic; Scenario B-1 = during pandemic with strong engagement in counterfactual thinking; Scenario B-2 = during pandemic with weak engagement in counterfactual thinking.

higher visitor flowrate from various source markets, they might present a higher perceived risk of infection during a pandemic, thus encouraging tourists to select alternative destinations.

## Implications and conclusion

### *Theoretical implications*

The theoretical contributions of this study can be summarized as follows. First, this study establishes the concept of "analogous post-pandemic." Anchored in the empirical data trajectory of confirmed cases and prevailing pandemic-related policies, subsequent COVID-19 waves have become discernible—marked by surges in confirmed cases since March 2022 after the questionnaire survey, coupled with corresponding policies such as the Zero-COVID policy. However, during the survey, daily confirmed cases were notably fewer compared to prior instances, and travel restrictions had been largely lifted across Chinese cities. With China implementing routine pandemic prevention measures and facilitating work resumption, the pandemic situation has been effectively controlled. Thus, we define the intervals between distinct pandemic waves as the "analogous post-pandemic" phase. Historically, many studies, including those focused on COVID-19 and other crises, have primarily categorized these events into pre-crisis, crisis, and post-crisis stages. However, crises typically encompass multiple phases, each characterized by varying levels of challenge and opportunity (e.g., the peaks and troughs of confirmed COVID-19 cases during the pandemic). In the context of the COVID-19 pandemic, individuals often perceive each trough as the conclusion of the crisis, only to subsequently encounter new waves of cases. Therefore, it is imperative to distinguish between individual preferences during peak and trough phases, with a specific emphasis on preference dynamics during the trough period (or an analogous post-pandemic phase). Importantly, considering the oscillations in risk during crisis-related periods, dynamic behavioral shifts must be identified within these intervals to effectively respond to and manage crises. We underscore this dynamic of preference and advocate for more intricate temporal divisions in crisis-related research.

The mechanism of tourist destination choice in a crisis context differs from that in a normal situation in at least four ways. First, our results show that tourists selected destinations with reference to their past experiences and preferred to avoid destinations with downgraded tourism attributes compared with those of the reference destinations. This verified the existence of reference dependence and loss aversion behavior in light of prospect theory in times of crisis. Second, in a normal situation, tourist destination preferences are relatively stable. However, the COVID-19 pandemic caused structural breaks in tourists' destination preferences following the dynamic of the crisis, such as the peaks and bottoms of confirmed cases and strictness of the control policies. Third, contrary to studies that have supported the status quo argument, this study found that tourists with higher risk perception tended to select alternative destinations rather than revisit prior destinations during the pandemic. Previously visited destinations are generally preferred by tourists; however, this has changed during the pandemic as they tended to avoid these popular destinations and instead searched for alternatives with superior medical services and hygiene. Fourth, the scenario-based intertemporal hybrid choice models proposed in this study are useful to explain tourist choice behavior according to both alternative specific factors and decision-makers psychological factors. The superior performance of this novel model implies that it can evaluate tourist preference heterogeneity better than other alternative models.

### *Practical implications*

Although the pandemic has hindered and even ruined the development of the tourism industry in some destinations, it has also provided the time and opportunity to consider recovery, improvement, and transformation (Zhang et al., 2021). First, our findings indicate that tourists highlighted the importance of destination safety and security when the pandemic situation was relatively severe.

Considering the powerful influence of social media on the perceptions of destinations during the pandemic (Li, Zhang, et al., 2021), marketers should work to deliver messages on social media that minimize tourists' safety concerns, such as by providing information that features hygiene and sanitation. Furthermore, apart from alternative-specific factors, the pandemic-related risk perception impelled tourists to select alternative destinations instead of prior destinations as they pursued higher levels of health, safety, and contactless services. Messaging via social media and marketing campaigns are important in shaping tourists' perceptions of destinations. Therefore, to retain repeat visitors, the safe image of a destination with high levels of hygiene and sanitation should be explicitly communicated to target tourists in the context of the infectious disease.

Second, smart tourism has become a vital attribute of numerous popular destinations, since the provision of smart tourism features can improve the tourism experience. Real-time information, such as visitation data, is useful for visitor flows and queue management, traffic control, and bus route service adjustments to minimize crowding and permit social distancing (Wen et al., 2020). In addition, as contactless services and service robots will likely remain popular since they eliminated some of the tourists' safety concerns, tourism business practitioners may continue to adopt these services to more broadly improve their daily operations. Nevertheless, this study found that smart tourism played a less important role in the post-pandemic era than during the pandemic. Thus, the impact of smart tourism on tourist decision-making is not permanent and instead depends on the specific situation of the COVID-19 pandemic. This suggests that destination management organizations can promote the utilization of smart tourism infrastructures and facilities in times of health crises but should not overemphasize their importance or overinvest in smart tourism-related attributes in tourist packages, particularly in normal circumstances.

Finally, tourism attractions and service quality became more important for tourists in the post-pandemic era. Based on self-transcendence and self-diminishment, the crisis caused tourists to seek meaning, purpose, and spiritual growth in their lives post-pandemic (Miao et al., 2022). Therefore, destination management organizations can consider providing unique tourism products with such themes and purposes and sell premium high-end products. Furthermore, considering the effects of loss aversion on destination choice, well-known destinations must continuously optimize their tourism attributes to sustain comparative advantages and attract repeat visitors.

## *Concluding remarks*

In this paper, we investigated the changes in tourists' preferences for the attributes of domestic destinations during- and post-pandemic using scenario-based intertemporal hybrid choice models. The study produced several insightful findings. First, the structure of tourists' preferences was changed by the pandemic. Tourists highlighted the importance of medical quality, hygiene conditions, and smart tourism when selecting destinations during the pandemic but were more concerned about tourism attractions and service quality after the pandemic. Furthermore, tourists with higher levels of risk perception tended to select alternative destinations to those they had previously visited. The findings of reference-dependence and loss aversion revealed the asymmetric choice behavior of individuals. Additionally, this study confirmed the value of counterfactual thinking in guiding individuals into an imagined scenario by modifying the antecedents of the unexpected events.

This study makes some unique contributions to the literature. First, it uncovered distinctive destination choice behaviors of tourists in different stages of a major public health crisis. Second, the study revealed an unexpectedly negative relationship between risk perception and revisit intention. Third, the framework based on prospect theory was confirmed as valid even in times of crisis. In terms of the methodological contributions, to the best of our knowledge, no prior studies have investigated the preference change of destination choice using scenario-based intertemporal hybrid choice models. The proposed model enhances the explanatory power of the estimation results as it appropriately incorporates additional relevant variables (Bolduc & Alvarez-Daziano, 2010). Finally, the estimation results have useful implications for destinations to restructure their attributes with the goal of attracting potential tourists.

The study has some limitations and opens avenues for future research. First, the latent variables were expressed as the structural equations of socio-demographic variables. However, individual attitudes and perceptions are always shaped by factors beyond socio-demographic information, such as personality traits, nationality, experiences, and lifestyles (Karl & Schmude, 2017). Therefore, future studies could consider incorporating more influential factors in the latent variable models to improve their explanatory power (Anable, 2005). Second, tourist behavior is likely to change with the evolution of latent variables over time. A dynamic hybrid choice model combining the discrete choice model with the hidden Markov model could thus be developed to investigate the dynamics of these changes in human behavior (Abou-Zeid & Ben-Akiva, 2014). In addition, diminishing sensitivity as one of the principles of the prospect theory, asserts that the impacts of gains and losses on tourist choice is diminished with distance from the reference point (Tversky & Kahneman, 1992). Future studies could further evaluate tourist preference change from the perspective of this principle using the hybrid choice model. Given that vaccination has been widely available in the majority of countries, the investigation of the preference differences between vaccinated and unvaccinated tourists could also be a potential research direction. Besides, future studies could estimate and evaluate other transformations of the hybrid choice model by replacing the random utility maximization approach with a random regret minimization model (Chorus et al., 2008, Koemle & Yu, 2020), replacing the linear utility function with the nonlinear function, or simultaneously estimating intra- and inter-personal heterogeneity (Hess & Train, 2011). Furthermore, future research should consider utilizing a more diverse and representative respondent sample for the questionnaire survey, while also incorporating extensive socio-demographic information, including the distribution of income and education levels in China. Moreover, due to the dynamic evolution of the COVID-19 pandemic beyond the scope of our questionnaire survey, prospective studies might contemplate conducting a longitudinal analysis. This approach could examine the evolution of tourists' destination preferences across distinct pandemic phases, encompassing recent pandemic dynamics.

## CRediT authorship contribution statement

**Hanyuan Zhang:** Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Visualization. **Richard T.R. Qiu:** Conceptualization, Methodology, Software, Formal analysis, Investigation, Writing – review & editing. **Long Wen:** Conceptualization, Methodology, Investigation, Writing – review & editing. **Haiyan Song:** Conceptualization, Investigation, Writing – review & editing, Supervision, Project administration, Funding acquisition. **Chang Liu:** Supervision, Project administration.

## Data availability

Data will be made available on request.

## Declaration of competing interest

None.

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## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.annals.2023.103680.

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