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Reinvestigating repurchase intentions for travel apps: a comparison of China's various tiers of cities

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ABSTRACT
The intense competition amongst travel apps, regardless of their popularity, has made repurchase intention a critical financial challenge for travel providers. By combining the Stimulus-Organism-Response (S-O-R) framework and the New Economic Geography (NEG) theory, this research examined how city tier disparities influence the experiential features of travel apps and user repurchase intentions. Survey data was acquired from 739 travel app users in China. The findings indicate that a set of context-based experiential features significantly influences utilitarian and hedonic values, and consequently leading to a notable increase in repurchase intentions. In addition, the outcomes of a multigroup analysis revealed that China's users located in tier 1 city (i.e. Beijing) and tier 3 city (i.e. Kunming) had distinct effects on the hypothesised relationships. Theoretically, the research provides extensive implications to information systems and tourism literatures; whilst offering some actionable insights to travel practitioners.

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Travel app; user experience; value; repurchase intention; city tier

Background

In 2022, travel app downloads worldwide reached 2,308.2 million users, marking a significant increase from the 1,320.2 million users recorded in 2020 (Statista, 2022a). This trend is mainly driven by tourists' demand for a "seamless travel experience" (Lim et al., 2022) and is attributed to post-pandemic "revenge travel spending" behaviour. In China, Statista (2022d) reported that over 80% of Chinese tourists purchased travel services through travel apps, underscoring the crucial role these apps play in the tourist purchasing journey. Considering the high demand from users, it is essential for travel practitioners to leverage travel apps to establish sustainable competitive advantages (İlkan et al., 2023).

It is important to note that the popularity of travel apps does not necessarily lead to repurchase intentions, which are vital for future financial sustainability for both app developers and practitioners (Jang et al., 2018). For instance, as reported by The Star in 2017, 88% of tourists would switch travel apps if their current one failed to meet their demands. Similarly, global data from Statista (2021c) revealed that the average annual retention rate for travel apps was only 31%. These statistics underscore the challenge of retaining travel app users and stimulating further purchase intentions. This is particularly crucial given that users from different geographical regions and economic backgrounds may have varying demands and expectations when using travel apps.

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Several empirical research studies agree that users from different city tiers in China may result in different perceptions when using travel apps (Bilby et al., 2016; Shin et al., 2021). Although most cities in China have a similar urban form in terms of infrastructure and land use (Ding et al., 2022), a significant discrepancy in economic development, personal income, and living standards is present (Crane et al., 2018; Mitra et al., 2022). Especially, significant differences exist in terms of gross domestic product (GDP), real per capita incomes, and household income between cities in the higher and lower tiers (Statista, 2022c; Zhao & Wan, 2021). For example, Beijing's GDP in 2021 (RMB 4,027 billion) is approximately fifty-five times that of Lhasa (RMB 74.2 billion), the poorest provincial capital city (Statista, 2022b). The substantial economic inequality among different city tiers has intensified disparities in social, economic, and spatial characteristics (Bilby et al., 2020; Zhao & Wan, 2021), leading to diverse lifestyles and consumption patterns (Zeljković, 2022). These variations are also reflected in technology usage. For instance, users in higher-tier cities, characterised by higher income levels and more advanced technology, have greater expectations and purchasing power when using travel apps compared to those in lower-tier cities. Consequently, it is prudent for travel providers to develop tailored strategies for travel apps that cater to the distinct needs of users from various geographical locations, such as different city tiers in China.

From a scholarly perspective, it has been documented that users typically assess the value of travel apps by considering the features that hold the greatest importance to them (Schiffman & Wisenblit, 2019). To enhance user experience and encourage repeat purchases, travel providers can benefit from understanding the "value systems" of travel app users. In tourism, simply providing utilitarian value is no longer sufficient, in light of the fact that hedonic values have increased in importance (Gretzel et al., 2020). For example, when using the travel app, utilitarian and hedonic values are appropriate for describing convenience, travel options, and the enjoyment of browsing tips and photos. Also, in the recent competitive era, it is becoming more important to carefully consider whether the values are relevant based on the context (Pandža Bajs, 2015). Accordingly, two research questions that underpin this research are:

Q1. What context-based experiential features motivate user value perception (i.e. utilitarian and hedonic value) and in-app repurchase intentions?

Q2. Do different city tiers (low vs. high) impact significantly the decision-making process?

This research integrated the stimulus-organism-response (S-O-R) framework and new economic geography (NEG) theory to more fully understand travel app usage in China. By using those two theories, a research framework was built, in particular to (i) identify the intercorrelations between experiential features (i.e. information quality, ease of use, interface attractiveness and personalisation), value perceptions (i.e. hedonic and utilitarian) and repurchase intentions; and (ii) to discover how disparities between city tiers with different socioeconomic growth (such as those between tier 1 cities like Beijing and tier 3 cities like Kunming) moderate those relationships.

This research offers two significant contributions. First, by applying the S-O-R framework, it demonstrates how an app's stimulus factors influence user emotional states and behaviours. This provides valuable insights into the expectations that users prioritise when using travel apps and how these expectations interact with perceptions, ultimately affecting behaviour. Second, this research expands the application of NEG theory within the context of tourism apps. By utilising this theory to explain significant differences in tourism app usage, the findings contribute to the existing literature by highlighting the importance of considering regional economic disparities when exploring technology usage on a broader scale. Practically, these findings are crucial for local and global system developers to tailor their digital strategies to local economic and cultural specifics, thereby enhancing sustainable usage. Furthermore, with this information, tourism providers can redesign marketing strategies within tourism apps, especially when targeting users from diverse geographical locations, both locally and internationally.

Literature review

Holistic view of travel app literature

To provide a comprehensive overview of the existing literature on current topics, a systematic literature review was conducted using the guideline of Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) (Julien et al., 2011; Moher et al., 2009; Petticrew & Roberts, 2006). The search term "TITLE-ABS-KEY ("travel app*")" was used to retrieve articles from the Web of Science and Scopus databases, with the subsequent criteria: subject areas in social sciences, business, management, tourism, and hospitality, empirical journal articles, and English language. Table 1 presents the results of the literature review, whereas Figure 1 illustrates the review procedure.

According to the review, although research on travel apps has been emerging in recent years, many researchers have focused on adoption intentions, such as travel app usage intentions (Fakfare & Manosuthi, 2022; Tak & Gupta, 2021), and continued use intentions (Liu et al., 2023; Zhou et al., 2022). Few, however, extended the adoption to purchase intentions or even repurchase intentions (Table 1), which financially supports travel providers in maintaining successful operations in the future (Jang et al., 2018). In addition, assuming homogeneity of travel app users offers insufficient insights for both practitioners and researchers. Research has shown that there are significant differences in economic development and disposable income among people living in different city tiers (Crane et al., 2018; Zhang et al., 2020). According to Bilby et al. (2016) and Shukla and Rosendo-Rios (2021), individuals located in higher-tier cities prefer more sophisticated and non-functional features (e.g. personalisation), while those in lower-tier cities prioritise functional features (e.g. information quality) compared to hedonic features. These differing priorities may be explained by the disparity in income levels and consumption cultures (Singh et al., 2023; Yin et al., 2023). To the best of the authors' knowledge, there has been no comparative research on the attitudes and perceptions of travel app users in different tiers of Chinese cities (Table 1), regardless of the potential effects of city tier disparities (e.g. Bilby et al., 2020; Huang & Wei, 2018; Shukla & Rosendo-Rios, 2021).

Stimulus-Organism-Response (S-O-R) framework

Mehrabian and Russell's (1974) S-O-R framework is one of the most popular theories to explain the impact of atmospheric factors on human behaviour (Cheah et al., 2022). This theory explains the relationship between environmental factors (i.e. stimulus) and human behaviour outcomes (i.e. response) via internal processes (i.e. organism). In contrast to popular technology-related theories such as the technology acceptance theory (TAM) and the unified theory of the acceptance and application of technology (UTAUT), the S-O-R framework does not emphasise a particular set of factors (Mehrabian & Russell, 1974). Rather, the "stimulus" and "organism" can encompass a broad range of elements due to the theory's inclusiveness and flexibility (Lim et al., 2021), which make it particularly well-suited for exploratory research.

Prior research on technology-based tourism has frequently used the term "stimulus" to represent the features of travel technology, the quality of the information system, and online consumer reviews that significantly impact users' internal states and behavioural intentions (Ali et al., 2021; Fang et al., 2017). The "organism" describes the internal states (cognitive and affective systems) between a stimulus and a person's response (Zhao & Liu, 2023). Recent tourism research has placed a greater emphasis on relationship marketing, where "relationship" relates to the psychological processes that contribute to service evaluations and behavioural intentions (Itani et al., 2019; Rather, 2020; Xiong et al., 2023). This shift has occurred because contemporary users are more informed, empowered, and place a greater emphasis on individuality (Claffey & Brady, 2015). In fact, value perception is often seen as a key indicator of relationship quality and behavioural intentions (Dabbous & Barakat, 2020; Fu et al., 2018; Itani et al., 2019). Finally, the "response" refers to the actions a person intends to take, influenced by environmental factors and internal thought processes. In this study, repurchase intentions are used as the measure of responses to better understand the behavioural tendencies of travel app users.

The S-O-R framework was applied to examine how key experiential features of travel apps, including information quality, ease of use, user interface attractiveness, and personalisation, affect users' psychological and emotional states, subsequently influencing behaviours like repurchase intentions. Focusing on these features as stimuli is essential for dissecting the complex dynamics of user engagement and satisfaction across diverse city tiers. These particular features were chosen because they directly interact with users' sensory and cognitive experiences, addressing immediate needs and enhancing overall interaction with apps. For example, well-presented information and straightforward functionality can decrease cognitive stress and improve user experience, while aesthetically pleasing interfaces and tailored content boost emotional engagement and loyalty. The emphasis on these features within the S-

Table 1. Systematic summary of research on travel apps attributes and varied intentions (empirical studies).

Author(s) (year)	Exogenous Constructs	Mediating Constructs	Moderating Constructs	Endogenous Constructs	Theory	Methodology
Research on travel app attributes and use intentions						
Lai (2015)	Information quality, performance expectancy, effort expectancy, social influence, facilitating conditions	Performance expectancy, effort expectancy	n/a	Behavioral intention	UTAUT	Quantitative (survey)
Lu et al. (2015)	Self-efficacy, performance outcomes, personal outcomes, advantages, compatibility, complexity, and social norms	n/a	n/a	App use intention	TAM; IDT; Social cognitive theory	Quantitative (survey)
Dickinson et al. (2017)	Mobile privacy, trust, desire to avoid mobile technology, obligation, safety, and sense of community	n/a	n/a	Willingness to use	n/a	Mixed (interview + survey), exploratory factor analysis
Gupta and Dogra (2017)	Performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit	n/a	n/a	Behavioral intentions, and use behaviour	UTAUT	Quantitative (survey)
Gupta et al. (2018)	Performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivations, price saving, habit, perceived risk, and perceived trust	n/a	n/a	Behavioral intentions (to use travel app), and use behavior	UTAUT2	Quantitative (survey)
Dastjerdi et al. (2019a)	Environmental attitude, satisfying existence needs, satisfying relatedness needs, satisfying growth needs, perceived usage difficulties, and information privacy concern	n/a	n/a	Adoption intention (of travel app)	Need theory	Quantitative (survey)
Dastjerdi et al. (2019b)	Goal-directed behavior (Gain motives, hedonic motives, and normative motives), technophilia, and social dynamic (institutional trust, social trust, and place attachment)	n/a	n/a	Situational use intention and adoption intention of travel apps	n/a	Quantitative (survey for exploratory factor analysis)
Ahmad et al. (2021)	Performance expectancy, effort expectancy, social influence, facilitating conditions, and perceived distrust	User experience	Self-transcendence, conservation, self-enhancement, and openness to change	Behavioral intention to use	UTAUT	Quantitative (survey)
Hung et al. (2020)	Perceived ease of use, perceived usefulness, information quality, service quality, perception of preference, self-reliance, social influence, technological barrier, and information security	n/a	n/a	Decision to use	TAM	Quantitative (survey)
Lin et al. (2020)	Perceived usefulness, perceived ease of use, usage attitude	n/a	n/a	Usage intention, and application information search behavior	TAM	Quantitative (survey)
Rianto et al. (2020)	Money saving, time saving, ease	n/a	n/a	Intention to use	TAM	Quantitative (survey)
Ali et al. (2021)	System quality, information quality, and service quality	User engagement, satisfaction, and love	n/a	Behavioral intentions	ISS model; S-O-R model	Quantitative (survey)

(Continued)

Table 1. Continued.

Author(s) (year)	Exogenous Constructs	Mediating Constructs	Moderating Constructs	Endogenous Constructs	Theory	Methodology
Ho et al. (2021)	Utilitarian value, hedonic value, performance expectancy, effort expectancy, social influence, facilitating conditions	n/a	n/a	Intended use of smart itinerary (travel apps)	UTAUT	Quantitative (survey)
Ledikwe (2021)	Entertainment, escapism, and aesthetics	Memorability, and satisfaction	n/a	Behavioral intentions	S-O-R model	Quantitative (survey)
Tak and Gupta (2021)	Visual design, navigation design, information design, and collaboration design	Consumer engagement	n/a	Behavioral intention to use	S-O-R model	Quantitative (survey)
Fakfare and Manosuthi (2022)	Travel information service, medical & emergency information, entertainment, and travel review	n/a	n/a	Travel app usage intention	TAM	Quantitative (survey)
Wu et al. (2022)	Perceived ease of use, perceived usefulness, attitude, and perceived behavior control	n/a	n/a	Travel apps usage intention	TPB; TAM	Quantitative (survey)
Research on travel app attributes and continued use intentions						
Choi et al. (2021)	Confirmation of expectation, privacy protection, and security	Satisfaction, and trust	Technology proficiency	Continued use intention of a travel app	TAM; ECM	Mixed (survey + interview)
Liu et al. (2023)	Information quality, system quality, and service quality, expectation confirmation, perceived usefulness, perceived ease of use, perceived enjoyment, perceived risk, and satisfaction	n/a	n/a	Continuance usage intention	ECM; ISS model	Quantitative (survey)
Wu et al. (2021)	Online atmospherics	Flow experience, perceived usefulness, perceived enjoyment, and attitude	n/a	Revisit intention, and further usage intention	S-O-R model; Media richness theory	Quantitative (survey)
Choi et al. (2019)	Perceived functional benefits, perceived ease of use, perceived financial benefits, and perceived enjoyment	Satisfaction, and trust	Familiarity	Travel app continued use intention	ECM	Mixed (interview + survey)
Zhou et al. (2022)	Perceived usefulness, perceived ease of use	Perceived enjoyment	n/a	Continuance use intention	TPB; TAM	Quantitative (survey)
Research on travel app attributes and purposes beyond usage intentions						
Fang et al. (2017)	User interface attractiveness, privacy and security, portability, compatibility, ease of use, and relative advantages	Psychological engagement, utilitarian benefit, hedonic benefit, and social benefit	n/a	Behavioral engagement intention	S-O-R model	Quantitative (survey)
Douglas et al. (2018)	Travel app functions (e.g. hotel check-in, flight seat choice etc.)	n/a	Gen Y, Gen X, B Boomers, Silent Gen	Travel app functions' importance and frequency	Generational theory	Quantitative (survey for frequency analysis)
Douglas (2019)	Travel app functions	n/a	Male, and Female	Travel app functions' importance and frequency		Quantitative (survey for frequency analysis)
Zhang et al. (2019)	Perception of app advantage (i.e. usefulness, and ease of use)	Satisfaction, and stickiness	Confucian culture, and switching cost	Word of mouth	TAM	Quantitative (survey)

(*Continued*)

Table 1. Continued.

Author(s) (year)	Exogenous Constructs	Mediating Constructs	Moderating Constructs	Endogenous Constructs	Theory	Methodology
Turulja and Činjarević (2021)	Online customer review (OCR) helpfulness	Trust, and attitude	n/a	Travel app downloading intention	S-O-R model	Quantitative (survey)
Tseng et al. (2021)	Expertise of amateur information publisher, perceived interactive atmosphere, perceived trust, experiential satisfaction, perceived information quality, and expectation confirmation	n/a	n/a	Switching intention	n/a	Quantitative (survey)
Dewan et al. (2022)	Kakao bus, kakao taxi, kakao navi, perceived usefulness, perceived ease of use, and travel satisfaction	n/a	Traveler's involvement	Life satisfaction	TAM	Quantitative (survey)
Chuang (2020)	Experiential marketing, and mobility	Perceived usefulness, and use context	n/a	Purchase intention	TAM	Quantitative (survey)
Lim et al. (2022)	Perceived relative advantages, perceived compatibility, perceived complexity, communicability, and perceived behavioral control	Attitude	Inertia	In-app purchase intention	IDT; TPB	Quantitative (survey)

Note. n/a (not applicable), TAM (Technology Acceptance Model), TPB (Theory of Planned Behavior), ECM (Expectation confirmation model), UTAUT (Unified theory of acceptance and the use of technology model), IDT (Innovation Diffusion Theory), S-O-R (Stimulus-Organism-Response) model, ISS (Information system success) model.

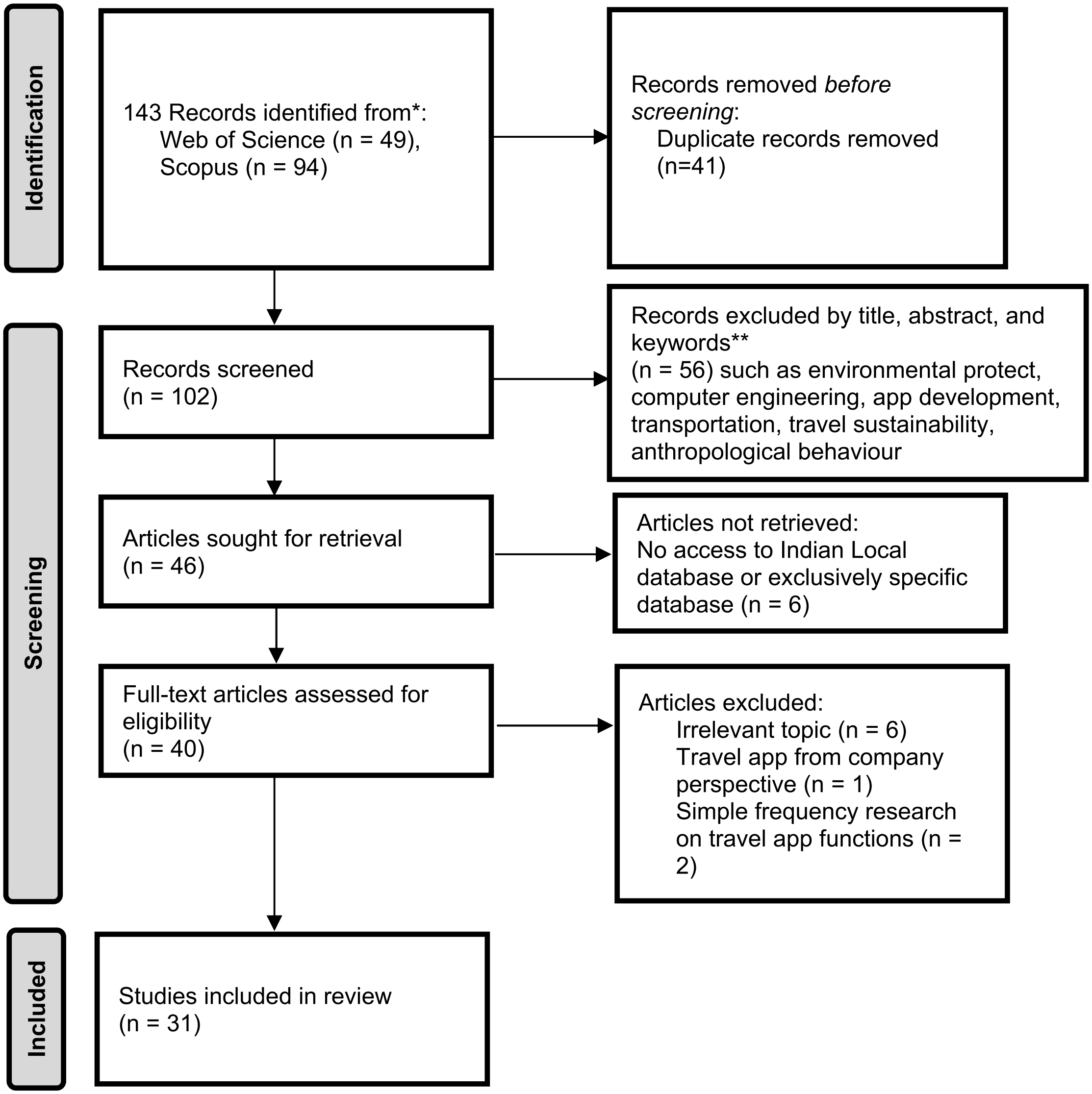

Figure 1. PRISMA flow diagram.

O-R framework acknowledges that initial interactions with app functionality significantly shape user attitudes and behaviours.

Repurchase intentions, which reflect the likelihood that a person will continue to buy a product or service, are crucial for the long-term success of travel apps, yet prior research has often focused only on initial adoption or continuous usage rather than on repurchasing behaviour (Lee et al., 2019; Vahdat et al., 2021). In the era of mobile dominance, in-app purchases integrated with e-wallets and online payment methods have become increasingly popular, offering the same products and services as traditional travel agencies but with added convenience and flexibility, potentially enhancing the experiential value for users (Dacko, 2017; Lim et al., 2022). Given that service quality and user experience are key determinants of travel app users' behavioural intentions, there is a pressing need to focus research on understanding factors that drive repurchase intentions within travel apps, especially considering how consumers' purchasing behaviours are evolving (Gretzel et al., 2015).

Then, mobile-based travel apps significantly shape user experiences and intentions, influencing interactions through critical features such as aesthetic quality, app content, and performance (Fakfare & Manosuthi, 2022; Fang et al., 2017; Tak & Gupta, 2021). Research by Fakfare, Promsivapallop, and Manosuthi (2023) categorises these attributes into the five essential areas of convenience, security, application design, application privilege, and communication, each designed to enhance user satisfaction and app usability. These attributes collectively improve the travel app experience by addressing a wide range of user needs and expectations. Convenience focuses on streamlining navigation and transaction processes to enhance app usability, while security involves protecting personal and financial information through advanced measures like encryption. Application design combines aesthetic appeal with functional usability to boost engagement, and application privilege offers unique benefits like loyalty programs to increase user loyalty and satisfaction. Communication supports strong interactions between users and service providers, enhancing community feelings and reliability through features like real-time support and feedback.

Adjustments to these features have been tailored for the Chinese market based on prior studies (e.g. Ali et al., 2021; Sun et al., 2016; Tak & Gupta, 2021), resulting in a focus on the four key attributes of information quality, ease of use, user interface attractiveness, and personalisation. These were selected to align with the sophisticated demands of Chinese consumers, emphasising customised services and reliable information, while eliminating less critical features like adaptable booking capabilities due to minimal concerns over loading speeds and the evolving preferences for flexibility in travel planning (Benítez-Aurioles, 2018; Jeong & Shin, 2020; Kim et al., 2017). This streamlined approach aims to optimize user engagement and loyalty by adapting app functionalities to the specific needs and technological trends within the regional context.

Value perception in tourism, influenced by experiential features, is essential for developing quality relationships and behavioural responses, where utilitarian and hedonic values each play a specific role (e.g. Cheung et al., 2022; Choi et al., 2019; Itani et al., 2019; Oriade & Schofield, 2019). Utilitarian value focuses on practical aspects like price, quality, and convenience offered by travel apps, such as detailed travel guides and efficient online booking systems, which directly meet user needs and encourage continued engagement and purchases (Cheung et al., 2022; Moon et al., 2018; Pandža Bajs, 2015). Conversely, hedonic value emphasises the emotional and experiential aspects of app usage, enhancing user satisfaction through enjoyable interactions and aesthetically pleasing designs (Cham et al., 2022; Lv et al., 2022; Morosan, 2021). These emotional experiences foster loyalty and provide travel firms with a competitive advantage by developing deeper emotional ties between users and the app (Itani et al., 2019). Both types of value are integral in online settings where physical contact is absent, guiding users through cognitive and affective evaluations that influence their decisions to continue using and purchasing through the app.

New economic geography (NEG) and city tiers in China

New economic geography (NEG), also known as the core–periphery model, a theoretical foundation that explains the relationship between regions with different levels of economic development (Krugman, 1991, 1998, 2011). According to NEG, there are two main concepts: the core and the periphery, which are shaped by centripetal and centrifugal forces. Centripetal forces refer to the agglomeration process and positive external effects, while centrifugal forces relate to dispersion and negative external effects (Klimczuk & Klimczuk-Kochańska, 2019). The theory suggests that regions with political, geographic, and economic advantages become the core regions, which attract continuous labour and external capital, leading to the development of larger economies. Peripheral regions, which are less attractive to external capital and have fewer natural and labour resources, are disadvantaged in their competition for these resources. As a result, core regions tend to become centres of economic and innovative activities (Florida, 2017), while the transfer of technical progress and knowledge to peripheral regions becomes more difficult due to the high costs of financial and intellectual inputs (Klimczuk & Klimczuk-Kochańska, 2015; Krugman, 2011).

Based on the aforementioned discussion, the city tier system in China reflects the core–periphery model, wherein populations in top-tier cities are significantly more prosperous than those in lower-tier cities (Bilby et al., 2020; Krugman, 2011). Established in the 1980s, the tier system was implemented by the central government as a strategy to prioritise infrastructure development and resource allocation among over 700 official cities (Starmass, 2022). Consequently, this system has led to a substantial imbalance in the development of infrastructure, technology, and human resources between the highest and the lowest-tier cities (Fakfare, Talawanich, & Wattanacharoensil, 2020; Huang et al., 2021).

While there is no academic consensus, five to seven tiers are typically recognised in China (Appendix 1). According to Bilby et al. (2020), the top three tiers have fundamentally distinct consumer cultures and values when compared to the lower tiers, which are often referred to as "undeveloped". This may be an exaggeration, but it highlights the substantial socioeconomic disparities between the top three tiers and the lower tiers (Huang et al., 2021; Shukla & Rosendo-Rios, 2021). Among the top three tiers, tier 2 cities are rapidly advancing in economic growth and infrastructure, increasingly resembling tier 1 cities in their purchasing habits and preferences, thus largely diminishing the differences between them. On the other hand, tier 3 cities generally uphold more traditional cultural values and lifestyles compared to tier 1 cities (Bilby et al., 2020; Huang & Qian, 2018). This study focuses on examining the distinctions between travel app users' behaviour in tier 1 and tier 3 cities. This approach aligns with the conclusion that, despite the significant economic disparities, the levels of development between these two tiers are still comparable (Bilby et al., 2016, 2020). Specifically, Beijing and Kunming were selected to represent tier 1 and tier 3 cities.

As the capital of China, Beijing has a stronger emphasis on traditional Chinese cultural customs, making it more representative of China as a whole. The GDP recorded in Beijing is found significantly larger (i.e. RMB 4,026 billion) as compared to those three cities in tier 1, such as Shanghai (RMB 4,321 billion), Guangzhou (RMB 2,823 billion) and Shenzhen (RMB 3,066 billion) (CEIC, 2022). In term of population size, more than 21.89 million people living in Beijing (National Bureau of Statistics, 2021), with a disposable income per capita of RMB 75,601 (Statista, 2021a). Residents in Beijing tend to have higher living standards and better disposable incomes, as well as a wider range of travel options than those in lower-tier cities (Zhao & Wan, 2021). As a result, users in Beijing may be more demanding about the features of travel apps and attach greater importance to personal preferences and individuality than their counterparts in lower-tier cities.

Kunming is one of the tier 3 cities in China, with GDP of RMB 722 billion (CEIC, 2022). This city is populated by almost 8.46 million population (Kunming Government, 2021b), with a disposable income per capita of RMB 38,762 (Kunming Government, 2021a). Focusing on Kunming compared to other tier 3 cities in China is strategically significant due to its unique position as a cultural and economic hub in Southwest China and a popular tourist destination (Marafa et al., 2022). Kunming's diverse demographic composition and its role as a gateway to Southeast Asia provide distinctive insights into consumer behaviour, making it an ideal setting for examining travel app usage in a rapidly developing urban environment. Its cultural heritage and scenic landscapes enhance the relevance of travel apps for residents, offering a rich context for exploring how these apps cater to specific regional needs. This focus allows for a deeper understanding of app functionalities and user engagement in a less economically dominant yet culturally significant city.

Consequently, the S-O-R framework combined with the NEG were applied to investigate the influence of city tier disparities between Beijing (tier 1) and Kunming (tier 3) on travel app users' decision-making process for repurchase intentions. These two cities have huge per capita income inequalities and are separated by a significant geographic distance of 2,795 kilometres, which may have an impact on cognitive and affective evaluation processes and individual preferences (Jensen et al., 2015).

Research model and hypotheses

Experiential features and value perception

Information quality has been acknowledged as an essential functional feature in much technology-related tourism literature (Jung & Hwang, 2023; Sharma et al., 2022), and was recognized as a key determinant in shaping users' perceptions of value and experiences (Kullada & Kurniadjie, 2021). Information quality indicates the credibility of travel apps, which may alleviate users' emotional anxiety.

Ease of use aims to simplify travel app usage for users, demonstrating the apps' commitment to understanding and attending to their users' needs (Bilgihan et al., 2016). Complexity negatively affects the attitudes of travel app users (Lim et al., 2022). In contrast, simplicity produces a feeling of control and certainty, leading to favourable emotions (Vahdat et al., 2021).

User interface attractiveness encompasses both aesthetics and interactivity of a travel app's user interface (Tak & Gupta, 2021). An attractive design can aesthetically and interactively satisfy users, delivering both functional and enjoyable experiences, whereas an unappealing interface may lead to low perceptions of pleasure and efficiency (Gao et al., 2023; Lin & Ryu, 2023).

The concept of *personalisation* flourished with the online marketing boom due to the skyrocketing capacity of data governance (Jeong & Shin, 2020). Personalised products and services may be tailored to users' consumption patterns; accordingly, users perceive less uncertainty and greater value in emotions and convenience (Reis et al., 2020; Vinod, 2020). These experiential features of travel apps (information quality, ease of use, user interface attractiveness, and personalisation) serve as stimuli that influence cognitive and emotional evaluations, the organisms, aligning with the S-O-R framework. Therefore, the following hypotheses were formulated:

H1: Information quality (***H1a***), ease of use (***H1b***), user interface attractiveness (***H1c***), and personalisation (***H1d***) positively associate with utilitarian value.

H2: Information quality (***H2a***), ease of use (***H2b***), user interface attractiveness (***H2c***), and personalisation (***H2d***) positively associate with hedonic value.

Value perception and repurchase intentions

Value perception reflects a cognitive (i.e. utilitarian value) and affective (i.e. hedonic value) evaluation of experiential features. The utilitarian value is generated by the functional features of travel apps while the hedonic value derives from enjoyment during usage. An overall positive value perception indicates emotional and behavioural inclinations (Cheung et al., 2022; Itani et al., 2019; Oriade & Schofield, 2019). In the online marketing context, both utilitarian and hedonic values have been demonstrated to have positive direct effects on attitudes and satisfaction (Hsu & Lin, 2016); behavioural engagement intentions (Fang et al., 2017); purchase intentions (Moon et al., 2018; Rauschnabel et al., 2018). Utilitarian value and hedonic value are seen as critical mediators that transform initial app interactions (stimuli) into repurchase tendencies (responses), illustrating the framework's applicability in predicting consumer loyalty. As a result, this research proposed these hypotheses:

H3: Utilitarian value positively links with in-app repurchase intentions.

H4: Hedonic value positively links with in-app repurchase intentions.

Moderating effect of city tier disparity

It is widely acknowledged that there are substantial differences in consumption attitudes and intentions between tier 1 and tier 3 cities (Atwal & Bryson, 2017; Heine et al., 2019). These differences may influence how people perceive and plan for travel, with those in lower-tier cities potentially being more conservative and having less refined tastes than those in higher-tier cities (Bilby et al., 2016; Shin et al., 2021). Additionally, research has found that consumers in tier 3 cities may be more sensitive to monetary and functional considerations (Huang & Qian, 2018), while those in tier 1 cities tend to have higher hedonic preferences (Shukla & Rosendo-Rios, 2021). People in higher-tier cities also seem to be more willing to engage in outbound travel (Huang & Wei, 2018). Based on NEG theory, the economic and cultural differences inherent in tier disparities influence how stimuli are received and processed by users, thereby affecting the organism and response relationship outlined in the S-O-R framework. NEG theory provides a nuanced understanding of regional influences on consumption patterns, enriching the analysis of spatial-economic impacts on technology adoption and usage behaviours in diverse urban contexts. Therefore, the following hypotheses were proposed (Figure 2).

H5: City tier disparity moderates the relationship between information quality (***H5a***), ease of use (***H5b***), user interface attractiveness (***H5c***); personalisation (***H5d***) and utilitarian value.

H6: City tier disparity moderates the relationship between information quality (***H6a***), ease of use (***H6b***), user interface attractiveness (***H6c***); personalisation (***H6d***) and hedonic value.

H7: City tier disparity moderates the relationship between utilitarian value (***H7a***) and hedonic value (***H7b***) and in-app repurchase intentions.

Methodology

Data collection

This study was conducted in Beijing and Kunming, utilising a self-administered survey. Due to COVID-19 concerns, the survey was delivered online by

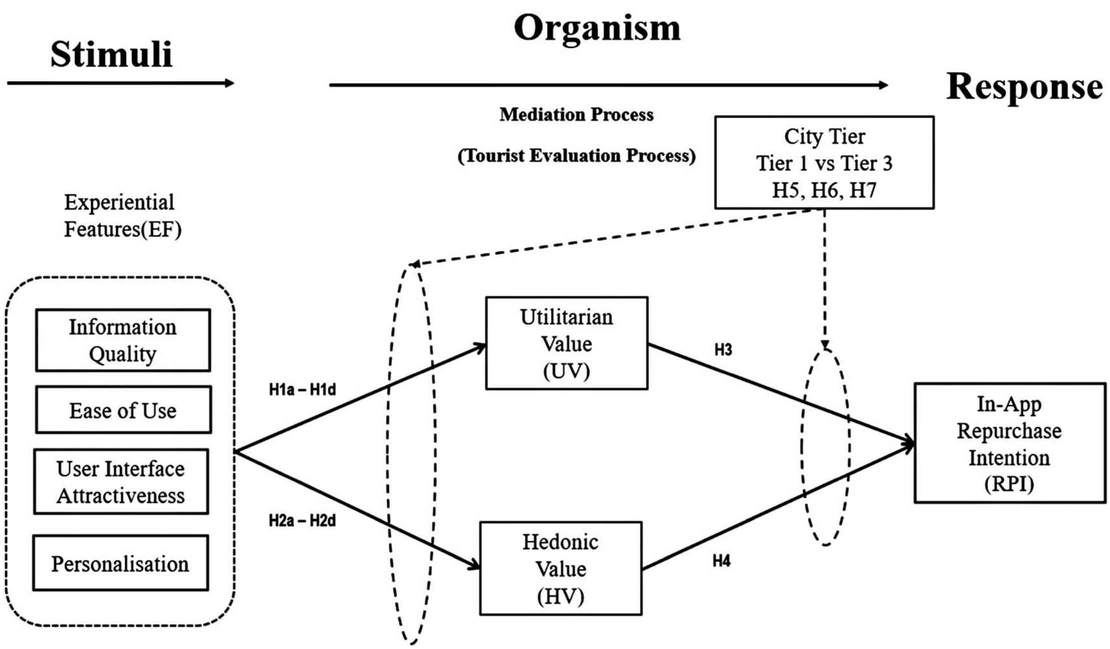

Figure 2. Research model.

restricting IP addresses from Beijing and Kunming via the *Wenjuanxing* questionnaire platform (a leading survey platform akin to Qualtrics in China). As previously established, these two cities are representative of China's tier 1 and tier 3 cities, which have a significant economic and income disparity (Statista, 2022c). In addition, this research focused on Ctrip (one of the top travel app in China) travel app users as this app has the biggest market share and the highest number of active users in China (Guo et al., 2021; Statista, 2021b). A purposive sampling technique was used to ensure the validity of the respondents (Saunders et al., 2015), where the respondents must: (i) have the experience using Ctrip app to purchase travel products or services; (ii) have used the app for at least six months; and (iii) a digital savvy segment (i.e. aged between 20 and 40 years old) (Bento et al., 2018).

This survey instrument was subjected to pre-testing and pilot testing. Initially, a panel of ten members provided some minor suggestions about grammar and wording in the pre-test. Subsequently, 50 Ctrip travel app users were investigated as a pilot test prior to the distribution of the questionnaires. The finalised instrument was used to collect the data between October 2021 and January 2022. In total, 779 responses were gathered (387 from Beijing and 392 from Kunming). However, only 739 responses (367 from Beijing and 372 from Kunming) were retained when straight-line responses were removed. According to Hair et al.'s (2023) guidelines, a sample size of 739 is sufficient, which also greatly exceeds the requirement (166) estimated by priori analysis using G*power 3.1 (9 predictors, 0.15 effect size, 95% power) (Faul et al., 2009). The majority of the respondents were female (54.8%), aged between 31 and 35 (44.8%). Clearly, there were substantial differences in monthly income between tier 1 Beijing and tier 3 Kunming respondents. The majority of respondents in tier 1 Beijing (52.3%) earned more than RMB 11,001 ($1,600) per month, whereas most respondents in tier 3 Kunming (73.3%) earned a monthly income below RMB 7,000 ($1,000) (Table 2).

Measures

All measurements were borrowed from prior studies on travel apps with slight modifications. Information quality and personalisation were measured with items from Seck and Philippe (2013) and Jeong and Shin (2020) respectively, while the scales of ease of use and user interface attractiveness were adapted from Fang et al. (2017). The scales from Jahn and Kunz (2012) were used to assess utilitarian and hedonic values, while the scale from Lee et al. (2019) was modified to measure repurchase intentions. All exogenous constructs (i.e. information

Table 2. Demographics of survey respondent ($n = 739$).

Characteristic	Item	Full dataset $n = 739$		Beijing dataset $n = 367$ as Tier 1 city		Kunming dataset $n = 372$ as Tier 3 city	
		Frequency	Percent (%)	Frequency	Percent (%)	Frequency	Percent (%)
Gender	Male	334	45.2	159	43.3	175	47.0
	Female	405	54.8	208	56.7	197	53.0
Age	20 years old and below	10	1.4	9	2.5	1	0.3
	21–25 years old	51	6.9	29	7.9	22	5.9
	26–30 years old	235	31.8	111	30.2	124	33.3
	31–35 years old	331	44.8	169	46.0	162	43.5
	36–40 years old	112	15.2	49	13.4	63	16.9
Monthly Income	Below RMB 3,000	18	2.4	7	1.9	11	3.0
	RMB 3,001-5,000	98	13.3	14	3.8	84	22.6
	RMB 5,001-7,000	213	28.8	35	9.5	178	47.8
	RMB 7,001-9,000	145	19.6	58	15.8	87	23.4
	RMB 9,001-11,000	72	9.7	61	16.6	11	3.0
	RMB 11,001-13,000	76	10.3	75	20.4	1	0.3
	RMB 13,001-15,000	66	8.9	66	18.0	0	0.0
	RMB 15,001 and above	51	6.9	51	13.9	0	0.0

quality, ease of use, personalisation, user interface attractiveness, utilitarian value, and hedonic value) were assessed using a five-point Likert scales, while the endogenous construct, i.e. repurchase intentions was measured using a seven-point Likert scale, with the highest number indicating stronger agreement.

Results

This study employed partial least squares structural equation modelling (PLS-SEM) (Ciavolino et al., 2022) as opposed to covariance-based structural equation modelling (CB-SEM) due to its less stringent requirements for the measurement model, sample size, and residual distributions (Sarstedt & Cheah, 2019). In addition, the exploratory nature of this study makes PLS-SEM more appropriate due to its predictive and exploratory orientation (Chin et al., 2020; Hair & Sarstedt, 2019). PLS-SEM has also shown greater effectiveness in evaluating intricate models, including the multigroup analysis (Cheah et al., 2021, 2023). The PLS-SEM analysis was carried out with the SmartPLS 4 software (Ringle et al., 2023).

Common method variance (CMV)

Both procedural and statistical techniques were used to ensure the validity of the findings and to reduce the potential influence of common method variance (CMV). To reduce ambiguity, procedural measures included offering contextual information and clear instructions, as well as measuring the exogenous and endogenous constructs using both five-point and seven-point Likert scales (Podsakoff et al., 2012). Also, statistical remedies such as the full collinearity test were used (Kock & Lynn, 2012) and Harman's single-factor test (Fuller et al., 2016; Podsakoff et al., 2012) were used. According to the results of Harman's single-factor test, the principal component explained only 40.92% of the total variance (less than 50%), showing that CMV was not a factor (Aguirre-Urreta & Hu, 2019; Fuller et al., 2016). The full collinearity test yielded variance inflation factors (VIFs) ranging from 1.029 to 2.259 (Table 3), all of which are less than the 3.33 threshold, indicating that the likelihood of CMV being a problem is low (Kock & Lynn, 2012).

Reflective measurement model

The reliability and validity of the measurement model for three datasets (i.e. tier 1 Beijing, tier 3 Kunming, and both cities) were assessed. First, the convergent validity of the constructs was assessed by outer loadings and the average variance extracted (AVE). As presented in Table 3, outer loadings of all items were above 0.60 (Bagozzi et al., 1991) and the AVE scores of all constructs were above the recommended value of 0.50 (Fornell & Larcker, 1981). As indicated in Table 3, composite reliability (CR) values of all constructs (greater than 0.70) showed satisfactory internal consistency (Hair et al., 2019).

Discriminant validity was evaluated with the Heterotrait-Monotrait (HTMT) ratio (Henseler et al., 2015). As depicted in Table 4, the HTMT values for all constructs fell below the conservative threshold of 0.85 (Hair et al., 2023; Henseler et al., 2015), indicating satisfactory discriminant validity for all datasets.

Table 3. Assessment of reliability and convergent validity.

		Full dataset ($n = 739$)			Beijing dataset ($n = 367$) as Tier 1 city			Kunming dataset ($n = 372$) as Tier 3 city		
Construct	Indicator	Outer Loading	CR	AVE	Outer Loading	CR	AVE	Outer Loading	CR	AVE
Information Quality	IFQ1	0.828	0.741	0.658	0.827	0.755	0.670	0.835	0.721	0.636
(FC = 1.643)	IFQ2	0.820			0.844			0.773		
	IFQ3	0.784			0.783			0.783		
Ease of Use	EOU1	0.818	0.719	0.638	0.820	0.726	0.643	0.813	0.713	0.633
(FC = 1.029)	EOU2	0.808			0.820			0.788		
	EOU3	0.770			0.763			0.785		
User Interface Attractiveness	UIA1	0.699	0.875	0.614	0.648	0.875	0.616	0.784	0.877	0.616
(FC = 2.152)	UIA2	0.788			0.797			0.768		
	UIA3	0.806			0.809			0.799		
	UIA4	0.799			0.806			0.788		
	UIA5	0.790			0.814			0.760		
	UIA6	0.815			0.819			0.809		
Personalisation	PSN1	0.827	0.770	0.684	0.801	0.770	0.684	0.859	0.764	0.675
(FC = 1.790)	PSN2	0.807			0.837			0.765		
	PSN3	0.839			0.841			0.838		
Utilitarian Value	UV1	0.830	0.810	0.634	0.838	0.798	0.620	0.820	0.829	0.656
(FC = 2.259)	UV2	0.772			0.756			0.793		
	UV3	0.757			0.737			0.788		
	UV4	0.824			0.814			0.838		
Hedonic Value	HV1	0.845	0.872	0.718	0.836	0.866	0.711	0.859	0.884	0.735
(FC = 2.201)	HV2	0.821			0.831			0.821		
	HV3	0.854			0.848			0.865		
	HV4	0.869			0.858			0.884		
In-App Repurchase Intention	RPI1	0.857	0.879	0.730	0.873	0.878	0.720	0.844	0.880	0.735
(FC = 1.860)	RPI2	0.863			0.877			0.853		
	RPI3	0.847			0.824			0.860		
	RPI4	0.851			0.818			0.873		

Note. FC (Full Collinearity); CR (Composite Reliability); AVE (Average Variance Extracted).

Measurement invariance of composite models (MICOM)

The invariance test using the MICOM was necessary before performing the multigroup analysis (MGA), as the MICOM helps to determine whether the individuals from different city tiers (i.e. Beijing as tier 1 and Kunming as tier 3) have a similar level of understanding on the construct measurements. First, configural invariance (i.e. whether the same factor structure exists in both groups) was found between the tier 1 Beijing and tier 3 Kunming datasets (Tables 3 and 4). Second, compositional invariance was established, as the permutation c-values did not differ significantly from one another. Specifically, the overall permutation value estimates (c = 1) for both the tier 1 Beijing and tier 3 Kunming datasets straddled between the upper and lower limits of 95% confidence interval (Table 5). Last, the full invariance was not established across two city tiers, as the difference in variance values from all pairs of comparison did not fall within the upper and lower limits of the 95% confidence interval. As a result, partial measurement invariance was established through the MICOM procedure, indicating that it was feasible to conduct MGA to compare and interpret group-specific differences in the relationships of constructs involved in the research model.

Structural model

In the structural model, the VIF was used to assess the presence of multicollinearity among the predictor variables. All VIF values (full data, data from tier 1 Beijing, and data from tier 3 Kunming) were found to be well below the guideline of 3.30, indicating a low risk of multicollinearity in the model (Becker et al., 2015) (Table 6).

Next, all hypotheses were statistically tested with the bootstrapping technique (10,000 sub-samples) (Becker et al., 2023) (Table 6). The results from the full dataset and the tier 1 Beijing dataset showed that most of the proposed path relationships were significant (H1a, H1b, H1c, H1d, H2b, H2c, H2d, H3, H4), except for information quality (H2a: $\beta = -0.001$, t-value = 0.031) on hedonic value. The analysis results for the tier 3 Kunming dataset also supported

Table 4. Assessment of discriminant validity using the HTMT.

Dataset	No	Construct	1	2	3	4	5	6	7
Full dataset	1	Ease of Use							
$n = 739$	2	Hedonic Value	0.597						
	3	Information Quality	0.673	0.562					
	4	Personalisation	0.623	0.680	0.648				
	5	In-App Repurchase Intention	0.563	0.634	0.612	0.620			
	6	User Interface Attractiveness	0.645	0.806	0.643	0.709	0.553		
	7	Utilitarian Value	0.763	0.732	0.729	0.734	0.768	0.649	
Beijing dataset	1	Ease of Use							
$n = 367$ as Tier 1 city	2	Hedonic Value	0.657						
	3	Information Quality	0.693	0.526					
	4	Personalisation	0.604	0.659	0.603				
	5	In-App Repurchase Intention	0.673	0.637	0.631	0.613			
	6	User Interface Attractiveness	0.668	0.847	0.616	0.715	0.624		
	7	Utilitarian Value	0.826	0.683	0.746	0.697	0.828	0.695	
Kunming dataset	1	Ease of Use							
$n = 372$ as Tier 3 city	2	Hedonic Value	0.501						
	3	Information Quality	0.634	0.624					
	4	Personalisation	0.644	0.708	0.724				
	5	In-App Repurchase Intention	0.397	0.637	0.575	0.631			
	6	User Interface Attractiveness	0.602	0.740	0.686	0.697	0.450		
	7	Utilitarian Value	0.677	0.804	0.719	0.794	0.718	0.591	

the proposed hypotheses (H1a, H1b, H1d, H2a, H2c, H2d, H3, H4), except for user interface attractiveness (H1c: $\beta = 0.073$, t-value = 1.472) on utilitarian value, and ease of use (H2b: $\beta = 0.013$, t-value = 0.282) on hedonic value (Figure 3).

The outcomes of coefficient determinations (R^2) are presented in Table 6. The full dataset illustrated the R^2 of 0.517 for utilitarian value, 0.536 for hedonic value, and 0.461 for repurchase intentions. Tier 1 Beijing's data presented the R^2 of 0.547 for utilitarian value, 0.576 for hedonic value, and 0.519 for repurchase intentions, while tier 3 Kunming's data exhibited the R^2 of 0.504 for utilitarian value, 0.499 for hedonic value, and 0.414 for repurchase intentions. Subsequently, the effect size (f^2) was assessed with Cohen's (1988) guidelines (<0.02 Trivial; 0.02 Small; 0.15 Medium; 0.35 Large) (Table 6). The findings showed that information quality on utilitarian value, personalisation on hedonic value, and hedonic value on repurchase intentions in all three datasets (full dataset, tier 1 Beijing dataset, and tier 3 Kunming dataset) exhibited small effect sizes of the impact (f^2 = 0.024-0.082) (i.e. H1a, H2d, and H4). In addition, the full dataset displayed trivial effect sizes (f^2 = 0.014-0.019) for H1c (user interface attractiveness → utilitarian value) and H2b (ease of use → hedonic value), small effect sizes (f^2 = 0.082-0.108) for H1b (ease of use → utilitarian value) and H1d (personalisation → utilitarian value), and medium effect sizes (f^2 = 0.280-0.323) for H2c (user interface attractiveness →

Table 5. Assessment of the measurement invariance.

	Compositional Invariance			Equal Mean Value		Equal Variances Value		
Construct	c = 1	CI	Partial Measurement Invariance Established	Diff	CI	Diff	CI	Full Measurement Invariance Established
Information Quality	0.999	[0.997;1.000]	Yes	0.133	[−0.119;0.117]	0.638	[−0.255;0.262]	No
Ease of Use	0.999	[0.997;1.000]	Yes	0.100	[−0.121;1.124]	0.427	[−0.243;0.243]	No
User Interface Attractiveness	1.000	[0.999;1.000]	Yes	0.093	[−0.131;0.127]	0.480	[−0.182;0.182]	No
Personalisation	0.999	[0.998;1.000]	Yes	0.086	[−0.125;0.127]	0.347	[−0.179;0.193]	No
Utilitarian Value	1.000	[0.999;1.000]	Yes	−0.040	[−0.126;.0128]	0.366	[−0.258;0.267]	No
Hedonic Value	1.000	[1.000;1.000]	Yes	0.058	[−0.125;0.119]	0.430	[−0.186;0.211]	No
In-App Repurchase Intention	1.000	[0.999;1.000]	Yes	0.296	[−0.122;0.121]	0.361	[−0.209;0.212]	No

Note. Diff = Differences; CI means Bias-Correlated Accelerated 95% Bootstrap Confidence Interval.

Table 6. Result of structural model (direct relationships).

Dataset	Path Relationship	Std. Beta	Std. Error	t-value	p-value	CI (5%, 95%)	VIF	f^2	R^2	Q^2_predict
Full Dataset $n = 739$	(H1a) Information Quality → UV	0.234	0.039	6.085	0.000**	(0.169, 0.295)	1.574	0.072 (S)	0.517	0.509
	(H1b) Ease of Use → UV	0.283	0.037	7.657	0.000**	(0.220, 0.342)	1.538	0.108 (S)		
	(H1c) User Interface Attractiveness → UV	0.130	0.040	3.255	0.001*	(0.064, 0.196)	1.799	0.019 (T)		
	(H1d) Personalisation → UV	0.257	0.039	6.540	0.000**	(0.189, 0.318)	1.669	0.082 (S)		
	(H2a) Information Quality → HV	0.046	0.035	1.321	0.093	(−0.009, 0.105)	1.574	NA	0.536	0.530
	(H2b) Ease of Use → HV	0.100	0.036	2.812	0.002*	(0.044, 0.163)	1.538	0.014 (T)		
	(H2c) User Interface Attractiveness → HV	0.520	0.039	13.252	0.000**	(0.454, 0.582)	1.799	0.323 (M)		
	(H2d) Personalisation → HV	0.186	0.039	4.799	0.000**	(0.122, 0.249)	1.669	0.045 (S)		
	(H3) UV → RPI	0.492	0.036	13.757	0.000**	(0.434, 0.551)	1.607	0.280 (M)	0.461	0.360
	(H4) HV → RPI	0.254	0.038	6.674	0.000**	(0.189, 0.314)	1.607	0.075 (S)		
Beijing Dataset $n = 367$ as Tier 1 city	(H1a) Information Quality → UV	0.238	0.051	4.646	0.000**	(0.151, 0.320)	1.548	0.080 (S)	0.547	0.535
	(H1b) Ease of Use → UV	0.332	0.052	6.385	0.000**	(0.244, 0.418)	1.598	0.153 (M)		
	(H1c) User Interface Attractiveness → UV	0.175	0.057	3.073	0.001*	(0.083, 0.270)	1.838	0.037 (S)		
	(H1d) Personalisation → UV	0.183	0.052	3.504	0.000**	(0.099, 0.272)	1.642	0.045 (S)		
	(H2a) Information Quality → HV	−0.001	0.045	0.031	0.488	(−0.075, 0.071)	1.548	NA	0.576	0.564
	(H2b) Ease of Use → HV	0.159	0.050	3.155	0.001*	(0.079, 0.243)	1.598	0.037 (S)		
	(H2c) User Interface Attractiveness → HV	0.576	0.057	10.060	0.000**	(0.480, 0.669)	1.838	0.426 (L)		
	(H2d) Personalisation → HV	0.129	0.055	2.343	0.010*	(0.040, 0.221)	1.642	0.024 (S)		
	(H3) UV → RPI	0.557	0.044	12.801	0.000**	(0.484, 0.627)	1.475	0.437 (L)	0.519	0.424
	(H4) HV → RPI	0.239	0.046	5.199	0.000**	(0.161, 0.313)	1.475	0.081 (S)		
Kunming Dataset $n = 372$ as Tier 3 city	(H1a) Information Quality → UV	0.225	0.051	4.391	0.000**	(0.141, 0.309)	1.637	0.063 (S)	0.504	0.488
	(H1b) Ease of Use → UV	0.209	0.048	4.311	0.000**	(0.130, 0.288)	1.462	0.060 (S)		
	(H1c) User Interface Attractiveness → UV	0.073	0.049	1.472	0.071	(−0.009, 0.154)	1.762	NA		
	(H1d) Personalisation → UV	0.370	0.049	7.498	0.000**	(0.285, 0.447)	1.738	0.158 (M)		
	(H2a) Information Quality → HV	0.119	0.050	2.387	0.009*	(0.034, 0.201)	1.637	0.017 (T)	0.499	0.484
	(H2b) Ease of Use → HV	0.013	0.046	0.282	0.389	(−0.063, 0.088)	1.462	NA		
	(H2c) User Interface Attractiveness → HV	0.429	0.045	9.455	0.000**	(0.354, 0.504)	1.762	0.208 (M)		
	(H2d) Personalisation → HV	0.267	0.049	5.448	0.000**	(0.186, 0.347)	1.738	0.082 (S)		
	(H3) UV → RPI	0.428	0.056	7.677	0.000**	(0.332, 0.516)	1.894	0.165 (M)	0.414	0.288
	(H4) HV → RPI	0.270	0.061	4.389	0.000**	(0.161, 0.366)	1.894	0.066 (S)		

Note: *$p < 0.050$; **$p < 0.001$; UV (Utilitarian Value); HV (Hedonic Value); RPI (In-App Repurchase Intention); CI (Confidence Interval Bias Corrected); Effect Size (T: Trivial; S: Small; M: Medium; L: Large); NA (Not Applicable).

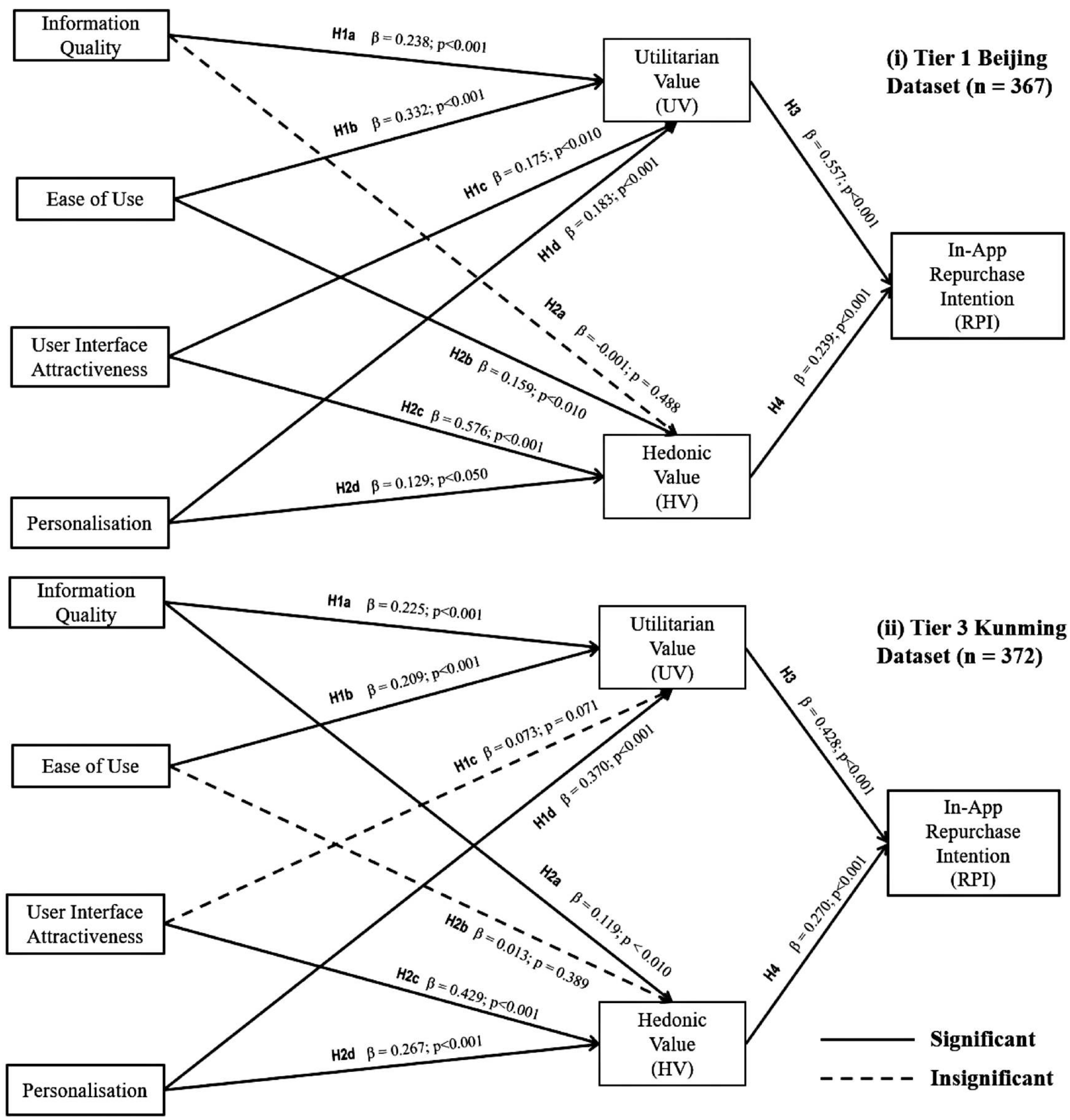

Figure 3. Comparison of the structural model results for Beijing and Kunming datasets.

hedonic value) and H3 (utilitarian value → repurchase intentions). The tier 1 Beijing dataset presented small effect sizes ($f^2 = 0.037\text{-}0.045$) for H1c (user interface attractiveness → utilitarian value), H1d (personalisation → utilitarian value), and H2b (ease of use → hedonic value), medium effect size ($f^2 = 0.153$) for H1b (ease of use → utilitarian value), and large effect sizes ($f^2 = 0.426\text{-}0.437$) for H2c (user interface attractiveness → hedonic value) and H3 (utilitarian value → repurchase intentions). The tier 3 Kunming dataset illustrated a trivial effect size ($f^2 = 0.017$) for H2a (information quality → hedonic value), a small effect size ($f^2 = 0.060$) for H1b (ease of use → utilitarian value), and medium effect sizes ($f^2 = 0.158\text{-}0.208$) for H1d (personalisation → utilitarian value), H2c (user interface attractiveness → hedonic value), and H3 (utilitarian value → repurchase intentions).

Finally, the predictive relevance was examined with both Q^2 (Geisser, 1975; Stone, 1974) and PLSpredict (or out-of-sample prediction) (Chin et al., 2020; Shmueli et al., 2016, 2019). The Q^2 values for all endogenous constructs in all datasets (i.e. full dataset, tier 1 Beijing dataset, and tier 3 Kunming dataset) were found to be greater than zero, ranging from 0.288 to 0.564. This indicates that the predictive quality of the model was satisfactory (Shmueli et al., 2019). In addition, the PLSpredict technique was applied to investigate the prediction relevance of the endogenous constructs (i.e. utilitarian value, hedonic value, and repurchase intentions). As shown in Table 7, all three datasets (i.e. full dataset, tier 1 Beijing dataset, and tier 3 Kunming dataset) presented that all three endogenous constructs have strong predictive power. These strong statistics demonstrated that this framework is applicable to diverse situations of predictive research.

Multigroup analysis (MGA)

As shown in Table 8, MGA results and its significances were examined with different techniques in the PLS-SEM, which assesses the differences between path coefficients of two groups (tier 1 Beijing and tier 3 Kunming in this study) (Cheah et al., 2023; Hair et al., 2018). The outcomes shown in Table 8 illustrate significant differences between datasets of tier 1 Beijing and tier 3 Kunming (p-value < 0.05). Specifically, significant differences occurred in all the relationships except for relationships between: (i) information quality and utilitarian value; (ii) user interface attractiveness and utilitarian value; and (iii) hedonic value and repurchase intentions. In particular, the results suggested that travel app users from tier 1 Beijing tend to place a greater emphasis on features such as ease of use and user interface attractiveness when perceiving both utilitarian and hedonic value. Users in tier 3 Kunming seemed to prioritise personalisation when considering these factors. Interestingly, the impact of information quality on hedonic value was found to be more significant for users in tier

Table 7. Assessment of PLS predict.

Dataset	Construct	Q2predict	PLS RMSE	PLS MAE	LM RMSE	LM MAE	PLS-LM RMSE	PLS-LM MAE	Predictive Power
Full dataset	UV1	0.375	0.596	0.468	0.593	0.458	0.003	0.010	Strong
$n = 739$	UV2	0.281	0.648	0.514	0.651	0.514	−0.003	0.000	
	UV3	0.291	0.654	0.520	0.654	0.520	0.000	0.000	
	UV4	0.339	0.625	0.498	0.631	0.502	−0.006	−0.004	
	HV1	0.413	0.672	0.544	0.683	0.549	−0.011	−0.005	Strong
	HV2	0.356	0.710	0.550	0.715	0.555	−0.005	−0.005	
	HV3	0.386	0.667	0.530	0.675	0.534	−0.008	−0.004	
	HV4	0.361	0.665	0.525	0.671	0.526	−0.006	−0.001	
	RPI1	0.299	0.864	0.679	0.867	0.677	−0.003	0.002	Strong
	RPI2	0.300	0.939	0.739	0.943	0.742	−0.004	−0.003	
	RPI3	0.242	1.064	0.846	1.065	0.840	−0.001	0.006	
	RPI4	0.200	1.001	0.798	1.013	0.804	−0.012	−0.006	
Beijing dataset	UV1	0.368	0.667	0.534	0.676	0.542	−0.009	−0.008	Strong
$n = 367$ as Tier 1 city	UV2	0.284	0.718	0.578	0.727	0.582	−0.009	−0.004	
	UV3	0.301	0.708	0.578	0.712	0.581	−0.004	−0.003	
	UV4	0.359	0.670	0.548	0.686	0.559	−0.016	−0.011	
	HV1	0.423	0.749	0.607	0.773	0.628	−0.024	−0.021	Strong
	HV2	0.389	0.769	0.572	0.788	0.595	−0.019	−0.023	
	HV3	0.419	0.724	0.571	0.750	0.589	−0.026	−0.018	
	HV4	0.365	0.718	0.570	0.731	0.571	−0.013	−0.001	
	RPI1	0.360	0.882	0.690	0.898	0.703	−0.016	−0.013	Strong
	RPI2	0.378	0.991	0.776	1.001	0.790	−0.010	−0.014	
	RPI3	0.235	1.170	0.900	1.181	0.901	−0.011	−0.001	
	RPI4	0.224	1.028	0.817	1.067	0.848	−0.039	−0.031	
Kunming dataset	UV1	0.409	0.511	0.401	0.506	0.387	0.005	0.014	Strong
$n = 372$ as Tier 3 city	UV2	0.270	0.575	0.454	0.589	0.470	−0.014	−0.016	
	UV3	0.281	0.594	0.456	0.604	0.463	−0.010	−0.007	
	UV4	0.311	0.577	0.452	0.587	0.462	−0.010	−0.010	
	HV1	0.407	0.584	0.480	0.595	0.484	−0.011	−0.004	Strong
	HV2	0.329	0.633	0.522	0.638	0.526	−0.005	−0.004	
	HV3	0.327	0.602	0.489	0.614	0.499	−0.012	−0.010	
	HV4	0.352	0.612	0.485	0.625	0.494	−0.013	−0.009	
	RPI1	0.222	0.838	0.662	0.858	0.674	−0.020	−0.012	Strong
	RPI2	0.206	0.861	0.683	0.872	0.693	−0.011	−0.010	
	RPI3	0.243	0.926	0.748	0.943	0.757	−0.017	−0.009	
	RPI4	0.170	0.950	0.756	0.977	0.782	−0.027	−0.026	

Note. UV (Utilitarian Value); HV (Hedonic Value); RPI (In-App Repurchase Intention).

Table 8. Assessment of the multigroup analysis.

Path Relationship	Std. Beta (Tier 1 Beijing)	Std. Beta (Tier 3 Kunming)	Std. Beta Difference (Beijing-Kunming)	MGA Techniques: Permutation *p*-value	MGA Techniques: PLS-MGA *p*-value	MGA Techniques: Parametric Test *p*-values	Welch–Satterthwaite *p*-values
H5a: Information Quality → Utilitarian Value	0.238	0.225	0.012	0.456	0.435	0.434	0.434
H5b: Ease of Use → Utilitarian Value	0.332	0.209	0.124	**0.044**	**0.042**	**0.041**	**0.041**
H5c: User Interface Attractiveness → Utilitarian Value	0.175	0.073	0.103	0.095	0.087	0.086	0.087
H5d: Personalisation → Utilitarian Value	0.183	0.370	−0.187	**0.010**	**0.005**	**0.005**	**0.005**
H6a: Information Quality → Hedonic Value	−0.001	0.119	−0.120	**0.041**	**0.037**	**0.036**	**0.036**
H6b: Ease of Use → Hedonic Value	0.159	0.013	0.146	**0.020**	**0.016**	**0.016**	**0.016**
H6c: User Interface Attractiveness → Hedonic Value	0.576	0.429	0.147	**0.027**	**0.024**	**0.022**	**0.022**
H6d: Personalisation → Hedonic Value	0.129	0.267	−0.138	**0.032**	**0.032**	**0.031**	**0.031**
H7a: Utilitarian Value → In-App Repurchase Intention	0.557	0.428	0.129	**0.038**	**0.033**	**0.034**	**0.034**
H7b: Hedonic Value → In-App Repurchase Intention	0.239	0.270	−0.030	0.344	0.344	0.347	0.346

Note. Bold means there is a significant difference between the group comparison.

3 Kunming. Additionally, the results indicated that the influence of utilitarian value on repurchase intentions was stronger for users in tier 1 Beijing compared to those in Kunming.

Post-hoc analysis with ANOVA test

To investigate whether demographics had an effect on the constructs of this study, a post-hoc analysis using ANOVA was conducted. The results showed that while gender and age did not impact the constructs, monthly income did have a significant influence on repurchase intentions (Table 9). To further understand this significance, the potential influence of monthly income on all constructs was examined in both the tier 1 Beijing and tier 3 Kunming datasets (Table 10). It was found that monthly income did not have a significant impact on the constructs within either city tier, indicating that city-tier disparities were the only source of the differences. According to the results presented in Table 11, a pairwise comparison analysis of the influence of monthly income on repurchase intentions in the full dataset revealed significant differences between those with monthly incomes less than RMB 7000 ($1,000) and those with incomes over RMB 11,001 ($1,600). This suggests that as the income disparity between different city tiers increases, the likelihood of significant differences in repurchase intentions also increases. This result corresponds to the substantial differences in monthly income between the respondents from tier 1 Beijing and tier 3 Kunming (Table 2). Specifically, a majority of respondents in Beijing (52.3%) earned more than

Table 9. Post-hoc test (i.e. ANOVA) of the impact of demographics on all constructs (full dataset).

Construct	Gender		Age		Monthly Income	
	F	*p*-values	*F*	*p*-values	*F*	*p*-values
Information Quality	0.082	0.774	2.154	0.073	1.099	0.362
Ease of Use	0.822	0.365	1.383	0.238	1.613	0.128
User Interface Attractiveness	1.172	0.279	0.672	0.611	1.896	0.067
Personalisation	0.399	0.528	0.223	0.925	1.442	0.185
Utilitarian Value	0.466	0.495	0.804	0.523	0.911	0.497
Hedonic Value	1.015	0.314	0.841	0.499	1.255	0.270
In-App Repurchase Intention	0.279	0.597	0.594	0.667	3.895	0.000**

Note. $^{**}p < 0.001$.

Table 10. Post-hoc test (i.e. ANOVA) of the impact of monthly income on all constructs in the Beijing and Kunming datasets.

	Tier 1 Beijing		Tier 3 Kunming	
Construct	*F*	*p*-values	*F*	*p*-values
Information Quality	0.962	0.459	0.416	0.838
Ease of Use	1.216	0.293	0.363	0.874
User Interface Attractiveness	1.362	0.220	1.127	0.346
Personalisation	0.825	0.567	1.499	0.189
Utilitarian Value	1.988	0.056	0.765	0.575
Hedonic Value	1.779	0.090	0.669	0.647
In-App Repurchase Intention	1.954	0.060	0.305	0.910

RMB 11,001 ($1,600) per month, while most respondents in Kunming (73.4%) earned a monthly income below RMB 7,000 ($1,000). In summary, the significant differences in repurchase intentions that were caused by monthly income were ultimately the result of city-tier disparities.

Discussion of findings and implications

Discussion of the findings

The aim of this research was to investigate the experiential features of travel apps that shape users' value perceptions before leading to repurchase intentions. A research model was developed based on the S–O–R framework, which posits that the repurchase intentions are influenced by a collection of context-based experiential features: information quality, ease of use, user interface attractiveness, and personalisation. By extension, the value processes (i.e. utilitarian and hedonic values) were investigated, through which repurchase intentions were indirectly influenced by experiential features. Furthermore, it is suggested that city-tier disparities may moderate the relationships between these constructs.

Information quality was found to influence utilitarian value significantly in both the tier 1 Beijing and tier 3 Kunming datasets (H1a was supported). This result aligns with previous research highlighting the importance of information quality as a key functional feature in the technology-based tourism literature (Jeong & Shin, 2020; Kullada & Kurniadjie, 2021). High-quality travel information is the key source that helps app users plan their trips effectively based on reasonable contents, which ultimately deliver a higher degree of perceived utilitarian value among all groups of users (Kullada & Kurniadjie, 2021). This thus justified the reason of no significant difference between users in tier 1 and tier 3 cities (H5a was not supported). It was noteworthy to discover that users in tier 1 Beijing were unable to perceive the hedonic value from information quality (H2a was not supported), whereas users in tier 3 Kunming did. This significant difference (H6a was supported) may be owing to the information overload and fast-paced life in Beijing, which make users anxious and insensitive to information-induced enjoyment. In comparison, limited access to travel information in tier 3 Kunming may lead to a greater sense of fulfilment and enjoyment when acquiring high-quality information.

Also, it was discovered that ease of use has significant impacts on utilitarian value in the tier 1 Beijing and tier 3 Kunming datasets (H1b was supported). This finding is in line with previous research (e.g. Bravo et al., 2021; Fang et al., 2017; Lim et al., 2022), indicating that users are more inclined to have favourable experiences and use a travel app more frequently when they can effortlessly search for and reserve travel products and services within the app. This feature can be especially beneficial for users with busy schedules who value convenience. However, users in tier 3 Kunming failed to recognise the significance of ease of use on hedonic value (H2b was not supported). The significant differences in ease of use between the two groups (H5b and H6b were supported) may be driven by the fact that users in tier 1 Beijing are overwhelmed by the plethora of technology options and

Table 11. Post-hoc test (i.e. ANOVA) of the impact of monthly income on in-app repurchase intention (full dataset).

Construct	Item	*N*	Mean	*F*	*p*-values
In-App Repurchase Intention	Below RMB 3,000	18	5.208	3.895	0.000
	RMB 3,001–5,000	98	5.153		
	RMB 5,001–7,000	213	5.191		
	RMB 7,001–9,000	145	5.295		
	RMB 9,001–11,000	72	5.465		
	RMB 11,001–13,000	76	5.622		
	RMB 13,001–15,000	66	5.394		
	RMB 15,001 and above	51	5.745		

Note. Pairwise comparison post-hoc analysis using Tukey's HSD revealed that there were significant differences between the monthly income groups in terms of RPI, particularly when comparing those with RMB lower than 7,000 to those with RMB higher than 11,001.

features for trips (Zhang et al., 2020), and therefore prefer a simpler and more straightforward app. However, this may not be the case for tier 3 Kunming users who may not be as stressed and hence may not appreciate the comfort that ease of use provides (Gupta et al., 2018).

Corresponding to Fang et al. (2017), significant relationships were found between user interface attractiveness and hedonic value in both city tiers (H2c was supported). This confirms the notion that a visually appealing and intuitive interface contributes to pleasant experiences (Coursaris & Van Osch, 2016; Gursoy, 2019). However, there was no significant effect of interface attractiveness on utilitarian value in the tier 3 Kunming dataset (H1c was not supported). This finding supports Bilby et al. (2020) in that people in tier-1 cities tend to have more refined tastes than those in lower-tier cities; users in tier 3 Kunming may have less sophisticated preferences in appreciating hedonic value compared to users in tier 1 Beijing (H6c was supported). Nonetheless, it is interesting to note that while tier 1 Beijing users may derive functional value from a more hedonic-centred user interface, this feature alone is not a reliable predictor of utilitarian value, resulting in insignificant differences in utilitarian value perceptions across the two groups (H5c was not supported).

Next, the findings support the hypotheses of personalisation on utilitarian and hedonic values in the tier 1 Beijing and tier 3 Kunming datasets (H1d and H2d were supported). This aligns with the findings of Kang and Namkung (2019) and Piccoli et al. (2017) that personalisation leads to favourable value perceptions for users through convenience and makes them feel as if they are receiving special attention from firms. As for group comparisons (H5d and H6d were supported), travel app users in higher-tier cities feel more empowered and less reliant on personalised services when planning journeys, as they have greater access to travel information and personalisation options (Shin et al., 2021). However, personalisation might be especially important in lower-tier cities that have limited access to high-quality personalised travel services and where individuals have less expertise in using technology to schedule trips.

As predicted, utilitarian and hedonic values are positive predictors of repurchase intentions (H3 and H4 were supported) across all datasets, which is in line with the growing importance of relationship management in the current online business climate (Itani et al., 2019). Users who perceive high value in a travel app are more likely to be satisfied with their experiences and encouraged to make future purchases (Pansari & Kumar, 2017). Regarding the potential discrepancies across city tiers, a significant difference was identified in the relationship between utilitarian value and repurchase intentions (H7a was supported), with travel app users in higher-tier cities (e.g. Beijing) placing greater emphasis on functionality when determining repurchase intentions. Travel app users in higher-tier cities (i.e. Beijing) typically have better incomes and more access to information about products and services (Li et al., 2021), which drives them to make more informed purchase decisions and prioritise high functional value to make repeat purchases (Gupta et al., 2018). In contrast, no significant difference was found in the relationship between hedonic value and repurchase intentions between higher and lower-tier cities (H7b was not supported). These findings suggest that while users in higher-tier cities may be more inclined to make repeat purchases based on perceived functional value, affective relationships are equally important for users in both city tiers to improve repurchase intentions.

As a result, the findings contradict the aforementioned assertions (e.g. Bilby et al., 2016, 2020; Huang & Qian, 2018; Shukla & Rosendo-Rios, 2021) that individuals in higher-tier cities prioritise non-functional perceptions (i.e. hedonic value) over functionality (i.e. utilitarian value) in consumption. This unexpected discovery may throw into doubt the concept that wealthy individuals are more interested in spiritual fulfilment, as it may have overlooked the fact that the greater people's economic power and cognitive ability, the more likely they are to make informed decisions (Gupta et al., 2018). This may indirectly cause them to be more concerned with functionality and cost-effectiveness. Additionally, while individuals in higher-tier cities may prioritise happiness and pleasure (Bilby et al., 2020), money-related behaviour (i.e. repurchase), instead of mere adoption, may diminish the impact of emotional values (i.e. hedonic value).

Theoretical implications

This research contributes to the current tourism marketing literature in several respects. First, it extends the S-O-R framework by considering the influence of city tier on user perceptions. It explores how different stimuli (i.e. information quality, ease of use, user interface attractiveness, and personalisation) affect the organism (represented by utilitarian and hedonic values) and lead to varied responses (such as repurchase intentions), with city tier acting as a modifying factor. This modification of the S-O-R framework provides fresh insights into its use in digital environments, suggesting potential adaptations and expansions that might be relevant in other contexts of digital commerce (Fakfare & Manosuthi, 2022; Fang et al., 2017).

Second, this research applies NEG theory (Krugman, 1991, 1998, 2011) to tourism to explore the boundary effects of city tier disparity. It contributes to the literature by detailing how economic factors tied to geographic location influence the acceptance and effectiveness of digital technologies, a relatively underexplored area in mobile commerce research. It challenges the conventional belief (e.g. Bilby et al., 2016, 2020; Shukla & Rosendo-Rios, 2021) that higher-tier city residents prioritise non-functional aspects by demonstrating that utilitarian values significantly influence user behaviour in cities such as Beijing, while hedonic values are consistently appreciated across different city tiers like Kunming. This revelation deepens the theoretical frameworks of economic geography and consumer behaviour by providing solid empirical evidence on how urban characteristics distinctly affect technology interactions, offering valuable insights for tailoring digital strategies to effectively meet the varied needs of users across diverse urban settings.

Practical implications

Travel app features should be designed with user needs in mind, as opposed to the company's perspective. In particular, user interface design should focus on aesthetics and interactivity to provide a visually appealing and highly responsive experience for users. One way to enhance the interface is by gradually introducing creative designs based on user familiarity, rather than making drastic changes that might confuse users. It can also be helpful to offer multiple themed interfaces for different types of users, such as those who are new to the app and those who are experienced. A visually appealing interface can help reduce anxiety and mental strain for app users, while a highly responsive interface can make the app easier to use. In practice, ease of use is accompanied by an interface with strong interactivity such as clear, logical menus and functional buttons, helpful tips and tutorials, which enables users to access the desired products or services effortlessly. Personalisation seeks to better comprehend the behavioural tendencies of travel app users to their preferences and needs. To better understand user preferences and needs, it is suggested that travel apps implement multiple-layer information collection systems, including automated tools for tracking usage behaviour and sorting feedback keywords, as well as human personnel for more in-depth communication with users. Following the preceding measures, information quality may be improved dramatically by presenting more relevant, accurate, and detailed information and images to users with appropriate pages and formats. Also, it is important for travel apps to offer personalised information, products, and services that are compatible with user needs, leading to a simpler and more enjoyable user experience.

Understanding the urban dynamics similar to China's city tier system can guide app development in other countries with varying levels of urbanisation and technological adoption. For instance, in emerging markets or smaller cities within larger countries, apps could be designed with simple, robust features that emphasise cost-effectiveness. In contrast, apps in more developed urban areas worldwide might focus on advanced functionalities and sophisticated personalisation to meet the greater expectations and tech engagement of consumers there.

Furthermore, educating users about app features through engaging methods, such as gamified tutorials, is crucial. These techniques can demystify technology, boost user engagement, and foster a stronger connection with apps. Tailoring marketing strategies to the local cultural and economic landscapes can optimise user acquisition and retention. For example, in technologically advanced regions, promoting complex features may appeal to a tech-savvy audience, whereas in less developed areas, focusing on reliability and simplicity could be more effective.

Lastly, customising travel apps to reflect the specific economic and cultural contexts of different regions is crucial. Ideally, the app should identify and label a user's "home" location based on their presence in a specific area for over 100 days consecutively. These home locations can be classified into categories such as affluent, developed, less developed, and economically challenged areas. For individuals from lower-tiered home locations traveling to more affluent areas, the app should provide cost-saving features like price comparison tools, real-time discount alerts, and promotions to help them manage budgets effectively. Conversely, for those from affluent home locations traveling to less developed areas, apps should facilitate exclusive experiences by partnering with high-end brands to offer special discounts and perks at luxury venues and upscale boutiques. This tailored approach will ensure that users receive relevant and beneficial features that enhance their travel experiences, regardless of their destination or economic background.

Conclusion and future research directions

The rising popularity of travel apps has highlighted the necessity for travel firms to understand how to motivate user repurchase intentions, which have become a financial performance indicator for long-term success (Jang et al., 2018). This research used the S-O-R framework and NEG theory to better understand the experiential features that influence repurchase intentions among travel app users in different tiers of cities, widening the applicable boundaries for both theories. In particular, a collection of context-based experiential features of travel apps and values (i.e. utilitarian and hedonic values) was suggested for repurchase intentions. It was found that these decision-making processes are influenced by city tier disparities, which may contradict commonly held beliefs (e.g. Bilby et al., 2016, 2020; Huang & Qian, 2018; Shukla & Rosendo-Rios, 2021) that people in higher tier cities tend to prioritise non-functional perceptions for consumption.

In addition to the valuable insights gained, this research has identified several areas that could be explored in future studies. First, given China's huge size (Shukla & Rosendo-Rios, 2021), this comparative research was limited to Beijing and Kunming as representatives, which may not be sufficient to provide a strong foundation for the city tier comparison. Future studies should include other potential cities, as recommended by Bilby et al. (2020), to increase the credibility of the city tier comparison. Second, this research was conducted in China with a similar culture (Crane et al., 2018), and as a result, the researchers were unable to explore the decision-making processes of travel app users across different cultures. As stated by a number of researchers (Badu-Baiden et al., 2023; Zheng et al., 2023), cultural differences (e.g. individualism and collectivism) may influence the attitudes and behavioural intentions of tourists. Hence, the impact of culture on travel app users should be investigated by future comparative research. Finally, this study revealed that the relationships between utilitarian value and repurchase intentions were stronger in the tier 1 Beijing dataset than in the tier 3 Kunming dataset, contrary to the assumptions of prior studies (e.g. Bilby et al., 2016, 2020; Huang & Qian, 2018; Shukla & Rosendo-Rios, 2021). This contradictory result necessitates more research into the boundary effect of city-tier disparities on individuals' utilitarian and hedonic value perceptions.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Data availability statement

Data will be made available upon reasonable request.

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Appendices

Appendix 1. China's City Tier Definitions

Author(s)	Report type	Tier classification	No. of Tiers
The State Council (2014)	Government statement	Classified by population. Tier 1: Super large-sized cities. Population > 10 million. Tier 2: Very large-sized cities. Population 5–10 million. Tier 3a: Large-sized cities: type I. Population 3–5 million. Tier 3b: Large-sized cities: type II. Population 1–3 million. Tier 4: Medium-sized cities. Population 500,000–1 million. Tier 5a: Small-sized cities: type I. Population 200,000–500,000. Tier 5b: Small-sized cities: type II. Population < 200,000.	5 (+2 sub-tiers)
National Bureau of Statistics of China (2016)	Government statistical report	Classified by median population. Tier 1: Megacities (8.9 million). Tier 2: Developed provincial capital cities (4.2 million). Tier 3: Developed medium sized cities and developing provincial capitals (1.7 million). Tier 4: Developing small cities (866,000). Tier 5: undeveloped cities (609,000).	5
Bilby et al. (2020)	Academic paper	Classified by economic development, and infrastructure. Tier 1: Most developed cities (i.e., Beijing, Shanghai, and Guangzhou). Tier 2: Cities experiencing rapid economic growth and significant infrastructure development (e.g., Shenzhen, Qingdao, and Dalian etc.) Tier 3: Less developed cities (e.g., Kunming, Ningbo, and Lanzhou etc.). Tier 4-6: Undeveloped cities with significantly different consumer cultures and values in comparison to the rest of China (e.g., Urumqi, and Sanya etc.)	6
Yicai (2022)	Industry report	Classified by economic development, infrastructure, amenities, and population size. Tier 1: 4 Megacities (i.e., Beijing, Shanghai, Guangzhou, and Shenzhen). Tier 2: 15 Developed provincial capital cities and sub-provincial cities (e.g., Chongqing, Hangzhou, and Qingdao etc.) Tier 3: 30 Developing provincial capital cities and developed coastal prefectural cities (e.g., Kunming, Harbin, and Lanzhou etc.). Tier 4: 70 Less developed provincial capital cities and developed prefectural cities (e.g., Urumqi, and Sanya etc.) Tier 5: 90 Developed prefectural cities (e.g., Qinhuangdao, and Yibing etc.) Tier 6: 128 Developing prefectural cities or developed county-level cities (e.g., Liupanshui, and Yan'an etc.).	6

Appendix 2. Measurement items

Construct
Information Quality (IFQ)
IFQ1: The Ctrip travel app provides me with useful information.
IFQ2: The Ctrip travel app meets my information needs.
IFQ3: Information at the Ctrip travel app is well updated.
Ease of Use (EOU)
EOU1: The Ctrip travel app is easy to use.
EOU2: Learning how to use the Ctrip travel app is easy for me.
EOU3: I would imagine that most people would learn to use the Ctrip travel app very quickly.
User Interface Attractiveness (UIA)
UIA1: The interface design of Ctrip travel app looks clean.
UIA2: The interface design of Ctrip travel app is sophisticated.
UIA3: The interface design of Ctrip travel app is fascinating.
UIA4: The interface design of Ctrip travel app is aesthetically pleasing.
UIA5: The interface design of Ctrip travel app is visually appealing.
UIA6: The interface design of Ctrip travel app is attractive.
Personalisation (PSN)
PSN1: The Ctrip travel app allowed me to receive tailored information.
PSN2: I could interact with the Ctrip travel app to get personalised information.
PSN3: The personalised information provided by the Ctrip travel app met my need.
Utilitarian Value (UV)
UV1: The Ctrip travel app is helpful for me.
UV2: The Ctrip travel app is useful for me.
UV3: The Ctrip travel app is functional for me.
UV4: The Ctrip travel app is practical for me.
Hedonic Value (HV)
HV1: The Ctrip travel app is fun.
HV2: The Ctrip travel app is exciting.
HV3: The Ctrip travel app is pleasant.
HV4: The Ctrip travel app is entertaining.
In-App Repurchase Intention (RPI)
RPI1: I intend to continue to purchase from Ctrip travel app.
RPI2: I intend to acquire products and services from Ctrip travel app.
RPI3: I intend to choose Ctrip travel app as the preferred brand for my future purchases.
RPI4: Except for any unanticipated reasons, I intend to continue to purchase from Ctrip travel app as usual.