Special Issue: Technological Revolution, Digital Economy, and Tourism Economics

TOURISM ECONOMICS
The Business and Finance of Tourism and Recreation

Tourism Economics
2025, Vol. 0(0) 1–19

DOI: 10.1177/13548166251374362
journals.sagepub.com/home/teu
Sage

Navigating the E-commerce journey: How tourism experience drives online shopping via third-party payments

Wenhui Yang
Guizhou University, China

Abstract

This study investigates the impact of tourism experiences on Chinese consumers' online shopping practices using household-level data from the China Household Finance Survey. Amid rapid technological advancement and the expanding digital economy, understanding how consumption patterns evolve is crucial, particularly in developing economies promoting domestic tourism demand. The results provide the first empirical evidence demonstrating a significant positive effect of tourism experience on subsequent online shopping expenditure. This finding remains robust to potential endogeneity concerns addressed through the instrumental variable method and a series of robustness tests. Employing the Technology Acceptance Model, I further explore the mechanism, identifying third-party payment adoption as a key mediator. Notably, perceived security is a more critical determinant driving third-party payment adoption than perceived convenience. These results underscore the significant influence of tourism on stimulating online consumer activity within the digital ecosystem and highlight the pivotal importance of perceived security in facilitating payment method adoption in developing countries.

Keywords

Tourism experience, Online shopping, Third-party payment, Technology acceptance model

JEL classification

D12, L83, O33

Corresponding author:
Wenhui Yang, School of Economics, Guizhou University, West Campus (Jiaxiu South Road), Huaxi District, Guiyang 550025, Guizhou, China.
Email: ywh952719@163.com

Introduction

Tourism has a pivotal influence on driving economic growth, particularly in emerging economies such as China, stimulating direct and indirect economic activities (Faber and Cecile, 2019). It fosters growth in sectors such as hospitality, transportation, and retail, while also serving as a key driver of household consumption (CAICT, 2020; Horner and Swarbrooke, 2020). China's strategic positioning emphasizes tourism as a catalyst for domestic consumption and sustainable economic development, aligning with efforts to reduce external reliance and promote long-term stability (Zhang and Chen, 2019). The focus on tourism underscores its transformative effect on household consumption, particularly online shopping.

The digital economy has reshaped consumption patterns (Zhang et al., 2022), with the rapid rise of e-commerce driven by digital platforms and third-party payment systems like Alipay and WeChat Pay (Zhang and Chen, 2019). These innovations enhance the convenience, speed, and security of online transactions, bridging tourism and digital consumption. This study investigates the influence of third-party payments as a mediator between tourism participation and online shopping practices, applying the Technology Acceptance Model (TAM) (Davis et al., 1989) to examine perceived security and perceived convenience as key factors influencing digital payment adoption (Li et al., 2024).

The empirical analysis draws on the China Household Finance Survey in 2019, which provides comprehensive data on Chinese households' economic practices across diverse socio-demographic groups. These data facilitate this examination of how engagement in tourism activities and digital payment adoption jointly influence household consumption patterns within the broader context of the digital economy.

The study employs rigorous econometric methods, including instrumental variable (IV) estimation and a series of robustness tests, to address potential endogeneity and confirms the positive impact of tourism experiences on online shopping. I examine third-party payments as a mediator using traditional and causal mediation methods to explore whether these payments (cash, card, and third-party) facilitate the relationship between tourism and online shopping. Furthermore, the study examines the influence of the TAM constructs of perceived security and perceived convenience on third-party payment adoption and online shopping practices.

This research contributes to the literature by identifying third-party payments as a critical mediator between tourism and online shopping. While previous studies have examined tourism's economic impact and the influence of digital payments, no studies have explored third-party payments as a mediating variable. The findings reveal the significant influence of third-party payment systems as transaction facilitators and key enablers of the tourism–online shopping connection. These insights are valuable for firms and regulators seeking to understand how technology influences consumer behavior. Policy recommendations include enhancing digital infrastructure, building consumer trust, and ensuring digital payment systems' security and convenience, which will promote tourism and digital consumption alike, contributing to domestic demand and economic growth.

The remainder of this paper is structured as follows. Section 2 reviews the literature on tourism, online shopping, and the TAM in tourism. Section 3 introduces the research background and hypotheses. Section 4 presents the data and variables. Section 5 outlines the study's methodology. Section 6 examines the mechanisms, and Section 7 concludes.

Literature review

Tourism and online shopping

Previous research on the relationship between tourism and online shopping can be categorized into two primary streams. The first stream explores how tourism experiences influence consumer practices, particularly purchasing decisions (Horner and Swarbrooke, 2020). Cultural shocks encountered during travel can provoke deep reflection, leading consumers to reassess their preferences (Richards et al., 2020; Zhang et al., 2022). This shift becomes apparent when travel exposes individuals to new values that affect their consumption patterns—particularly in terms of eco-friendly products after exposure to natural landscapes (Zhang et al., 2022a). Negative or memorable travel experiences, whether emotional or traumatic, can leave lasting impressions that significantly impact individuals' post-trip consumption decisions (Kim, 2022; Servidio & Ruffolo, 2016; Vada et al., 2019). These (positive and negative) experiences are crucial drivers in shaping future consumer behavior. Marketing strategies employed by online travel agencies also have a significant influence on consumer decisions. Personalized recommendations and targeted discounts that consumers encounter when booking a trip can carry over into broader travel-related purchases (Ma et al., 2021; Ye et al., 2019). Similarly, promotional offers such as hotel discounts directly affect accommodation choices, and attractive offers can sway consumers' preferences (Ma et al., 2021; Shin et al., 2022). These factors underscore the importance of marketing tactics in guiding consumer choices. Finally, value cocreation during the travel process that engages multiple stakeholders strengthens consumer loyalty and fosters future purchase intentions. Engaging in cocreation activities such as sharing experiences or reviews fosters deeper emotional connections with a brand or destination, driving repeat business (Sugathan & Ranjan, 2019; Rong-Da Liang, 2017).

The second stream of research examines the influence of offline experiences on online shopping practices. These studies primarily investigate how offline social capital such as interactions with neighbors, acquaintances, or community members affects online purchase decisions (Ramirez and Wang, 2008). Key studies explore various dimensions, including the influence of word-of-mouth, geographic proximity, and online shopping convenience. Additionally, research has examined the differences between online and offline shopping experiences and how offline social networks intersect with online consumption patterns (Kim et al., 2019). The influence of in-store experiences such as interactions with sales staff or the tactile experience of physical products is also analyzed for its impact on online shopping behavior (Lemon and Verhoef, 2016). This body of literature highlights the dynamic interplay between offline social experiences and online purchasing, shedding light on how both dimensions shape consumer decision-making.

Despite these insights, a notable gap in the literature exists regarding the relationship between tourism experiences and online shopping. While previous research predominantly focuses on travel products and services, a limited understanding of how tourism experiences influence online consumption patterns more broadly remains. This gap presents an opportunity to explore how offline tourism experiences shape consumers' online shopping practices, particularly in the context of the growing digital economy. The study addresses this gap by investigating the influence of tourism experiences on online shopping behavior, enhancing our understanding of the intersection between tourism and e-commerce.

Technology Acceptance Model in tourism

The TAM is a theoretical framework for understanding how tourists adopt and use digital technologies within the tourism sector (Davis et al., 1989). While numerous studies have extended this model, this study focuses on the original formulation of TAM. TAM emphasizes perceived ease of use (PEOU) and perceived usefulness (PU), which influence users' decisions to accept and adopt new technologies (Venkatesh et al., 2012). The model has been widely applied in fields such as e-commerce, healthcare, and tourism to assess the acceptance of technologies like virtual reality

(VR) (El-Said and Aziz, 2022; Wang et al., 2024), augmented reality (AR) (Tom Dieck & Jung, 2018), and mobile applications (Hew et al., 2018).

In the tourism sector, VR and AR technologies can significantly enhance the travel experience by offering engaging, immersive, and value-added online interactions. When these technologies improve users' experience, they can positively influence tourists' perceptions and increase engagement with online tourism products or services. This can subsequently drive purchasing behaviors as users are more likely to invest in experiences they perceive as enjoyable and useful. Therefore, the PU and PEOU of VR and AR technologies are pivotal in shaping tourists' practices and decision-making (Li et al., 2024; Sousa et al., 2024).

The TAM has also been extended to investigate the influence of emerging technologies like the Metaverse (Liu and Park, 2024), autonomous vehicles (Phaosathianphan and Leelasantitham, 2021), and ChatGPT (Zhu et al., 2024) in shaping the tourist experience. While these studies shed light on the factors influencing technology adoption, they often overlook the crucial aspect of causal identification. While TAM can identify factors influencing technology acceptance, it cannot fully address the causal relationships between these factors. This gap in the literature motivates this study, which applies causal inference methods to better understand the drivers of technology adoption in tourism, particularly concerning tourism experiences and online shopping.

Research background and hypotheses development

Background

In 2019, China's digital economy became a key driver of global economic development, reaching 35.8 trillion yuan, or 34.8% of the nation's GDP (CAICT, 2020). This growth reflects technological advancements that are reshaping industrial structures and China's rising prominence in the global digital economy. Core sectors such as e-commerce, digital payments, and cloud computing have significantly expanded, with e-commerce and third-party payments standing out.

China's e-commerce sector has been a major contributor to the digital economy. In 2019, online retail transactions totaled 8.5 trillion yuan, representing a 19.5% increase (CAICT, 2020). This growth accompanied a shift in consumer practices, with emerging business models such as online retail, social e-commerce, and cross-border e-commerce transforming traditional retail. Consumers increasingly rely on online platforms for purchasing decisions, while technological innovations enhance shopping convenience and accessibility with personalized services. Third-party payment systems have been integral to this transformation. In 2019, China's third-party payment market reached 277 trillion yuan, with nearly 700 million active users. Payment methods now include online, mobile, and scenario-based payments, with platforms such as Alipay and WeChat Pay revolutionizing consumer payment options through cashless transactions, instant payments, and cross-border services. These platforms have also facilitated growth in sectors such as consumer finance, cross-border e-commerce, and digital currencies.

China's vast population of digital adopters has been crucial in driving this growth. With 700 million internet users and 282 million digital natives (Zhang and Chen, 2019), China benefits from a large, tech-savvy consumer base that is eager to adopt new technologies. Compared with India, which had only 60% of China's internet users in 2016, and the United States, with fewer than 300 million users, China's digital infrastructure and adoption outpace many other nations. This extensive adoption combined with government support has positioned China as a competitive force in the global digital economy.

The expanding digital economy has also impacted traditional sectors, most notably retail, finance, and tourism, where digital technologies such as intelligent platforms, cloud computing, and big data analytics have enhanced productivity and service quality. In tourism, the integration of digital payments and online booking platforms has transformed consumer experiences, providing convenience, transforming payment methods, and enabling personalized and immediate travel services. These developments have established a strong foundation for further research into the intersection of tourism, online shopping, and digital payment systems.

Hypotheses

Considering China's strategic promotion of tourism to stimulate consumption and expand domestic demand, coupled with the remarkable growth of the nation's digital economy, this study hypothesizes that tourism fosters individual engagement in online shopping. Specifically, tourism exposes travelers to novel environments beyond their usual residence, facilitating material exchanges and cultivating emotional attachments that shape consumption preferences beyond the travel experience. Travelers encounter locally distinctive products—items imbued with cultural, ecological, or commemorative value—that differ from their everyday consumption options, sparking new interests and tastes. The emotional dimensions of travel such as relaxation, value affirmation, and a sense of belonging further enhance the appeal of such goods, embedding them with symbolic meaning. Upon returning home, travelers constrained by physical limitations like luggage restrictions or the unavailability of certain products in local markets, are expected to increasingly turn to online platforms to fulfill their consumption desires.

During travel, individuals engage in material exchanges and acquire regionally specific products such as artisanal goods or cultural artifacts that carry emotional weight as tangible reminders of a trip. These purchases are not merely transactional; they serve as markers of identity or status, deepening their value to the consumer. The emotional attachments formed during travel persist after a trip ends, motivating travelers to seek out similar or complementary products online. China's robust digital economy, with its advanced e-commerce platforms and efficient logistics (Zhang et al., 2022b), facilitates this shift by offering convenient access to a vast array of travel-inspired goods. Therefore, I propose the following hypothesis:

> **Hypothesis 1 (H1):** Household expenditure on tourism has a significant positive effect on household online shopping expenditure.

I further posit that third-party payment platforms mediate the relationship between household tourism expenditure and online shopping expenditure. Compared with other payment methods (e.g., cash or card), consumers are more likely to use digital payment platforms for booking accommodations, paying for transport, and purchasing goods during their travels. As these platforms integrate more deeply into daily life, they provide a seamless transition for consumers to continue using them for online shopping (Quan et al., 2023). The convenience and security offered by platforms such as Alipay and WeChat Pay encourage consumers to use them during travel and in subsequent online shopping. Therefore, the use of third-party payment platforms is expected to mediate the effect of tourism expenditure on increased online shopping expenditure. Based on this conjecture, I propose the following hypothesis:

> **Hypothesis 2 (H2):** The use of third-party payment platforms mediates the relationship between household tourism expenditure and online shopping expenditure.

Finally, based on the TAM, which highlights PU and PEOU[1], I hypothesize that the perceived security of third-party payment systems strengthens the relationship between household tourism expenditure and online shopping expenditure. Security concerns are a major barrier to online shopping; however, as consumers become more familiar with secure payment systems during their travels, their trust in these platforms grows, and this increased trust is likely to positively influence their likelihood of engaging in online shopping post-tourism. Therefore, consumers' perception of payment security is expected to function as a facilitator, encouraging greater online spending after a tourism experience, leading to the following proposed hypothesis:

> **Hypothesis 3 (H3):** Perceived security in third-party payment systems has a critical influence on facilitating the relationship between household tourism expenditure and online shopping expenditure.

Data and variables

Data

The China Household Finance Survey (CHFS), conducted by Southwestern University of Finance and Economics, is a nationally representative, longitudinal survey initiated in 2011, with biennial data collection. The most recent wave, collected in 2019, employs a three-stage stratified Probability Proportional to Size sampling method to ensure the randomness and representativeness of the sample. The survey gathers detailed microlevel data on a wide range of household financial and nonfinancial variables, encompassing assets, liabilities, income, consumption, credit constraints, social security, commercial insurance, intergenerational transfers, demographic characteristics, employment, and payment habits. These data provide a comprehensive snapshot of household economic conditions and consumption practices, offering valuable insights for academic research and policy analysis.

This study uses the 2019 wave of the CHFS[2], which includes data on third-party payment use, online shopping, and tourism-related expenditure. The survey covers 29 provinces, 345 districts/counties, and 1360 neighborhood/village committees, with a total sample size of 34,643 households, excluding Tibet, Xinjiang, Hong Kong, Macao, and Taiwan. The 2019 wave captured a peak period in China's digital economy development, reflecting a crucial moment in the evolution of consumption and payment practices. The 2019 CHFS provides a robust dataset for analyzing the relationships between household consumption patterns and payment systems, particularly in the context of tourism and online shopping.

Variables

The following defines the main variables used in this study, including the outcome variable, the variable of interest, mediating, and control variables. To capture the effect of household total income on consumption (Yang et al., 2023), I compute ratios for all economic variables by dividing each variable by household total income (*income*), which is transformed using the following inverse hyperbolic sine (IHS) function:

$$IHS\left(income_{ifj}\right) = \ln\left(income_{ifj} + \sqrt{income_{ifj}^{2} + 1}\right) \tag{1}$$

Total household income includes all sources of income, covering wages, agricultural income, income from industry and commerce, property income, and transfer income. In some instances, household total income may be negative, which is primarily attributable to losses from business operations or financial market investments. The IHS transformation is widely used in wealth effect studies (Bellemare and Wichman, 2020) as it corrects for skewed data similar to the natural logarithm but can accommodate nonpositive values and retain the sample size, avoiding excessive sensitivity at zero-value points. Descriptive statistics and a correlation matrix for the main variables are provided in Tables A1 and A2.

Outcome variable: Online shopping. To capture online shopping behavior, I extract data from a survey question[3] on total household expenditure on online shopping, which includes spending on various products across different websites and platforms. I compute the ratio between total household online shopping expenditure and *income* (as defined previously). To ensure that the data fits appropriately without distorting its characteristics or introducing zero values, I apply the natural logarithm of this ratio, adding a small constant (1×10^{-6}) to measure online shopping expenditure (Fu and Jian, 2021).

Variable of interest: Tourism. This study captures tourism expenditure using data extracted from a survey question[4] on total household expenditure on tourism, which includes expenses such as meals, transportation, tickets, guides, accommodations, and related costs both locally and abroad. I calculate the ratio by dividing this tourism expenditure by *income* (defined as before). To fit the data without its characteristics or introducing zero value, I use the natural logarithm of this ratio plus 1×10^{-6} to measure *Tourism*.

Mediating variable: The third-party payment. To capture households' use of third-party payment systems, I extract data from a question[5] in the survey regarding whether the household has activated accounts with platforms such as Alipay, WeChat Pay, JD Pay, Baidu Wallet, and others. Using this information, I construct a binary variable that is assigned a value of 1 when the household has activated one or more of these third-party payment accounts, while a 0 value indicates they have not. This variable enables me to measure households' adoption of third-party payment systems.

Mediating variables in the TAM: Perceived security and perceived convenience. Based on the TAM, I define PU as the perception of security (*perceived security*) and PEOU as the perception of convenience (*perceived convenience*) in using third-party payment systems. I extract these constructs from the survey[6], with *perceived security* representing the perception of low risk and security, and *perceived convenience* representing the convenience of using these payment systems for transactions. I then operationalize both constructs as binary variables, where a value of 1 indicates that the respondent perceives the system as secure or convenient, and a value of 0 indicates the opposite. This enables me to measure the influence of perceived security and convenience on the adoption of third-party payment systems.

Control variables. Tourism experience and online shopping practices are influenced by individual needs and personal experiences; therefore, I do not restrict or filter the sample. Referencing Suri and Jack, 2016, I control for several individual and household characteristics to account for various factors that might influence online shopping behavior.

First, I control for *age*, calculated as the difference between the survey year and the individual's year of birth. An age of 0 indicates the individual is under 1 year old. Second, I control for *gender* to explore potential gender differences in online shopping practices. Third, I include household registration status (*hukou*) as a categorical variable in which 0 = No household registration or unclear status, 1 = Agricultural, 2 = Nonagricultural, and 3 = Unified resident household. I also control for years of education (*education*) to assess the influence of education on online shopping habits. *Marital status* is also included, using a categorical variable where 1 = Single, 2 = Married, 3 = Cohabiting, 4 = Separated, 5 = Divorced, and 6 = Widowed to examine how marital status impacts online shopping behavior. Finally, I control for household assets, specifically whether the household owns a *car* or a *home*. These assets are considered important indicators of socioeconomic status that may influence purchasing decisions and online shopping behavior.

These control variables isolate the effect of tourism experience on online shopping behavior, accounting for individual and household-level factors. I assume these variables are exogenous in the short run, and avoid controlling for endogenous variables such as household credit to prevent potential issues with inflated R-squared (R^2) and bad control (Angrist and Pischke, 2009).

Methodology

Baseline estimates

To test Hypothesis 1, I construct the following equation:

$$Online\,shopping_{ifj} = \alpha_0 + \alpha_1 Tourism_{ifj} + \alpha_2 X_{ifj} + \alpha_3 X_{fj} + \delta_j + \varepsilon_{ifj} \tag{2}$$

where *Online shopping* is measured by the total annual expenditure on online shopping per household, and *Tourism* is measured by the household's total annual expenditure on tourism. Subscripts i, f, and j refer to the individual, household, and province, respectively. X_{ifj} denotes the series of individual control variables (age, gender, household registration status (*hukou*), years of education, and marital status). $\boldsymbol{X_{fj}}$ represents household control variables, including *car* and *home* ownership status. As individuals and households may be influenced by provincial policies, economic conditions, and cultural heterogeneity, I also control for province fixed effects (δ_j). The residuals ε_{ifj} in equation (2) are clustered at the provincial level to account for potential intraprovince correlation.

Table 1 presents the baseline estimates, revealing that the correlation between online shopping and tourism is positive and statistically significant, supporting Hypothesis 1. Moreover, most control variables are significant in explaining online shopping practices. Age has a negative and statistically significant relationship with online shopping, indicating that older individuals are less likely to engage in online shopping. Gender also has a negative relationship with online shopping, indicating that males are less likely to shop online than females. Additionally, household registration type (*hukou*) is positively associated with online shopping. Higher education is positively correlated with online shopping, indicating that more educated individuals are more inclined to engage in online shopping. Married individuals exhibit a higher tendency to shop online, possibly reflecting higher household income or purchasing power. The coefficient for car ownership is highly significant, indicating that car owners are more likely to purchase goods online, potentially due to higher disposable income or logistical convenience. Notably, homeownership is negatively correlated with online shopping, suggesting that homeowners may prefer traditional shopping methods or have more time for in-store purchases.

Table 1. Baseline estimates.

Dependent variable	Online shopping
Tourism	0.241*** (27.73)
Age	– 0.117*** (– 15.79)
Gender	– 0.446*** (– 10.28)
Hukou	0.485*** (4.05)
Education	0.751*** (14.79)
Marital	0.513*** (11.19)
Car	4.703*** (24.21)
Home	– 0.694** (– 2.35)
Constant	– 1.555** (– 2.70)
Province FE	Yes
N	39,267
R^2	0.308

Notes: Regression includes province fixed effects and the full set of individual-level controls (age, gender, hukou, education, marital status) and household-level controls (car and home ownership, household size). t-statistics clustered at the province level are reported in parentheses. ***, **, and * denote significance at the 1 %, 5 %, and 10 % levels, respectively.

Reduced sample estimates

As estimates using equation (2) may suffer from reverse causality, I conduct reduced sample estimates to justify that the potential bias due to reverse causality is negligible. The formula is as follows:

$$Online\,shopping_{ifj} = \alpha_0 + \alpha_1 Tourism_{ifj} + \alpha_2 X_{ifj} + \alpha_3 X_{fj} + \delta_j + \varepsilon_{ifj}, if\, f \epsilon F \tag{3}$$

I only include a subset of the sample in the reduced sample estimation to address potential reverse causality, where online shopping may serve as a substitute for tourism. According to a study (Zhou and Wang, 2014), online shopping tends to be more frequent in wealthier or more densely populated areas. To ensure that the results reflect the effect of tourism on online shopping and are not confounded by this substitution effect, I reduce the sample by focusing on less-developed and less-densely populated regions. First, I focus on rural areas, excluding households located in towns (Li et al., 2020). Compared with rural areas, towns typically have higher economic development, which can make it more likely for online shopping to serve as a substitute for tourism. Second, I concentrate on tier-3 cities by excluding households in cities with higher development. Unlike more populous and wealthier cities, tier-3 cities tend to have smaller populations and lower economic development. Third, I restrict the analysis to households in China's least-developed western region (Donaldson and Hornbeck, 2016). By excluding households from more developed regions, I focus on areas with inferior infrastructure, which makes them less likely to engage in frequent online shopping, ensuring that I capture the genuine effect of tourism on online shopping.

These reduced sample regressions are intended to verify whether tourism's influence on online shopping remains consistent across these specific contexts. Columns (1)–(3) of Table 2 report results for households located in tier-3 cities, rural areas, and the western region, respectively. The reduced sample estimates mirror the baseline findings, indicating that potential reverse causality bias is negligible.

Table 2. Reduced sample estimates.

	Online shopping		
Dependent variable	Tier-3 cities	Rural	Western
Tourism	0.262*** (17.62)	0.256*** (9.87)	0.242*** (19.44)
Age	− 0.093*** (− 11.55)	− 0.068*** (− 9.44)	− 0.093*** (− 6.29)
Gender	− 0.498*** (− 7.98)	− 0.378*** (− 7.89)	− 0.497*** (− 6.51)
Hukou	0.529** (2.67)	0.518* (1.87)	0.580** (2.57)
Education	0.753*** (12.48)	0.541*** (10.03)	0.810*** (8.02)
Marital	0.483*** (8.30)	0.442*** (8.64)	0.469*** (5.02)
Car	4.673*** (16.47)	4.891*** (10.09)	4.792*** (10.81)
Home	− 0.346 (− 0.76)	0.281 (0.53)	− 0.516 (− 0.73)
Constant	− 5.592*** (− 8.62)	− 5.259*** (− 5.29)	− 4.337*** (− 3.36)
Province FE	Yes	Yes	Yes
N	23,956	12,584	11,507
R^2	0.247	0.191	0.272

Notes: Each column reports OLS estimates for a different reduced sample designed to alleviate reverse-causality concerns. Column (1) restricts the sample to households located in tier-3 cities, column (2) to those in rural areas, and column (3) to households in China's western provinces. All specifications include province fixed effects and the full set of individual-level controls (age, gender, *hukou*, education, marital status) and household-level controls (car and home ownership). *t*-statistics clustered at the province level are reported in parentheses. ***, ** and * indicate significance at the 1 %, 5 % and 10 % levels, respectively.

Propensity score matching

Travel choices are not random, but are influenced by various factors such as family income, personal preferences, and the impact of online promotions, which can result in self-selection bias. Additionally, the research sample in this study is derived from the CHFS, which does not capture all families and individuals across China. As a result, the sample may not be fully representative of the broader population, potentially introducing sample selection bias into the findings. To address this concern, I employ propensity score matching (PSM) to mitigate the potential endogeneity bias that may arise from sample selection (Dehejia and Wahba, 2002).

I employ the nearest neighbor matching method without replacement, using a 1:1 matching ratio. The covariates selected for PSM matching include age, gender, hukou, education, marital status, car ownership, and homeownership. Matching observations based on these covariates controls for the differences between treated (tourism-experiencing) and untreated (nontourism-experiencing) households to address potential sample selection bias.

Figure A1 illustrates how propensity-score matching improves overlap between the treatment and comparison groups. Panel A plots kernel-density estimates of propensity scores before matching: the control group is heavily concentrated near $p \approx .10$, whereas a non-trivial share of treated observations lies above $p \approx .60$, indicating limited common support. Panel B re-draws the same densities after 1:1 nearest-neighbor matching without replacement. After matching on the dull set of covariates, the two curves overlap across almost the entire score range, and the sample size falls from 39,267 to 17,254. This suggests that the common-support assumption is satisfied and observable heterogeneity has been largely removed.

Following the matching procedure, I regress the adjusted sample using equation (2). As shown in Column 1 of Table A3, the causal relationship between tourism and online shopping remains positive and statistically significant at the 1% level, confirming that sample selection bias does not undermine the robustness of the baseline findings.

Robustness tests

To assess the robustness of the benchmark findings, I conduct four additional regression analyses by restricting the sample and incorporating variables that may influence online shopping practices. First, I restrict the sample to household heads, as household heads' characteristics are considered a critical determinant of household expenditure (Suri and Jack, 2016). Second, I introduce an interaction term between years of education and tourism participation as higher education may affect how individuals engage in tourism, which could subsequently influence online shopping habits (Zhou and Wang, 2014). Third, I include the squared term of age to capture potential nonlinear effects as age may not exhibit a linear relationship with online shopping and younger and older individuals may demonstrate different consumption patterns. Fourth, I account for self-assessed health status, considering that individuals in better health might prioritize different consumption choices and exhibit distinct online shopping practices compared with those in poorer health Aron-Dine et al. (2013). Finally, I incorporate a measure of subjective wellbeing, hypothesizing that individuals with higher reported wellbeing are more likely to engage in discretionary spending, including online shopping (Zhu et al., 2021).

If the inclusion of these variables does not substantially alter the main results, it will indicate that the baseline findings are not sensitive to the omission of these factors, reinforcing the robustness of the baseline conclusions. As shown in Columns (2)–(6) of Table A3, the causal relationship between tourism and online shopping remains robust and statistically significant across all regressions, consistent with the baseline results. Specifically, in Column (2), which restricts the sample to household heads, the effects of homeownership and gender become less pronounced. This attenuation suggests that household heads have a more central influence on shaping online shopping practices, potentially diminishing the influence of other household characteristics. In Column (3), the significantly negative interaction term between education and tourism indicates that individuals with higher education levels may perceive tourism as a substitute for online shopping. In Column (4), the squared term of age reveals a significantly negative relationship, indicating a nonlinear effect, with engagement in online shopping likely decreasing as individuals age. In Column (5), the negative effect of self-assessed health status implies that individuals in poorer health are less likely to engage in online shopping. Finally, in Column (6), subjective wellbeing has a positive and significant effect, indicating that individuals with higher subjective wellbeing are more likely to engage in online shopping, particularly for leisure and satisfaction. The consistency of the results across various model specifications strengthens the reliability of our conclusions, supporting the validity of the observed relationship between tourism expenditure and online shopping.

Instrumental variable estimates

This study next conducts IV estimation to address endogeneity concerns. The chosen IV is the distance between a household's location (at the county or district level) and its affiliated city-level administrative area (Nunn and Wantchekon, 2011). I compute the distance based on the longitude and latitude of the household's county/district and the affiliated city. To ensure that the distance variable does not contain zero values, I adjust it by adding 1 and then take its reciprocal. This transformation is reflected in equation (4). The underlying assumption is that the probability of engaging in tourism decreases with the distance from the city as greater distance leads to higher travel costs, which reduces the likelihood of travel (Yang et al., 2018).

$$F(Distance_{ifj}) = \frac{1}{Distance_{ifj} + 1} \tag{4}$$

For an IV to be valid, it must be correlated with the endogenous explanatory variable (household tourism expenditure) but should not directly affect the dependent variable (household online shopping expenditure) except through its effect on the endogenous variable. The distance measure, after transformation, meets these criteria as it is strongly correlated with the decision to engage in tourism since longer distances increase travel costs, reducing the probability of travel. Moreover, distance is an exogenous variable that is determined by geographic factors, which makes it unlikely to have a direct impact on online shopping expenditure other than through its effect on tourism expenditure. Therefore, I contend that this IV is theoretically valid.

More practically, I examine the validity of our IV according to the following equations:

$$Tourism_{ifj} = \alpha_0 + \alpha_1 Distance_{ifj} + \alpha_2 X_{ifj} + \alpha_3 X_{fj} + \delta_j + \varepsilon_{ifj} \tag{5}$$

$$Online\,shopping_{ifj} = \alpha_0 + \alpha_1 Tourism_{ifj} + \beta Distance_{ifj} + \alpha_2 X_{ifj} + \alpha_3 X_{fj} + \delta_j + \varepsilon_{ifj} \tag{6}$$

where *Distance* is the distance between a household's location (at the county/district level) and the affiliated city-level administrative area, while all other variables in Equations (5) and (6) are defined as before. The validity of the IV first requires the coefficient α_1 in equation (5) to be significant. According to the IV literature (Conley et al., 2012; Nunn and Wantchekon, 2011), the direct effect of an IV on the dependent variable can be represented by the coefficient of the IV with the variable of interest being controlled for. Therefore, the validity of the IV also requires the coefficient β in equation (6) to be insignificant.

If our IV coefficients satisfy the above two requirements, I can then conduct second-stage estimation using the following equation:

$$Online\,shopping_{ifj} = \alpha_0 + \gamma \widehat{Tourism}_{ifj} + \alpha_2 X_{ifj} + \alpha_3 X_{fj} + \delta_j + \varepsilon_{ifj} \tag{7}$$

where the fitted value of *Tourism* is estimated from equation (5). In particular, Equations (5) and (7) form a two-stage least squares (2SLS) methodological framework. If the estimates are robust to potential endogeneity bias, the coefficient γ should be significantly positive as before.

The IV estimates are presented in Table 3. As Column (1) demonstrates, our IV is positively and significantly correlated with tourism expenditure, supporting the relevance of our IV. The F-statistics from the 1st-stage estimates exceed 10, indicating that the chosen IV is not weak. Furthermore, Column (3) shows that the direct effect of our IV is insignificant once tourism expenditure is controlled for, confirming that our IV meets the validity criteria. Therefore, I proceed with 2SLS estimates, presenting the second-stage results in Column (2) of Table 3. As Table 3 shows, the coefficient of tourism is 0.578,which is significant at the 95% level (recall that the baseline estimates of the variable of interest is 0.242). Household tourism expenditure is significantly and positively correlated with online shopping, with all control variables in the IV estimation maintaining their signs as in the baseline estimation. Therefore, our results are robust to potential endogeneity bias, providing further support for Hypothesis 1.

Table 3. Instrumental variable estimates.

	First-stage estimates	Second-stage estimates	Exclusion restriction test
Dependent variable	Tourism	Online shopping	Online shopping
Tourism		0.578** (2.22)	0.241*** (24.39)
Distance	2.196*** (4.39)		0.738 (1.19)
Age	0.038*** (9.92)	− 0.126*** (− 9.45)	− 0.114*** (− 16.61)
Gender	− 0.508*** (− 10.23)	− 0.276* (− 1.94)	− 0.446*** (− 9.82)
Hukou	1.167*** (7.84)	0.092 (0.22)	0.484*** (3.10)
Education	1.041*** (22.18)	0.397 (1.38)	0.748*** (14.44)
Marital	− 0.019 (− 0.46)	0.508*** (10.55)	0.501*** (10.96)
Car	3.503*** (15.34)	3.600*** (3.86)	4.777*** (23.96)
Home	0.620** (2.19)	− 0.484 (− 1.56)	− 0.275 (− 0.88)
Constant	− 16.289*** (− 25.20)	2.890 (0.66)	− 2.586*** (− 4.29)
F-statistics	19.24		
Province FE	Yes	Yes	Yes
N	35,429	35,429	35,429
R^2	0.194	0.240	0.307

Notes: Column (1) reports the first-stage regression of Tourism on the excluded instrument—the inverse of a household's distance to its affiliated city. Column (2) presents the second-stage 2SLS estimates of Tourism's effect on online-shopping expenditure. Column (3) re-regresses the outcome directly on the instrument (adding Tourism to the control set) to examine the exclusion restriction: a statistically insignificant coefficient on instrument would support the assumption that Distance affects online shopping only through Tourism. All regressions include province fixed effects and the control variables described in the notes to Table 1. The first-stage F-statistic on the excluded instrument appears at the bottom of column (1). t-statistics clustered at the province level in parentheses; ***, **, * denote 1 %, 5 %, 10 % significance.

Mechanism test

Building on the theoretical framework and background analysis, this section further investigates the mediating influence of third-party payments on the relationship between tourism participation and online shopping practices. In addition, using the TAM, I examine whether perceived security and/or perceived convenience have the more significant influence on this mechanism.

Third-party payment

In this section, I conduct a mediating effect analysis to examine how third-party payment systems mediate the relationship between tourism experience and online shopping behavior. I hypothesize that third-party payments significantly mediate the causal effect of tourism on online shopping.

To test this, I first apply the traditional mediating method using third-party, cash, and card payment methods to verify whether these methods mediate the relationship between tourism and online shopping. The process employs the following two key equations:

$$M_{ifj} = \eta_0 + \eta_1 Tourism_{ifj} + \eta_2 X_{ifj} + \eta_3 X_{fj} + \delta_j + \varepsilon_{ifj} \tag{8}$$

$$Online\,shopping_{ifj} = \theta_0 + \theta_1 Tourism_{ifj} + \theta_2 M_{ifj} + \theta_3 X_{ifj} + \theta_4 X_{fj} + \delta_j + \varepsilon_{ifj} \tag{9}$$

where *M* is the mediating variable third-party (defined as before), cash, and card payments. Cash is measured as the ratio of the household's cash holdings to *income*, and I use the natural logarithm of this ratio plus 1×10^{-6} to measure *Cash*. Card is measured by the number of bank savings cards or current deposit books held by the household. The traditional mediating effect method suggests conducting separate regressions according to equations (8) and (9). The mediating effect of interest is the product of the coefficient of *Tourism* in equation (8) with the coefficient of the mediator in equation (9) $(\eta_1\theta_2)$. To robustly examine the mediating effect of third-party payment, I extend the analysis by incorporating cash and card payment methods as control variables to ensure that the importance and validity of third-party payment as a mediator are not confounded by other payment channels. However, the traditional method is not founded with a formal framework for causal inference (Hicks and Tingley, 2011). Therefore, I adopt a causal mediating method (Imai et al., 2010), calculating the average causal mediating effect (ACME) on the influence of tourism on online shopping. Therefore, this study employs a causal mediating method that calculates the product after "simulating predicted values of the mediator or outcome variable, which I do not observe, and then calculating the appropriate quantities of interest" (Hicks and Tingley, 2011). To ensure the reliability of the ACME approximation, I control for individual- and household-level variables, consistent with the baseline regression. Additionally, I include province-level FEs to account for regional heterogeneity. These controls can mitigate potential bias from unobserved individual characteristics and regional factors, ensuring the robustness of our estimates.

As Table 4 shows, in Column (1), the relationship between third-party payments and tourism is positive and statistically significant. In Column (2), the results suggest that third-party payments are a significant mediator in the relationship between tourism and online shopping. In Table A4, the traditional mediating analysis reveals that *Cash* acts as a significant mediator, while *Card* does not have a significant mediating effect. When *Cash* and *Card* are included as control variables in the third step of the mediating process, only third-party payments remain statistically significant at the 99% level, and the coefficient is 7.711, confirming the critical role of third-party payments as a mediator. Table A5 presents the results of the ACME analysis, indicating that all indirect effects of tourism on online shopping through third-party payments are statistically significant, with an ACME of 0.067, accounting for 26.9% of the total effect. After controlling for *Cash* and *Card*, the ACME decreases slightly to 0.054, and the proportion of the total effect mediated by third-party payments drops to 24.4%. This suggests that third-party payments continue to serve as a significant mediator, albeit with a slightly reduced effect, confirming Hypothesis 2.

Table 4. Mediating effect estimates.

Dependent variable	Third-party	Online shopping
Tourism	0.008*** (18.92)	0.177*** (21.14)
Third-party		7.917*** (36.87)
Control variables	Yes	Yes
Province FE	Yes	Yes
N	41,623	38,980
R^2	0.255	0.441

Notes: Column (1) reports the first step of the mediation analysis, regressing the proposed channel—Third-party payment adoption—on Tourism. Column (2) estimates the second step, regressing the log ratio of online-shopping expenditure to annual household income on both Tourism and Third-party payment adoption. All regressions include province fixed effects and the full set of controls (age, gender, hukou, education, marital status, car and home ownership). t-statistics clustered at the province level are reported in parentheses. ***, ** and * indicate significance at the 1 %, 5 % and 10 % levels, respectively.

Perceived security

Building on the findings of the previous section, this study next adopts the TAM framework to further investigate the mediating role of third-party payments in the relationship between tourism experience and online shopping practices. The objective of this section is to identify whether perceived security or perceived convenience have a more significant influence on facilitating third-party payment adoption and influencing online consumption. To achieve this, I replicate the methodological approach used in Section 6.1, employing traditional and the causal mediating methods. The traditional mediating approach estimates the indirect effect by calculating the product of coefficients, while the causal mediating method provides a more robust causal interpretation by simulating unobserved mediator and outcome variables to compute the ACME. As in the previous analysis, I include the same control variables to ensure the results' robustness. This approach isolates the contribution of PU and PEOU to the mediating mechanism while addressing potential confounding factors.

Table 5 explores the influence of perceived security and perceived convenience as potential mediators in the context of the TAM. In Column (1), the relationship between perceived security and tourism is positive and significant, indicating that security concerns influence tourism practices. Similarly, Column (2) demonstrates that perceived convenience also has a positive and significant effect on tourism, aligning with the TAM framework. In Columns (3) and (4), perceived security and perceived convenience act as significant mediators in the relationship between tourism and online shopping. Table A6 presents the results of the causal mediating effect analysis for perceived security and perceived convenience. The ACME for perceived security is 0.003, which is statistically significant at the 95% level, accounting for 2.2% of the total effect, indicating that perceived security has a significant role in mediating the relationship. In contrast, the ACME for perceived convenience is 0.001 and insignificant at 90%, only contributing 1.2% to the total effect. This supports Hypothesis 3, demonstrating that perceived security is the more significant mediator in the relationship between tourism and online shopping. These findings underscore the relative importance of security over convenience when adopting payment methods, with individuals prioritizing security over convenience in their decision-making.

Table 5. Further mediating effect estimates.

Dependent variable	Perceived security	Perceived convenience	Online shopping	
Tourism	0.002** (2.12)	0.003*** (2.91)	0.138*** (9.41)	0.139*** (8.99)
Perceived security			0.938** (2.26)	
Perceived convenience				1.385*** (3.00)
Control variables	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
N	4565	4565	4075	4075
R^2	0.041	0.031	0.161	0.166

Notes: Column (1) regresses the first mediator—*Perceived Security* of online payments—on *Tourism*; column (2) repeats the first-stage regression for the second mediator—*Perceived Convenience*. Columns (3) and (4) estimate the second stage, adding each mediator in turn to the baseline specification with online shopping as the dependent variable. All regressions include province fixed effects and the full set of controls (age, gender, hukou, education, marital status, car and home ownership). t-statistics clustered at the province level are reported in parentheses. ***, ** and * indicate significance at the 1 %, 5 % and 10 % levels, respectively.

Conclusion

This study examines the relationship between tourism, online shopping, and third-party payment adoption, highlighting third-party payment as a mediator. Using the CHFS dataset, I provide empirical evidence demonstrating that tourism significantly fosters online consumption, with third-party payments facilitating this connection. I employ reduced sample, PSM, robustness, and IV methods to address endogeneity bias between tourism and online shopping. Traditional and causal mediating approaches confirm the mediating influence of the third-party payment on this relationship.

Integrating the TAM, I explore the important psychological factors of perceived security and perceived convenience that may affect third-party payment adoption. The findings indicate that perceived security is a more prominent mediator than perceived convenience, underscoring the importance of trust in third-party payment adoption. This insight enriches the understanding of how tourism influences e-commerce and consumer practices with significant theoretical contributions to digital payment and consumption literature.

This study addresses gaps in existing research by focusing on third-party payments as a mediator, an underexplored area in previous studies. The representative dataset, capturing various socio-economic groups, enables a nuanced analysis of how tourism and digital payments interact across different demographics. The robustness of the results is supported by rigorous econometric methods, ensuring their reliability and relevance to the Chinese context, with implications for other developing economies experiencing similar shifts in digital consumption.

From a policy perspective, ensuring secure, industry-certified payment systems at tourist sites will build traveler trust and drive digital transactions. Coupling this with partnerships that deploy multilingual, geo-fenced e-wallets and QR-code payments and offering merchants incentives such as tax credits or cash-back rewards will accelerate third-party platform adoption. By embedding secure-transaction volumes into tourism performance metrics and implementing harmonized payment standards with linked online-shopping platforms, policymakers can amplify tourism's spillover into e-commerce. These measures are equally relevant for other developing countries aiming to leverage their tourism sectors to spur digital-commerce growth.

This study offers valuable insights into how digital payment systems shape consumer behavior, contributing to academic research on digital payments and providing actionable guidance for policymakers and businesses. Future research could expand on this work by exploring other payment systems or examining additional regions to further advance our understanding of how technology drives consumption practices in diverse contexts.

Declaration of conflicting interests

The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The authors disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: Guizhou Province University Humanities and Social Science Research Base Project (No. GDZX2024020), Guizhou University Humanities and Social Science Project (No. GDZX2024002), and Young Academic Pioneer of Guizhou.

ORCID iD

Wenhui Yang https://orcid.org/0009-0005-7889-9778

Supplemental Material

Supplemental material for this article is available online

Notes

1. I define PU as perceived security, and PEOU as perceived convenience in the context of using third-party payment systems. Further details are provided in Section 4.2.4.
2. The publicly available 2019 CHFS data can be downloaded from the official website: https://chfser.swufe.edu.cn/datas/.
3. "How much did your family spend on online shopping last year?".
4. "Last year, how much did your family spend in total on travel-related expenses, including food, transportation, tickets, tour guides, accommodation, etc., both domestically and internationally?".
5. "Currently, does your family have any third-party payment accounts such as Alipay, WeChat Pay, JD Wallet, Baidu Wallet, etc.?".
6. "What is the main reason for your family to buy internet-based financial products such as Alipay and WeChat Pay services? Convenience for transfers/payments/online shopping; Low risk and safety".

References

Angrist JD and Pischke JS (2009) *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton: Princeton University Press.

Aron-Dine A, Einav L and Finkelstein A (2013) The RAND health insurance experiment, three decades later. *Journal of Economic Perspectives* 27(1): 197–222.

Bellemare MF and Wichman CJ (2020) Elasticities and the inverse hyperbolic sine transformation. *Oxford Bulletin of Economics and Statistics* 82(1): 50–61.

China Academy of Information and Communication Technologies. (2020). Digital economy development in China 2020.

Conley TG, Hansen CB and Rossi PE (2012) Plausibly exogenous. *The Review of Economics and Statistics* 94(1): 260–272.

Davis FD, Bagozzi RP and Warshaw PR (1989) Technology acceptance model. *J Manag Sci* 35(8): 982–1003.

Dehejia RH and Wahba S (2002) Propensity score-matching methods for nonexperimental causal studies. *The Review of Economics and Statistics* 84(1): 151–161.

Donaldson D and Hornbeck R (2016) Railroads and American economic growth: A "market access" approach. *The Quarterly Journal of Economics* 131(2): 799–858.

El-Said O and Aziz H (2022) Virtual tours a means to an end: an analysis of virtual tours' role in tourism recovery post COVID-19. *Journal of Travel Research* 61(3): 528–548.

Faber Benjamin and Cecile Gaubert (2019) "Tourism and Economic Development: Evidence from Mexico's Coastline." *American Economic Review* 1096: 2245–2293.

Fu T and Jian Z (2021) Corruption pays off: how environmental regulations promote corporate innovation in a developping country. *Ecological Economics* 183: 106969.

Hew JJ, Leong LY, Tan GWH, et al. (2018) Mobile social tourism shopping: a dual-stage analysis of a multi-mediation model. *Tourism Management* 66: 121–139.

Hicks R and Tingley D (2011) Causal mediation analysis. *The Stata Journal* 11(4): 605–619.

Horner S and Swarbrooke J (2020) *Consumer Behaviour in Tourism*. 4th edition. Milton Park: Routledge.

Imai K, Keele L and Tingley D (2010) A general approach to causal mediation analysis. *Psychological methods* 15(4): 309.

Kim JH (2022) Destination attributes affecting negative memory: scale development and validation. *Journal of Travel Research* 61(2): 331–345.

Kim J, Kim M, Choi J, et al. (2019) Offline social interactions and online shopping demand: does the degree of social interactions matter? *Journal of Business Research* 99: 373–381.

Lemon KN and Verhoef PC (2016) Understanding customer experience throughout the customer journey. *Journal of marketing* 80(6): 69–96.

Li J, Wu Y and Xiao JJ (2020) The impact of digital finance on household consumption: evidence from China. *Economic Modelling* 86: 317–326.

Li S, Zhu B and Yu Z (2024) The impact of cue-interaction stimulation on impulse buying intention on virtual reality tourism E-commerce platforms. *Journal of Travel Research* 63(5): 1256–1279.

Liu H and Park KS (2024) Exploring the impact of metaverse tourism experiences on actual visit intentions: an integrated model of presence, the Technology Acceptance Model, and the Theory of Planned Behavior. *International Journal of Tourism Research* 26(1): e2616.

Ma S, He Y and Gu R (2021) Joint service, pricing and advertising strategies with tourists' green tourism experience in a tourism supply chain. *Journal of Retailing and Consumer Services* 61: 102563.

Nunn N and Wantchekon L (2011) The slave trade and the origins of mistrust in Africa. *The American Economic Review* 101(7): 3221–3252.

Phaosathianphan N and Leelasantitham A (2021) An intelligent travel technology assessment model for destination impacts of tourist adoption. *Tourism Management Perspectives* 40: 100882.

Quan W, Moon H, Kim SS, et al. (2023) Mobile, traditional, and cryptocurrency payments influence consumer trust, attitude, and destination choice: Chinese versus Koreans. *International Journal of Hospitality Management* 108: 103363.

Ramirez A and Wang Z (2008) When online meets offline: an expectancy violations theory perspective on modality switching. *Journal of Communication* 58(1): 20–39.

Richards G, King B and Yeung E (2020) Experiencing culture in attractions, events and tour settings. *Tourism Management* 79: 104104.

Rong-Da Liang A (2017) Considering the role of agritourism co-creation from a service-dominant logic perspective. *Tourism Management* 61: 354–367.

Servidio R and Ruffolo I (2016) Exploring the relationship between emotions and memorable tourism experiences through narratives. *Tourism Management Perspectives* 20: 151–160.

Shin HH, Jeong M, So KKF, et al. (2022) Consumers' experience with hospitality and tourism technologies: Measurement development and validation. *International Journal of Hospitality Management* 106: 103297.

Sousa N, Alén E, Losada N, et al. (2024) Influencing wine tourists' decision-making with VR: the impact of immersive experiences on their behavioural intentions. *Tourism Management Perspectives* 51: 101235.

Sugathan P and Ranjan KR (2019) Co-creating the tourism experience. *Journal of Business Research* 100: 207–217.

Suri T and Jack W (2016) The long-run poverty and gender impacts of mobile money. *Science* 354(6317): 1288–1292.

Tom Dieck MC and Jung T (2018) A theoretical model of mobile augmented reality acceptance in urban heritage tourism. *Current Issues in Tourism* 21(2): 154–174.

Vada S, Prentice C and Hsiao A (2019) The influence of tourism experience and well-being on place attachment. *Journal of Retailing and Consumer Services* 47: 322–330.

Venkatesh V, Thong JY and Xu X (2012) *Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology*. MIS quarterly, 157–178.

Wang J, Sun Y, Zhang L, et al. (2024) Effect of display methods on intentions to use virtual reality in museum tourism. *Journal of Travel Research* 63(2): 314–334.

Yang Y, Liu H, Li XR, et al. (2018) A shrinking world for tourists? Examining the changing role of distance factors in understanding destination choices. *Journal of Business Research* 92: 350–359.

Yang J, Wu Y and Huang B (2023) Digital finance and financial literacy: evidence from Chinese households. *Journal of Banking & Finance* 156: 107005.

Ye BH, Barreda AA, Okumus F, et al. (2019) Website interactivity and brand development of online travel agencies in China: the moderating role of age. *Journal of Business Research* 99: 382–389.

Zhang ML and Chen MS (2019) *China's Digital Economy: Opportunities and Risks*. International Monetary Fund.

Zhang Y, Wang M, Li J, et al. (2022a) Do greener urban streets provide better emotional experiences? An experimental study on Chinese tourists. *International Journal of Environmental Research and Public Health* 19(24): 16918.

Zhang J, Zhang H and Gong X (2022b) Mobile payment and rural household consumption: evidence from China. *Telecommunications Policy* 46(3): 102276.

Zhou Y and Wang XC (2014) Explore the relationship between online shopping and shopping trips: an analysis with the 2009 NHTS data. *Transportation Research Part A: Policy and Practice* 70: 1–9.

Zhu Z, Ma W, Leng C, et al. (2021) The relationship between happiness and consumption expenditure: evidence from rural China. *Applied Research in Quality of Life* 16: 1587–1611.

Zhu CZG, Hall CM, Fong LHN, et al. (2024) Examining the effects of ChatGPT on tourism and hospitality student responses through integrating technology acceptance model. *International Journal of Tourism Research* 26(4): e2727.

Author biography

Wenhui Yang is a postgraduate student at the School of Economics, Guizhou University. His research focuses on industrial organization and development economics across sectors.