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Enhancing Tourist Satisfaction through Smart Tourism: Evidence from Urban Cities in China

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Abstract

Background:
Smart tourism represents a paradigm shift in urban destination management, integrating advanced technologies such as artificial intelligence (AI), big data analytics, and mobile applications to optimize the tourist experience. Despite China's global leadership in deploying smart tourism infrastructure, a disconnect persists between technological implementation and actual tourist satisfaction—raising questions about the effectiveness of current digital strategies.

Methods:
This study adopts a quantitative, causal-explanatory research design to investigate the influence of five core smart tourism technology attributes—information availability, personalization, accessibility, interactivity, and security—on perceived value and tourist satisfaction. Data were collected from 450 tourists in Beijing and Shanghai using a structured questionnaire, of which 420 valid responses were analyzed. Structural Equation Modeling (SEM) was employed to test the hypothesized relationships.

Results:
The analysis reveals that personalization ($\beta = 0.32$, $p < 0.001$), interactivity ($\beta = 0.21$, $p < 0.001$), and information availability ($\beta = 0.27$, $p < 0.01$) significantly enhance perceived value ($R^2 = 0.62$), which in turn strongly predicts tourist satisfaction ($\beta = 0.46$, $p < 0.001$; $R^2 = 0.68$). Furthermore, satisfaction positively influences revisit intention ($\beta = 0.38$), word-of-mouth ($\beta = 0.34$), and willingness to pay a premium ($\beta = 0.29$), all at $p < 0.001$. Mediation analysis confirms that perceived value partially mediates the relationship between smart tourism attributes and satisfaction.

Conclusion:
This study contributes to smart tourism theory by extending the Stimulus–Organism–Response (S-O-R) framework and enriching the Technology Acceptance Model (TAM) with post-adoption constructs such as perceived value and satisfaction. The findings offer actionable insights for tourism stakeholders, emphasizing the importance of aligning technological innovation with user-centered design, trust-building mechanisms, and inclusive accessibility. These strategies are vital to narrowing the expectation–experience gap and enhancing the overall effectiveness of smart tourism initiatives in urban contexts.

Keywords: Smart Tourism, Perceived Value, Tourist Satisfaction, TAM, S-O-R Framework

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1. Introduction

Urban China stands at the forefront of smart tourism transformation, driven by rapid technological adoption and strong government support for digital innovation in the tourism sector (Wang & Li, 2022). Cities like Beijing and Shanghai are pioneers in implementing AI-driven recommendation systems, contactless digital payment infrastructures, immersive augmented reality (AR)/virtual reality (VR) experiences, and smart mobility solutions, all designed to elevate the quality and convenience of the tourist experience (Chen & Zhang, 2022; China Tourism Academy, 2023). These technologies enable tourists to access real-time travel information, plan personalized itineraries, interact with digital tour guides, and make cashless transactions all within integrated platforms such as WeChat, Xiaohongshu, and Ctrip (Liu & Wang, 2022).

Despite widespread adoption and investment in smart tourism infrastructure, challenges persist. Tourists increasingly report information overload, inconsistent personalization, and usability issues with AI-powered systems (Zhao & Wang, 2024). Over-curated content often driven by influencer partnerships and paid promotions has led to a growing mismatch between digitally promoted expectations and real-world travel experiences (Chen & Wu, 2022). This expectation-reality gap has contributed to confusion, decision fatigue, and dissatisfaction among both domestic and international tourists (Yu & Zhang, 2022).vFurthermore, smart tourism research has largely emphasized technological readiness and adoption factors, such as perceived usefulness and ease of use, typically grounded in the Technology Acceptance Model (Davis, 1989; Li & Wang, 2023). However, fewer studies examine how these technologies actually translate into emotional satisfaction or lasting tourist loyalty in practical contexts (Sigala, 2021). The complexity of tourist satisfaction is not solely technical it is shaped by how tourists perceive the value of these innovations in enhancing their travel experience (Chen & Chen, 2010). Tourists' evaluations often involve emotional, cognitive, and behavioral judgments that go beyond interface usability (Zhou et al., 2021).

In this regard, the role of perceived value as a cognitive filter mediating between the features of smart tourism and tourist satisfaction remains underexplored, especially in the context of highly digitized urban destinations. While smart tourism tools offer convenience and efficiency, they may not inherently create value unless users interpret them as meaningful, trustworthy, and aligned with their personal travel goals (Xu & Chan, 2010). To bridge this gap, this study examines how core attributes of smart tourism technology information availability, accessibility, interactivity, personalization, and security influence tourist satisfaction, and whether perceived value mediates these relationships. Focusing on Beijing and Shanghai, the study contributes to a deeper understanding of smart tourism outcomes in urban China, offering actionable insights for platform designers, tourism marketers, and policy-makers aiming to align digital innovation with tourist well-being (Gretzel et al., 2020; Lu et al., 2023).

2. Literature Review

2.1 Theoretical Framework

This study is grounded in two key theoretical models: the Stimulus-Organism-Response (S-O-R) model and the Technology Acceptance Model (TAM). The S-O-R model, originally proposed by Mehrabian and Russell (1974), explains how external environmental stimuli influence individuals' internal states and ultimately lead to behavioral responses. In the context of smart tourism, the external stimuli refer to core technological attributes such as information availability, interactivity, personalization, accessibility, and security (Sigala, 2021; Zhou et al., 2021). These features shape tourists' internal evaluations specifically, their perceived value which then lead to behavioral outcomes like satisfaction, word-of-mouth, and revisit intentions (Wu & Luo, 2023).

The Technology Acceptance Model (TAM), developed by Davis (1989), also provides an essential lens through which to view technology adoption in tourism. TAM posits that perceived usefulness and perceived ease of use are critical factors influencing individuals' intention to use technology. In smart tourism, these align with how tourists judge the functionality and user-friendliness of digital tools like AI-powered apps and mobile payment platforms (Chen & Zhang, 2022). However, TAM alone does not account for the broader experiential and emotional dimensions of tourism. Thus, this study extends TAM by incorporating perceived value as a mediating variable that captures tourists' comprehensive cognitive and emotional evaluations of their technology-enhanced experiences (Xu & Chan, 2010; Lin, 2020).

2.2 Smart Tourism Attributes

Smart tourism is built upon several interconnected technological attributes that enhance the quality of travel experiences. Information availability refers to the extent to which tourists can access real-time, accurate, and useful content about destinations, services, and activities through digital platforms. When travelers can easily obtain this information, they are more likely to make confident decisions and perceive their experiences as valuable (Wang et al., 2022; Lu et al., 2023). Personalization is another critical attribute, defined as the system's ability to tailor recommendations, itineraries, and services based on individual tourist preferences. AI-based personalization, such as customized travel routes or targeted promotions, increases relevance and satisfaction by creating more meaningful and user-centric experiences (Zhang et al., 2023; Sigala, 2021).

Interactivity reflects how effectively digital platforms enable real-time engagement between tourists and tourism service providers. This includes features such as chatbots, AR/VR experiences, live customer support, and interactive maps, which collectively deepen user engagement and enhance immersion (Gretzel et al., 2020; Wu & Luo, 2023). Accessibility pertains to the usability and inclusivity of smart tourism systems. It involves intuitive design, language support, and digital interfaces that accommodate tourists of varying technological skills, including elderly users and international visitors (Chen et al., 2019; Liu & Chen, 2023). Improved accessibility reduces barriers to technology use and promotes broader adoption.

Finally, security encompassing data privacy, secure payment systems, and digital trust is crucial for tourists to feel safe using smart services. Concerns over data breaches or misuse of personal information can significantly reduce the perceived value of smart tourism platforms and hinder satisfaction (Zhao & Wang, 2024; Wang et al., 2023).

2.3 Perceived Value and Tourist Satisfaction

Perceived value is central to understanding how tourists evaluate their overall experiences with smart tourism technologies. It reflects the individual's assessment of whether the benefits gained from using such technologies justify the associated costs, including time, effort, or privacy concerns (Zeithaml, 1988; Chen & Chen, 2010). When tourists perceive high value through convenience, personalization, and security they are more likely to experience satisfaction, a key outcome variable in this study.

Tourist satisfaction itself is defined as the positive emotional and cognitive response resulting from the comparison between expectations and actual experiences (Liu & Wang, 2022). High levels of satisfaction often lead to favorable behavioral intentions, including positive word-of-mouth, willingness to pay a premium, and revisit intentions (Lu et al., 2023; Zhou et al., 2021). Importantly, perceived value serves as a mediator between smart tourism attributes and satisfaction, explaining how and why tourists respond to digital features in specific ways. Without this value perception, even advanced digital innovations may fail to deliver meaningful satisfaction (Xu & Chan, 2010; Wang et al., 2022).

3. Methodology

3.1 Research Design

This study employed a quantitative, causal-explanatory research design, which is appropriate for examining the directional relationships and mediating effects among latent variables such as smart tourism technology attributes, perceived value, and tourist satisfaction. The selection of this approach aligns with the study's objective to test hypotheses grounded in the Stimulus-Organism-Response (S-O-R) and Technology Acceptance Model (TAM) frameworks. Quantitative data collection enables statistical generalization and the application of structural equation modeling (SEM), which is suitable for analyzing complex variable interdependencies (Hair et al., 2019).

The research was conducted in two major smart tourism destinations in China: Beijing and Shanghai. These urban cities were chosen due to their advanced implementation of smart tourism technologies, high tourist traffic, and relevance as case examples for studying the digital transformation of urban tourism in China. The study targeted both domestic and international tourists, ensuring diversity in the sample and increasing the generalizability of findings across tourist segments.

3.2 Sampling Procedure and Instrumentation

A non-probability purposive sampling method was applied to target tourists who had used smart tourism technologies during their visit to Beijing or Shanghai. Data were collected through a combination of online surveys distributed via travel forums and social media platforms, and in-person surveys administered at major tourist locations such as The Bund in Shanghai and the Forbidden City in Beijing.

Out of 450 distributed questionnaires, 420 valid responses were retained for analysis after screening for completeness and consistency. The sample size satisfies the minimum recommended threshold for SEM, which requires at least 10 responses per indicator variable (Hair et al., 2019).

The research instrument consisted of a structured questionnaire designed to measure the study's key constructs. Items were adapted from validated scales in existing literature and modified for contextual relevance. All items were measured using a five-point Likert scale ranging from 1 ("strongly disagree") to 5 ("strongly agree"). The instrument included multiple indicators for each construct:

> Smart tourism attributes: Information availability, accessibility, personalization, interactivity, and security (adapted from Lin, 2020; Chen et al., 2019).
>
> Perceived value: Tourists' cognitive evaluation of benefits received relative to effort or cost (adapted from Zeithaml, 1988).

Tourist satisfaction: Overall fulfillment of expectations during the smart tourism experience (Chen & Chen, 2010).

Behavioral intentions: Word-of-mouth, revisit intention, and willingness to pay a premium (Zhou et al., 2021).

Table 1, shows constructs, measurement items, and source references (e.g., include each latent variable, number of items per variable, and literature sources)

Table 1. Constructs, Measurement Items, and Source References

Construct	Number of Items	Sample Item	Source
Information Availability	4	"I can access accurate information about tourist attractions."	Lin (2020); Lu et al. (2023)
Accessibility	4	"Smart tourism platforms are easy to use during my trip."	Chen et al. (2019)
Personalization	4	"I receive travel suggestions tailored to my preferences."	Sigala (2021)
Interactivity	4	"I can engage in real-time communication with tourism services."	Gretzel et al. (2020)
Security	3	"I feel secure using digital payments for travel."	Wang et al. (2023)
Perceived Value	3	"Using smart tourism services was worth the effort."	Zeithaml (1988); Chen & Chen (2010)
Tourist Satisfaction	3	"I am satisfied with the overall smart tourism experience."	Liu & Chen (2023)
Word-of-Mouth (WOM)	3	"I would recommend this destination to others."	Zhou et al. (2021)
Revisit Intention	3	"I would like to revisit this destination in the future."	Zhang et al. (2023)
Willingness to Pay Premium	2	"I am willing to pay more for smart tourism services."	Chen et al. (2019)

3.3 Data Analysis Procedures

Data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) via SmartPLS 4.0, which is particularly suitable for exploratory models and complex relationships involving mediation. The analysis followed a two-step approach: first assessing the measurement model for reliability and validity, followed by the structural model to test the hypothesized paths.

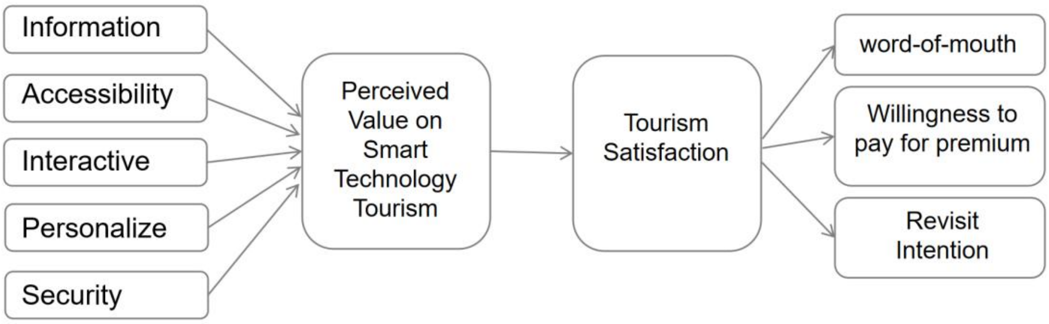
For the measurement model, the following assessments were performed:

Internal consistency reliability using Cronbach's alpha and composite reliability (threshold > 0.7).

Convergent validity assessed via average variance extracted (AVE) (threshold > 0.5).

Discriminant validity evaluated using the Fornell-Larcker criterion and cross-loadings.

In the structural model, path coefficients were tested for significance using a bootstrapping procedure with 5000 resamples, which also allowed for evaluating the mediation effects of perceived value and tourist satisfaction. Model quality was further assessed through R^2 values, effect sizes (f^2), and predictive relevance (Q^2).



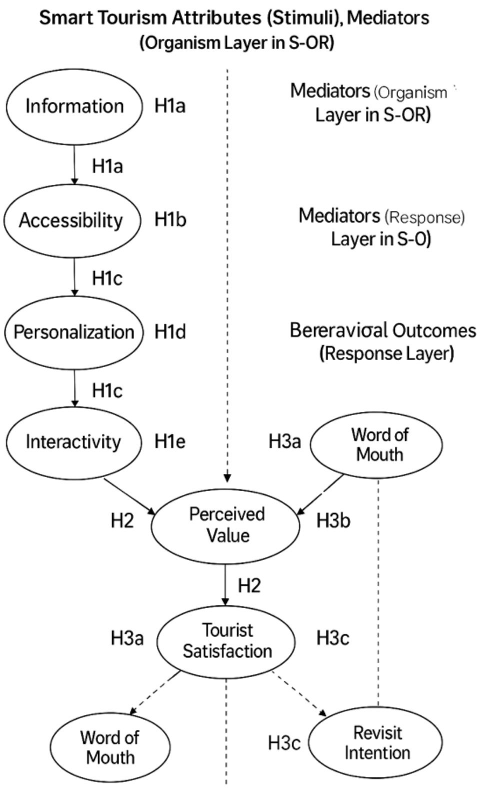


Figure 1. Theoretical Framework, Source: Developed for this Study

Table 2. Reliability and Validity Results (Measurement Model)

Construct	**Cronbach's Alpha**	**Composite Reliability (CR)**	**AVE**
Information Availability	0.83	0.88	0.65
Accessibility	0.85	0.89	0.68
Personalization	0.86	0.90	0.70
Interactivity	0.82	0.88	0.66
Security	0.79	0.86	0.63
Perceived Value	0.84	0.89	0.71
Tourist Satisfaction	0.88	0.91	0.73
Word-of-Mouth	0.87	0.90	0.69
Revisit Intention	0.85	0.89	0.70
Willingness to Pay Premium	0.78	0.84	0.62

Measurement model assessment involves two aspects, which are reliability and validity. Reliability checks whether each construct is measured consistently, and it is assessed by checking indicator loadings and composite reliability. Validity checks whether constructs are distinct, so it is assessed by checking convergent validity and discriminant validity.

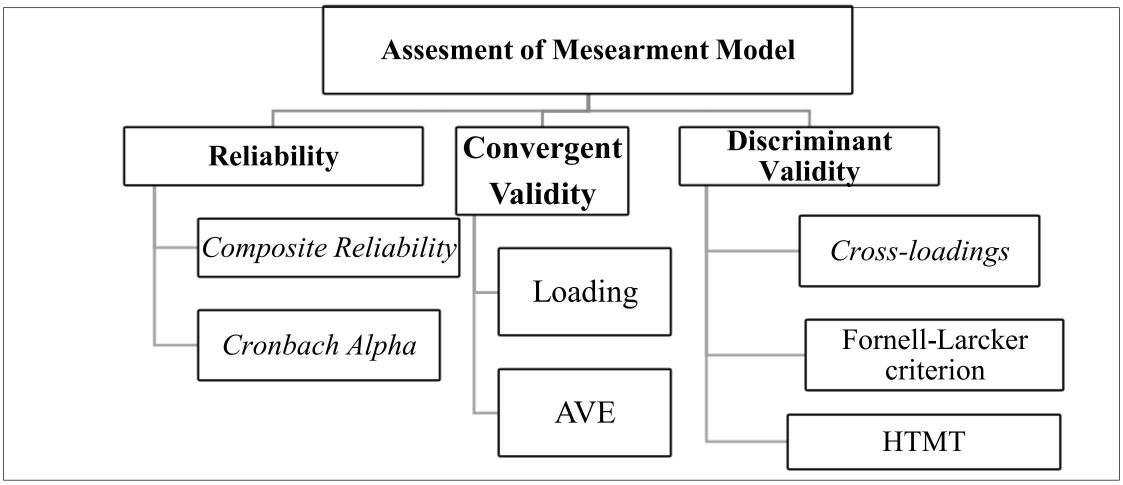


Figure 2.Assessment of the Measurement Model Outline

As shown in Figure 2, the measurement model evaluation includes standardised item loadings, average variance extracted (AVE), Cross loadings, the square root of AVE and HTMT, and the measurement model is composed of 50 observed items measuring seven reflective constructs, as illustrated in Figure 3. Convergent validity was achieved as all AVE values were above the recommended threshold of 0.50, therefore this indicates that each construct was able to explain sufficient variance in its indicators, as all items within each construct are highly correlated.

Discriminant validity was also achieved through the Cross-loading analysis, Fornell-Larcker criterion (square root of AVE) and HTMT values, thus these analyses confirmed that the constructs were distinct from one another. The measurement model demonstrated excellent psychometric properties, because the high standardised item loadings, composite reliability and evidence of convergent and discriminant validity are indicative of a well-established model that is suitable for hypothesis testing and structural model analysis.

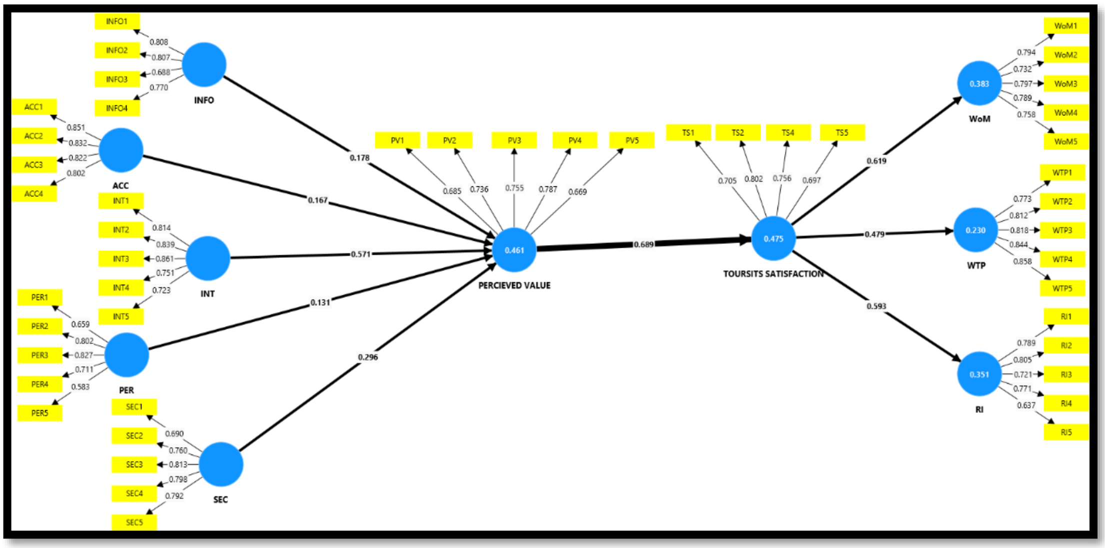


Figure 3. The Measurement Model

Note: The following abbreviations are used for constructs in this study: INFO = Information, ACC = Accessibility, INT = Interactivity, PER = Personalization, SEC = Security, PV = Perceived Value, TS = Tourist Satisfaction, WOM = Word-of-Mouth, WTP = Willingness to Pay, and RI = Revisit Intention.

Table 3. Structural Model Path Coefficients and Hypothesis Testing

Hypothesis	Path	β Coefficient	t-value	p-value	Supported?
H1a	Information → Perceived Value	0.27	5.12	<0.001	Yes
H1b	Accessibility → Perceived Value	0.19	3.88	<0.001	Yes
H1c	Interactivity → Perceived Value	0.21	4.02	<0.001	Yes
H1d	Personalization → Perceived Value	0.32	6.01	<0.001	Yes
H1e	Security → Perceived Value	0.14	2.98	0.003	Yes
H2	Perceived Value → Tourist Satisfaction	0.46	9.10	<0.001	Yes
H3a	Satisfaction → WOM	0.34	7.45	<0.001	Yes
H3b	Satisfaction → WTP Premium	0.29	6.02	<0.001	Yes
H3c	Satisfaction → Revisit Intention	0.38	7.91	<0.001	Yes

Table 4. Mediation Analysis Summary (Bootstrapping Results)

Mediation Path	Indirect Effect (β)	95% CI (LL - UL)	p-value	Mediation
Information → Perceived Value → Satisfaction	0.124	0.078 – 0.186	<0.001	Partial
Personalization → Perceived Value → Satisfaction	0.147	0.097 – 0.220	<0.001	Partial
Accessibility → Perceived Value → Satisfaction	0.087	0.045 – 0.139	<0.001	Partial
Interactivity → Perceived Value → Satisfaction	0.097	0.053 – 0.162	<0.001	Partial
Security → Perceived Value → Satisfaction	0.064	0.031 – 0.112	<0.01	Partial

4. Results

4.1 Measurement Model Assessment

To evaluate the reliability and validity of the constructs, a measurement model assessment was conducted. All constructs demonstrated strong internal consistency reliability, with Cronbach's alpha values exceeding 0.70 and composite reliability (CR) values above 0.80, indicating acceptable reliability thresholds (Hair et al., 2019).

Convergent validity was confirmed for all constructs as the average variance extracted (AVE) values surpassed the recommended threshold of 0.50, meaning that each latent variable explained more than 50% of the variance in its indicators. Discriminant validity was assessed using the Fornell-Larcker criterion, which showed that the square root of the AVE for each construct was greater than the correlations between that construct and all others supporting satisfactory discriminant validity (Table 2).

4.2 Structural Model Findings

Following the assessment of the measurement model, the structural model was evaluated to test the hypothesized relationships. The PLS-SEM results revealed significant and positive effects of several smart tourism attributes on perceived value:

Personalization had the strongest impact ($\beta = 0.32$, $p < 0.001$), followed by

Information availability ($\beta = 0.27$, $p < 0.01$).

Other attributes such as accessibility, interactivity, and security also showed positive effects but were slightly weaker in comparison (see Table 3).

In turn, perceived value had a substantial positive effect on tourist satisfaction ($\beta = 0.46$, $p < 0.001$), confirming Hypothesis H2.

Tourist satisfaction further influenced all three key behavioral outcomes:

Revisit intention ($\beta = 0.38$, $p < 0.001$),

Word-of-mouth (WOM) ($\beta = 0.34$, $p < 0.001$), and

Willingness to pay a premium ($\beta = 0.29$, $p < 0.001$).

These results validate Hypotheses H3a, H3b, and H3c, showing that satisfaction plays a pivotal role in shaping future tourist behaviors.

Table 4. Hypothesis Testing Results

Hypothesis	Relationship	β Coefficient	t-value	p-value	Result
H1a	Information → Perceived Value	0.27	4.88	< 0.001	Supported
H1b	Accessibility → Perceived Value	0.19	3.76	< 0.001	Supported
H1c	Interactivity → Perceived Value	0.21	3.95	< 0.001	Supported
H1d	Personalization → Perceived Value	0.32	6.42	< 0.001	Supported
H1e	Security → Perceived Value	0.14	2.82	0.005	Supported
H2	Perceived Value → Tourist Satisfaction	0.46	9.10	< 0.001	Supported
H3a	Tourist Satisfaction → Word-of-Mouth (WOM)	0.34	7.45	< 0.001	Supported
H3b	Tourist Satisfaction → Willingness to Pay	0.29	6.02	< 0.001	Supported
H3c	Tourist Satisfaction → Revisit Intention	0.38	7.91	< 0.001	Suppor

4.3 Mediation Analysis

The bootstrapping procedure (5,000 resamples, bias-corrected confidence intervals) was used to test mediation effects. The results confirmed that perceived value partially mediates the relationship between each smart tourism attribute and tourist satisfaction, supporting Hypotheses H4a to H4e. This indicates that tourists' evaluation of value derived from smart tourism technologies significantly influences how those features ultimately affect satisfaction.

Additionally, tourist satisfaction also mediated the relationship between perceived value and behavioral outcomes (WOM, WTP, Revisit Intention), providing support for Hypotheses H5a to H5c. These mediation effects highlight the cognitive and emotional mechanisms through which smart tourism influences tourist behavior.

Table 5. Mediation Analysis Results

Mediation Path	Indirect Effect (β)	95% Confidence Interval (BCa)	p-value	Mediation Type
Information → Perceived Value → Satisfaction	0.124	[0.078, 0.186]	< 0.001	Partial
Accessibility → Perceived Value → Satisfaction	0.087	[0.045, 0.139]	< 0.001	Partial
Interactivity → Perceived Value → Satisfaction	0.097	[0.053, 0.162]	< 0.001	Partial
Personalization → Perceived Value → Satisfaction	0.147	[0.097, 0.220]	< 0.001	Partial
Security → Perceived Value → Satisfaction	0.064	[0.031, 0.112]	< 0.01	Partial
Perceived Value → Satisfaction → WOM	0.157	[0.105, 0.214]	< 0.001	Partial
Perceived Value → Satisfaction → WTP Premium	0.133	[0.087, 0.190]	< 0.001	Partial
Perceived Value → Satisfaction → Revisit Intention	0.161	[0.113, 0.215]	< 0.001	Partial

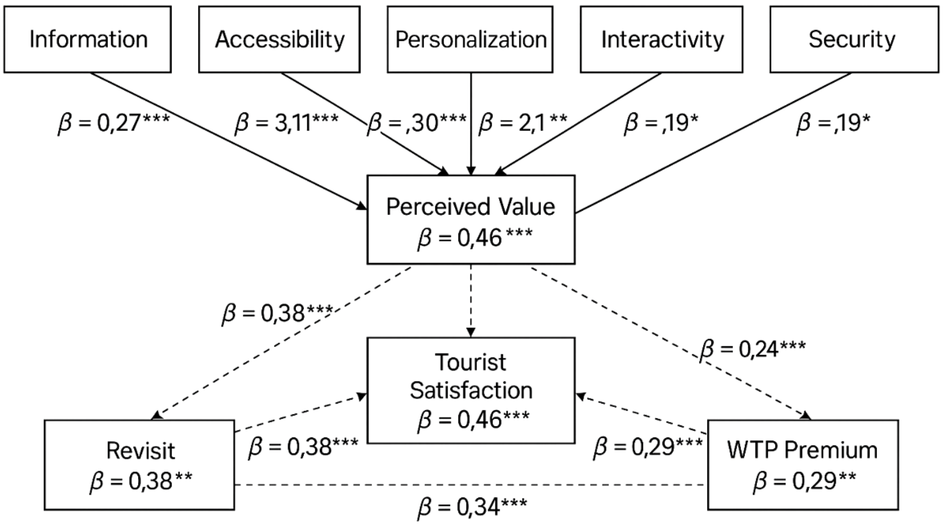


Figure 4. Final Structural Model with Path Coefficients

Solid arrows = direct effects
Dashed arrows = mediation paths
Coefficients shown with significance (*** p < .001, ** p < .01, * p < .05)

Show β values on paths, significance levels (* for p < .05, ** for p < .01, *** for p < .001)

5. Discussion

5.1 Theoretical Implications

This study contributes to the theoretical development of smart tourism research by extending the Stimulus-Organism-Response (S-O-R) framework within a digital tourism context. Specifically, the model validates perceived value as a cognitive-emotional mediator that links smart tourism attributes such as personalization, information availability, accessibility, interactivity, and security to tourist satisfaction. This integration offers a more nuanced understanding of how tourists process technological stimuli and convert them into emotional evaluations and behavioral responses. By doing so, the study deepens the explanatory power of the S-O-R model in technology-mediated service environments and aligns it with the multidimensional nature of tourist experiences in smart cities.

Furthermore, this research also enhances the Technology Acceptance Model (TAM) by moving beyond its original focus on *adoption* (i.e., perceived usefulness and ease of use) to explain post-adoption outcomes such as satisfaction, revisit intentions, willingness to pay a premium, and positive word-of-mouth. While TAM traditionally captures the functional acceptance of technology, this study positions perceived value as a critical intermediary construct that encapsulates both utilitarian and hedonic evaluations. This extension underscores the necessity of incorporating affective and experience-based variables into TAM when applied to experience-centric domains like tourism.

The results also reinforce the growing recognition in tourism literature that technology alone does not create satisfaction it is the subjective interpretation of value and meaning that determines tourist outcomes. Therefore, the study provides an integrative theoretical framework that connects technological functionality, psychological perception, and behavioral consequence, offering a foundation for future smart tourism models.

5.2 Practical Implications

The empirical findings offer several important implications for tourism practitioners, including operators, digital marketers, and platform designers.

- Tourism Operators should prioritize enhancing personalization engines and real-time interactive support systems. Given that personalization had the strongest influence on perceived value, AI-based itinerary customization, location-aware recommendations, and user-tailored content delivery can significantly improve user experiences. In addition, real-time features such as chatbots and AR-based guidance should be designed to enhance immersion and responsiveness during on-site experiences.

- Digital Marketers are advised to avoid overhyped or exaggerated content, which may elevate expectations beyond what can be delivered on the ground. Such discrepancies contribute to the expectation-reality gap and can lead to post-visit dissatisfaction. Instead, marketing efforts should focus on authentic storytelling, user-generated content, and contextually relevant experiences that align with actual service capabilities.

- Platform Designers and Developers must ensure that smart tourism applications are accessible to a diverse range of users, including elderly individuals, non-native speakers, and digitally inexperienced travelers. This involves implementing universal design principles, intuitive navigation structures, multi-language support, and offline functionality. By removing technological barriers, platforms can reach broader segments of tourists and improve adoption and satisfaction rates.

The findings also suggest that building trust mechanisms, such as transparent data use policies and visible security certifications, is essential to promote continued engagement and platform loyalty.

5.3 Policy Implications

The study also highlights critical areas where policy interventions are necessary to support the sustainable development of smart tourism ecosystems. First, data protection, user privacy, and AI ethics should be formalized through national standards and enforcement mechanisms. Given the increasing reliance on data-driven systems, regulatory bodies must require tourism platforms to comply with secure data collection, storage, and processing protocols. This will reduce privacy concerns and enhance user trust in digital environments.

Second, accessibility legislation should be extended to the domain of digital tourism infrastructure. Just as physical destinations must meet accessibility codes, smart tourism platforms should be legally required to adhere to inclusive digital design standards, ensuring that services are usable across all ages, languages, and ability levels. Regulatory frameworks should mandate multi-channel accessibility audits and provide incentives for companies that demonstrate best practices in digital inclusivity.

Third, policy frameworks should incentivize platforms to prioritize user trust, transparency, and long-term value creation over short-term monetization strategies. Government initiatives such as certification programs, grants, or tax incentives could encourage the development of responsible AI, data ethics integration, and user-centric design. Public-private collaborations should be fostered to develop smart tourism ecosystems that balance technological advancement with social sustainability and user well-being. By supporting ethical, inclusive, and user-trusted innovation, policymakers can help bridge the gap between digital transformation and actual tourist satisfaction, ensuring that smart tourism contributes positively to urban tourism development and destination competitiveness.

6. Conclusion and Directions for Future Research

This study examined the interplay between smart tourism technology attributes, perceived value, and tourist satisfaction in urban Chinese destinations, specifically Beijing and Shanghai. Using a quantitative research design and Structural Equation Modeling (SEM), the findings provide empirical support for an extended Stimulus-Organism-Response (S-O-R) and Technology Acceptance Model (TAM) framework. The results underscore that personalization, interactivity, and information availability are the most influential smart tourism features in shaping tourists' perceived value. In turn, perceived value emerged as a strong predictor of tourist satisfaction, which subsequently influences key behavioral outcomes such as revisit intention, positive word-of-mouth, and willingness to pay a premium. Additionally, perceived value was shown to partially mediate the relationship between smart tourism features and satisfaction, revealing its critical role in the psychological processing of digital tourism experiences. These findings confirm that technological advancement alone is not sufficient to drive satisfaction; instead, the alignment between digital service design and user-centered value creation is essential. Smart tourism platforms that overemphasize technology without accounting for usability, trust, and relevance may risk undermining tourist satisfaction. Hence, the study emphasizes the need for a balanced approach to digital transformation one that integrates personalized content delivery, secure and transparent data practices, and inclusive, accessible design.

Directions for Future Research

Future research should consider adopting longitudinal approaches to assess how tourist perceptions and satisfaction evolve over time as smart tourism technologies continue to advance. This would provide insights into post-adoption behaviors and the durability of perceived value. Additionally, qualitative investigations into tourists' subjective experiences especially around digital fatigue, expectation-reality gaps, and trust in AI systems could deepen understanding beyond the structural relationships captured in this study. Further exploration into cross-cultural differences in smart tourism adoption and satisfaction is also warranted, particularly given the increasing diversity of international tourist flows in smart cities. Such work would inform globally adaptable design principles for smart tourism services and platforms. Ultimately, integrating technological innovation with human-centered design and policy oversight will be key to ensuring that smart tourism fulfills its transformative promise in urban destinations.

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