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IoT Sensor-enabled Smart Guiding Systems for Heritage Village Tourism: Linking System Performance to Revisit Intention

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In this study, we investigate how the performance of sensor-enabled IoT smart guiding systems in heritage village tourism environments translates into tourists' revisit intention (RV) through psychological response mechanisms. Using Xixi Heritage Village in Dongguan as the empirical setting, a chained structural model linking smart service quality (SSQ), tourist experience (EXP), tourism image (IM), and RV is proposed and empirically validated. The smart guiding system integrates sensor-based location detection and mobile interpretation services, enabling visitors to access heritage information through an IoT-enabled sensing environment. Valid responses from a total of 700 questionnaire respondents were collected and divided into two subsamples: Sample A (n = 300) for item analysis and exploratory factor analysis, and Sample B (n = 400) for confirmatory factor analysis and structural equation modeling. The results show that the measurement model demonstrates satisfactory model fit, reliability, convergent validity, and discriminant validity. Structural equation modeling indicates that SSQ significantly enhances EXP, which further affects both IM and RV, while IM also significantly influences RV. In addition, IM partially mediates the relationship between EXP and RV, accounting for 60.6% of the total effect. The findings suggest that the effectiveness of IoT smart guiding systems depends not only on technological deployment but also on whether visitors perceive the sensor-supported system as accurate, accessible, interactive, and trustworthy. Such perceived system performance enhances visitor experience, strengthens IM, and ultimately increases RV, providing insights for the design and management of sensor-integrated heritage tourism systems.

1. Introduction

1.1 Smart tourism, sensors, and IoT-enabled services

With the rapid development of sensing technologies, mobile devices, wireless communication, and edge computing, the IoT has evolved from an early technology framework focused mainly

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on device connectivity and data collection into a sensor-driven, context-aware service ecosystem capable of responding to users' locations, environmental conditions, and real-time behavioral needs. In tourism environments, sensor networks and mobile platforms enable destinations to collect spatial and behavioral data that can support location-aware information services and interactive visitor experiences. In the tourism field, this technological transformation has accelerated the development of smart tourism systems. Gretzel *et al.* argued that the essence of smart tourism lies not in a single device or platform but in the integration of information and communication technology infrastructure, sensing technologies, and data connectivity that allows large-scale data streams to be transformed into service value that tourists can perceive and utilize.(1) Such integration is particularly important in cultural heritage environments such as heritage villages, historic settlements, and old streets. In these settings, points of interest are spatially dispersed, visitor routes are nonlinear, and tourists often rely on self-guided exploration. Traditional static signage and one-way interpretation therefore struggle to meet contemporary visitors' expectations for immediacy, interactivity, and personalized information access.

In IoT-enabled heritage tourism environments, sensing infrastructure such as quick response (QR) code/near-field communication (NFC) triggers, Bluetooth beacons, and mobile positioning services can connect visitors with cultural nodes and digital content in real time. However, the value of these systems does not depend solely on the existence of technological functions but rather on how visitors perceive the quality and reliability of the smart service system during actual use. From the perspective of service-quality evaluation, the Electronic Service Quality (E-S-QUAL) framework proposed by Parasuraman *et al.* emphasizes that electronic service quality should be evaluated on the basis of users' overall perceptions of the entire service process, including efficiency, system availability, fulfillment reliability, and privacy/security.(2) This perspective is particularly relevant for sensor-enabled smart-guiding systems, where engineering inputs such as location prompts, route navigation, point of interest (POI) information pushes, and interactive feedback mechanisms influence visitor experience only when they are perceived as useful, accessible, and trustworthy. Following this reasoning, in the present study, we treat SSQ as the front-end driving factor influencing visitors' subsequent experience evaluation and propose the first hypothesis.

H0: SSQ has a positive effect on tourist experience (EXP).

1.2 EXP and tourism image (IM)

In tourism research, EXP has been regarded as a more powerful construct than simple service contact for explaining perceived value and behavioral outcomes. Pine and Gilmore's experience economy perspective suggests that modern service competition is driven not only by the delivery of products or services but also by the creation of memorable and participatory experiences.(3) Otto and Ritchie further emphasized that tourism experiences possess measurable service attributes formed through contact, participation, and evaluation processes.(4) Similarly, Kim *et al.* demonstrated that memorable tourism experiences often involve multiple dimensions such as hedonism, knowledge acquisition, local cultural interaction, meaningfulness, involvement, and novelty.(5) The results of those studies indicate that EXP is a multidimensional construct that can be operationalized and empirically measured rather than a purely abstract emotional response. In the context of IoT-enabled tourism services, visitor experience may also be influenced by how effectively sensor-based guiding systems support navigation, information discovery, and interaction with cultural content. In the present study, EXP is therefore conceptualized through sensory, affective, cognitive, action-oriented, and relational dimensions, representing visitors' overall responses during the use of smart-guiding services in Xixi Heritage Village.

Xixi Heritage Village is located in Liaobu Town, Dongguan, Guangdong Province, and serves as a representative cultural heritage tourism site in the region. According to official information released by the Liaobu Town Government, the village covers an area of approximately 4.2 km^2, with a registered population of about 5,410 and a permanent resident population of approximately 35000. Administratively, the village consists of seven natural villages and eleven villagers' groups, reflecting a relatively complex spatial and social structure. These characteristics make it a suitable case for examining the interaction between heritage tourism environments and IoT-enabled smart-guiding systems. From a geographical perspective, Xixi Heritage Village is located near the center of Liaobu Town and is accessible via major local transportation routes, facilitating tourist access and on-site mobility. The village features a mixture of historic alleys, ancestral halls, traditional residential buildings, and waterfront landscapes, forming a typical open and spatially distributed heritage tourism environment. To provide a clearer contextual understanding of the study site, official web resources are included for verification and visualization. Detailed administrative and demographic information can be found at the following site.
https://www.dg.gov.cn/liaobu/gk/xzcj/content/post_1705402.html

Representative photos and descriptions of the heritage tourism environment are available at the following site.
https://www.dg.gov.cn/liaobu/mllb/tslb/content/post_2188432.html

For international readers, an English-language feature page with additional photos and descriptions is also available.
https://www.cathaypacific.com/cx/en_TW/inspiration/travel/xixi-ancient-village-why-visit-dongguan.html

Meanwhile, IM, or destination image (DIM), has long been recognized as an important mediating construct linking travel experience and behavioral outcomes. Baloglu and McCleary suggested that DIM is shaped jointly by stimulus factors and tourists' personal characteristics.(6) Chen and Tsai further demonstrated that DIM influences behavioral intentions both directly and indirectly and can connect service-quality evaluation, perceived value, and loyalty tendencies.(7) Accordingly, the following hypothesis is proposed.

H1: EXP has a positive effect on IM.

1.3 Revisit intention (RV) and research hypotheses

RV is one of the most widely used indicators for evaluating tourism behavioral outcomes. It usually includes the intention to revisit the destination, to prioritize it in future travel planning, to recommend it to others, and to revisit with companions. Previous studies have shown that DIM plays an important role in shaping these behavioral tendencies. Chen and Tsai found that DIM influences not only immediate evaluations but also future behavioral intentions.(7) Therefore, when visitors develop a clear and positive perception of a destination such as Xixi Heritage Village, they are more likely to revisit the site, recommend it to others, and treat it as a preferred option in future leisure travel. In addition to DIM, EXP itself may directly influence RV. Pai *et al.* demonstrated that a perceived smart-tourism technology experience positively affects both tourism experience and RV.(8) This finding suggests that in IoT-enabled tourism environments, technological interaction does not remain at the level of functional use alone but can influence more stable behavioral intentions through experiential mechanisms. On the basis of the above reasoning, we propose the following hypotheses.

H2: IM has a positive effect on RV.

H3: EXP has a positive effect on RV.

H4: IM mediates the relationship between EXP and RV.

In summary, in this study, we address the following research question: in an IoT- and sensor-enabled heritage tourism environment, can the perceived quality of smart-guiding services influence RV through the translation mechanisms of EXP and IM? To answer this question, a chained structural model is developed in which SSQ acts as the antecedent variable, EXP and IM function as mediating mechanisms, and RV serves as the behavioral outcome. The conceptual framework and analytical procedures are described in the following section.

2. Methodology

2.1 Study site and IoT smart-guiding service scenario

In this study, we focus on Xixi Heritage Village, located in Liaobu Town, Dongguan, Guangdong Province, as the empirical setting for examining the user experience and behavioral effects of IoT smart-guiding services in a heritage village tourism environment. Xixi Heritage Village features historic alleys, ancestral hall spaces, old residential buildings, waterfront scenery, and local living textures, making it a representative open cultural heritage tourism site. Compared with enclosed museums or single-route exhibition spaces, heritage villages are characterized by dispersed POIs, diversified walking paths, varying dwell times, and a high proportion of self-guided exploration. Such spatial characteristics make heritage villages suitable environments for examining how IoT guiding evolves from a simple information-delivery tool into a sensor-supported interactive service system. Prior research on smart tourism suggests that the value of IoT, mobile platforms, and data integration technologies lies in whether location, content, and visitor feedback behaviors can be organized into a service experience that visitors can clearly perceive.(1,2) According to the operational definition used in the questionnaire, smart guiding in Xixi Heritage Village refers to a mobile-centered digital guiding scenario integrating multiple sensing and interaction modules. These include QR-based entry to guiding pages, digital maps and navigation, location-triggered interpretation push (e.g., beacon signals), audio/text interpretation, crowd alerts, and interactive tasks such as stamp-collecting activities.

Specifically, the sensing layer of the smart-guiding system involves multiple types of practical sensing and positioning technologies, including QR code markers, NFC tags, Bluetooth Low Energy (BLE) beacons for proximity detection, Wi-Fi access points for coarse localization, and mobile-device-based sensing (e.g., GPS positioning, user interaction logs, and movement trajectories). These sensing components enable the real-time detection of visitor location, proximity to points of interest, and interaction behaviors within the heritage environment. In this study, although the primary evaluation method is based on a structured questionnaire, the four latent constructs (SSQ, EXP, IM, and RV) are explicitly designed to reflect users' perceived responses to the performance of the underlying sensing-enabled IoT system. In particular, SSQ captures perceived system-level performance indicators such as information accuracy, accessibility, responsiveness, and interaction effectiveness, which are directly associated with sensing-triggered services (e.g., location-based content delivery and navigation support). EXP reflects user interaction outcomes during sensor-triggered service encounters, while IM and RV represent higher-level cognitive and behavioral responses resulting from these sensing-supported experiences. Therefore, the proposed evaluation framework can be interpreted as a user-centric performance assessment of a multisensor IoT guiding system, where sensor data acquisition (location, proximity, and interaction signals) is indirectly evaluated through user perception and behavioral intention. This approach provides an initial step toward linking sensing-system deployment with human-centered service evaluation in heritage tourism environments.

The SSQ items were designed to correspond to five service characteristics: informativeness, accessibility and ease of use, interactivity and immersion, personalization and route support, and reliability and trust. Thus, IoT guiding in this study is treated not merely as an abstract technology adoption concept but as a system-performance input directly perceived by visitors during on-site use. As shown in Fig. 1, the IoT smart-guiding system in Xixi Heritage Village

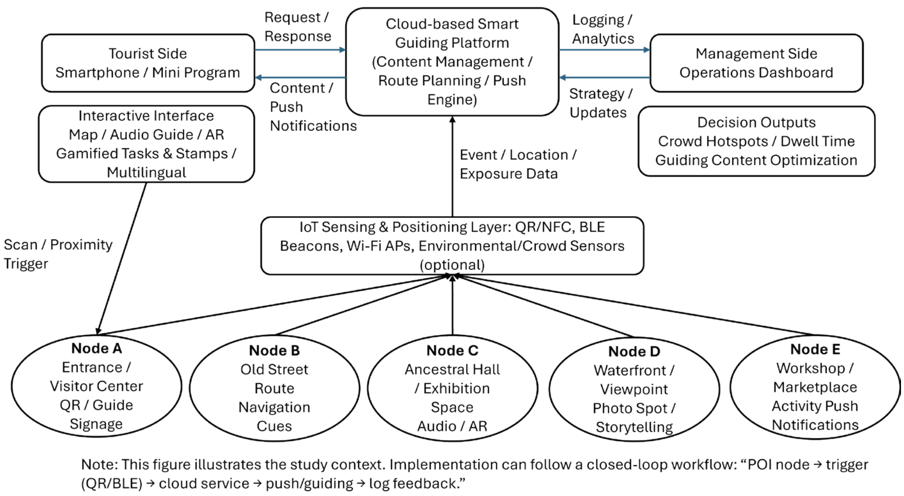

Fig. 1. System architecture of the IoT smart-guiding scenario in Xixi Heritage Village. The diagram illustrates the visitor interface, cloud platform, management interface, IoT sensing/positioning layer, and representative POI nodes.

can be conceptualized as a multilayer service architecture consisting of the visitor side, a cloud-based smart-guiding platform, a management interface, an IoT sensing/positioning layer, and distributed POI nodes. At the front end, visitors interact with the system through mobile phones or mini-program interfaces for searching, locating, reading, listening, and interacting with cultural content. At the middleware layer, QR/NFC triggers, BLE beacons, Wi-Fi access points, and other positioning mechanisms link visitors with cultural nodes, route information, and event notifications. At the back end, the cloud platform manages content distribution, route planning, push services, and usage-record collection, thereby enabling functions such as crowd monitoring, content optimization, and on-site management support.

In the Xixi Heritage Village smart-guiding system, a multilayer sensing and interaction architecture was implemented to support location-aware and context-aware services. The sensing layer includes several types of practical sensing technologies: (1) QR code markers deployed at entrances, key intersections, and POIs to provide location-specific content access; (2) NFC tags installed at selected cultural nodes for short-range interaction; (3) BLE beacons distributed along main walking routes and clustered around major POIs (typically 10–30 m spacing) to enable proximity detection and trigger location-based content delivery; and (4) Wi-Fi and GPS-based positioning, which provide coarse-grained localization and connectivity across the site. In addition, mobile-device interaction logs (e.g., click behavior, dwell time, and navigation records) were collected as behavioral sensing data. These sensing modules are integrated into a hierarchical system in which front-end sensing inputs (QR/NFC triggers and BLE signals) are processed through mobile devices and transmitted to a cloud platform for content delivery and system management. Spatially, sensing nodes are deployed in accordance with site function: high-density sensing (QR/NFC + BLE) at major POIs, medium-density BLE along primary routes, and lower-density coverage in peripheral areas supported by GPS/Wi-Fi. This configuration ensures both continuous coverage and sufficient interaction precision for guiding services.

2.2 Scale design and measurement

To enhance research transparency and reproducibility, detailed information regarding the measurement instrument and data-collection procedure is provided. The structured questionnaire was administered through a field-based intercept survey conducted by trained student investigators from Dongguan City University at major entrances and key points of interest within Xixi Heritage Village. All investigators followed a standardized instruction protocol to explain the study purpose and guide respondents through the questionnaire. Participation was voluntary, and informed consent was obtained prior to data collection. The survey was conducted anonymously, and no personally identifiable information was collected, ensuring data privacy and consistency across responses. Because of the large volume of collected data and considerations related to participant privacy and data confidentiality, the full questionnaire and dataset are not directly included herein. However, to support transparency and reproducibility, the measurement instrument and related materials can be made available upon reasonable request by contacting the authors.

Structured questionnaires were used for data collection. All perceptual items were measured on a seven-point Likert scale ranging from 1 = strongly disagree to 7 = strongly agree. The instrument included four latent constructs: SSQ, EXP, IM, and RV. SSQ was initially designed with 15 items covering informativeness, accessibility and ease of use, interactivity and immersion, personalization and route support, and reliability and trust. EXP was initially designed with 21 items and, following theories of experience economy and memorable tourism experiences, was divided into five subdimensions: sensory, affective, cognitive, action-oriented, and relational experience.(3–5) IM was initially designed with 15 items and, on the basis of DIM theory, was divided into four dimensions: product/attractiveness, quality/atmosphere, service/convenience, and price/value.(6,7) RV was initially designed with five items measuring revisit intention, priority choice, recommendation behavior, and willingness to revisit with family or friends. After item purification, RV4 was removed from the final model, leaving four indicators for the formal analysis. Overall, the scale design integrates the engineering perspective of IoT-enabled smart tourism services with behavioral theories related to experience, DIM, and behavioral intention. As illustrated in Fig. 2, the analytical framework follows the sequential logic SSQ → EXP → IM → RV, and hypotheses H0–H4 are used to evaluate how smart-guiding system performance influences subsequent behavioral outcomes through psychological translation mechanisms.

2.3 Sampling design, data collection, and sample allocation

Valid responses from a total of 700 questionnaire respondents were obtained in this study. In terms of usage context, 90.43% of respondents reported using the smart-guiding service at Xixi Heritage Village for at least 3 min during their visit. Regarding function usage (multiple responses allowed), the most frequently used features were QR-code entry (90.43%), map/navigation (63.14%), audio guide (52.71%), and location-triggered interpretation or push-based guidance (47.57%). In contrast, route recommendation (33.71%), crowd alerts or diversion (27.86%), and interactive tasks or stamp collection (24.29%) were less frequently used. Usage duration was primarily concentrated in the ranges of 10–20 min (30.86%) and 5–10 min (27.86%). Most visitors were accompanied by friends (39.14%) or family members (29.29%).

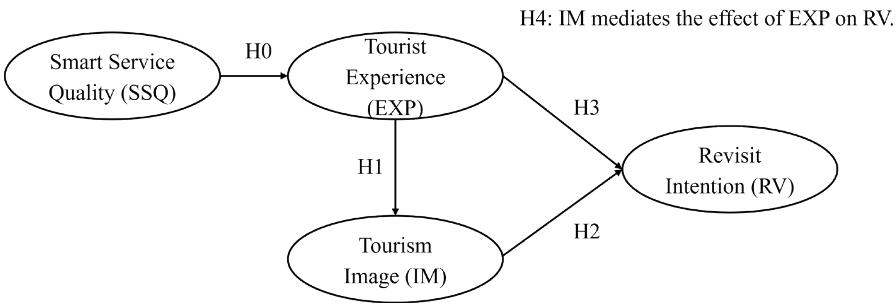

Fig. 2. Conceptual model and hypotheses. H0–H4: hypothesized paths.

First-time visitors accounted for 58.14% of the sample, and visits occurred mainly during daytime hours (57.57%). In terms of demographic characteristics, the gender distribution was relatively balanced (female 50.29%, male 47.71%). The dominant age groups were 21–40 years, with 32.14% aged 21–30 and 27.71% aged 31–40. Educational attainment was primarily at the senior high/vocational (29.29%) and university (30.71%) levels. The main occupational groups were the service industry (33.71%) and self-employed individuals (20.86%). Monthly income levels were distributed across the eight categories defined in the questionnaire.

The formal survey targeted the 700 valid responses and divided them into two subsamples in accordance with the research design: Sample A (n = 300) for exploratory factor analysis (EFA) and item purification, and Sample B (n = 400) for confirmatory factor analysis (CFA) and structural equation modeling (SEM).

To enhance reproducibility, this randomization procedure can be implemented using a fixed random seed. To ensure the comparability of the two subsamples, statistical tests were conducted on key demographic variables (e.g., gender, age, education level, occupation, and income) and usage-context variables (e.g., smart-guiding usage, functions used, duration of use, companion type, visit frequency, and visit period). The results indicated no statistically significant differences between Sample A and Sample B (chi-square tests and/or independent-sample t-tests; all $p > 0.05$), supporting the validity and robustness of the split-sample design for subsequent measurement and structural analyses. This split-sample strategy avoids conducting exploratory and confirmatory analyses on the same dataset, thereby reducing the risk of model overfitting and strengthening the robustness of inferences regarding both measurement and structural models.[9,10] In addition to the four core constructs, the questionnaire was also used to collect information on usage context and demographic characteristics for descriptive and grouping analyses. Usage-context variables included whether smart guiding was used, which functions were used, duration of use, companions, number of previous visits, and visit period. Demographic variables included gender, age, education level, occupation, and monthly income.

2.4 Item purification and EFA (Sample A)

Before estimating the formal model, Sample A was used for item screening and EFA. Earlier mixed PCA attempts tended to fragment the four constructs into too many components, and the outcome construct RV was easily absorbed by the high covariance structure of EXP and IM in pooled analyses. Therefore, in this study, we adopted a subscale-based EFA strategy with oblique rotation (Promax) and analyzed SSQ, EXP, IM, and RV separately. This approach follows methodological recommendations suggesting that theoretically related psychological constructs should first be examined using oblique rotation and that the number of retained factors should not rely solely on the eigenvalue-greater-than-one rule but should also consider parallel analysis and scree-plot inspection.[9,10] Item-retention criteria were defined as follows: a primary loading of at least 0.50, preferably above 0.60; when multiple factors appeared, a cross-loading gap of at least 0.20; communality values above 0.40 (equivalently, uniqueness below 0.60); and at least three retained items per factor to ensure stable estimation in subsequent CFA and SEM procedures.[10]

2.5 Confirmatory factor analysis and structural equation modeling (Sample B)

After item purification using Sample A, Sample B was used to estimate the measurement and structural models through CFA and SEM. The measurement model included four first-order latent variables: SSQ, EXP, IM, and RV, with RV measured by indicators RV1, RV2, RV3, and RV5. CFA was conducted to verify whether each observed item reliably reflected its corresponding latent construct and to evaluate convergent and discriminant validity. SEM was then applied to test the structural relationships specified in H0–H4, including the effect of SSQ on EXP, the effect of EXP on IM, the direct effects of IM and EXP on RV, and the mediating role of IM in the relationship between EXP and RV. Model fit was evaluated using several commonly adopted indices, including the comparative fit index (*CFI*), Tucker–Lewis index (*TLI*), normalized fit index (*NFI*), root mean square error of approximation (*RMSEA*), and standardized root mean square residual (*SRMR*). Model-fit evaluation followed commonly adopted SEM criteria, including chi-square statistics, *CFI*, *TLI*, *NFI*, *RMSEA*, and *SRMR*. In general, *CFI* and *TLI* values above 0.90 indicate acceptable model fit, and values above 0.95 indicate good fit. *RMSEA* and *SRMR* values below 0.08 are typically considered acceptable, with *RMSEA* values below 0.06 regarded as desirable.[11] Convergent and discriminant validity were evaluated using standardized factor loadings, average variance extracted (*AVE*), Cronbach's alpha, composite reliability (*CR*), and the heterotrait–monotrait ratio (*HTMT*).[12,13]

2.6 Analytical procedure

The analytical procedure can be summarized as follows. First, the initial questionnaire framework was developed referring to the literature on smart tourism, electronic service quality, EXP, DIM, and RV.[1–8] Second, pretesting and item diagnosis were conducted to revise items with ambiguous wording or excessive context dependence, resulting in the formal version of the measurement scale. Third, after formal data collection, the 700 valid responses were divided into Sample A and Sample B, which were used for EFA and CFA/SEM analyses, respectively. Finally, measurement-model validation, structural-path estimation, and effect decomposition were performed to examine how SSQ influences RV through EXP and IM.

3. Results and Discussion

3.1 Item analysis and subscale EFA summary (Sample A)

Before confirmatory factor analysis and structural model estimation, Sample A was used for item analysis and EFA to examine item discrimination, internal consistency, and structural stability. In the context of the IoT smart-guiding system supported by sensing and mobile interaction technologies, the item-analysis results indicated that the measurement items were directionally consistent with their intended constructs. After earlier revisions, items that had previously shown unstable wording or blurred construct boundaries were improved, and the subscale items exhibited adequate preliminary quality for factor-structure examination. Given that the study involved four theoretically related but distinct latent constructs (SSQ, EXP, IM, and RV), and that pooled PCA tended to create excessive component fragmentation, a subscale-based, Promax-rotated, one-factor EFA strategy was adopted. This approach allows the factor structure of each construct to be evaluated independently while maintaining theoretical consistency within the sensor-enabled IoT-guiding service context. The results showed that all four subscales demonstrated good sampling adequacy and factor-structure stability, as summarized in Table 1. As shown in Table 1, all four subscales supported one-factor structures, indicating that the instrument had good structural stability before formal validation. In particular, RV showed the clearest one-dimensional solution after RV4 was removed, and no severe low-loading or nonassignable items were observed in SSQ, EXP, or IM. These results suggest that the measurement items provided a stable representation of visitors' evaluations of the sensor-supported IoT smart-guiding service system in the heritage tourism environment.

3.2 CFA measurement model (Sample B)

After item check and EFA in Sample A, CFA was conducted on Sample B to verify the overall fit, reliability, and validity of the four-construct measurement model. Descriptive statistics indicated that respondents' mean scores for the construct items were generally at the middle-to-high level, suggesting that most visitors held positive evaluations of the IoT smart-guiding system and its sensing-enabled service functions, as well as of their tourism experience and overall impression of Xixi Heritage Village, and also reported a certain level of RV. The CFA results indicated that the measurement model achieved a good overall fit, as shown in Table 2.

In terms of reliability and validity, all four latent constructs performed well, as summarized in Table 3. Cronbach's alpha and *CR* values for SSQ, EXP, IM, and RV were all above 0.90, indicating strong internal consistency of the measurement items used to evaluate the sensor-enabled IoT smart-guiding service system and related visitor responses. *AVE* exceeded 0.50 for all constructs except IM, for which *AVE* was 0.499. Although the *AVE* for IM was slightly below the conventional threshold, the shortfall was marginal and remained acceptable in light of the overall fit, reliability, and *HTMT* results. Taken together, Tables 2 and 3 indicate that the CFA

Table 1
Summary of subscale EFA results (Promax rotation, one-factor solutions; Sample A).

Construct	Items	KMO	Bartlett (chi-square, df, *p*)	Model chi-square (df), *p*	Eigenvalue/ Variance explained	Loading range/ Uniqueness range
SSQ	15	0.977	3341.763, 105, <.001	93.264 (90), .386	9.003/ 60.0%	0.655–0.881/ 0.224–0.572
EXP	21	0.982	4439.202, 210, <.001	193.448 (189), .397	11.802/ 56.2%	0.614–0.866/ 0.249–0.623
IM	15	0.964	2366.679, 105, <.001	115.453 (90), .037	7.492/ 49.9%	0.634–0.771/ 0.406–0.598
RV	4	0.846	849.386, 6, <.001	6.386 (2), .041	2.935/ 73.4%	0.809–0.894/ 0.200–0.346

Note: All four EFA analyses adopted Promax rotation. Values were taken from the same JASP output.

Table 2
CFA measurement-model fit indices (Sample B).

Fit index	Value	Common threshold	Decision
chi-square (df), *p*	1471.136 (1424), 0.188	$p > 0.05$	Accepted
CFI	0.997	>= 0.90 (ideal >= 0.95)	Accepted
TLI	0.997	>= 0.90 (ideal >= 0.95)	Accepted
RMSEA (90% CI)	0.009 (0.000–0.016)	<= 0.08 (ideal <= 0.06)	Accepted
SRMR	0.030	<= 0.08	Accepted
NFI	0.913	>= 0.90	Accepted
GFI	0.888	Reporting index	Acceptable

Note: Fit statistics were obtained from the CFA output.

Table 3
Summary of reliability and validity (Sample B).

Construct	Cronbach's alpha	*CR*	*AVE*	Max *HTMT*
SSQ	0.958	0.958	0.610	0.614
EXP	0.966	0.966	0.577	0.723
IM	0.937	0.937	0.499	0.723
RV	0.913	0.915	0.729	0.698

Note: *AVE*, average variance extracted; *HTMT*, heterotrait–monotrait ratio. Common thresholds: alpha/*CR* >= 0.70; *AVE* >= 0.50 (*IM* = 0.499 is regarded as marginally acceptable); *HTMT* < 0.85, or more conservatively, < 0.90.

results for Sample B support a stable and acceptable measurement model that can be used for subsequent structural-model estimation and hypothesis testing in evaluating the sensor-enabled IoT smart-guiding service system and its associated visitor responses.

3.3 Structural model and hypothesis testing (Sample B)

After support for the measurement model was established, SEM was used to test the theoretical model SSQ → EXP → IM → RV, representing the behavioral translation pathway of the sensor-enabled IoT smart-guiding service system. The overall fit of the structural model was satisfactory, as shown in Table 4. From a system-evaluation perspective, the model links the perceived operational quality of the smart-guiding system with visitor perceptions and behavioral responses. SSQ represents the perceived performance of the IoT guiding system, including information delivery, accessibility, and interactive responsiveness. EXP reflects visitors' experiential responses during interaction with the guiding system, while IM represents the cognitive and affective DIM formed through this experience. RV serves as the final behavioral outcome reflecting visitors' willingness to revisit or recommend the destination. Overall, the structural model indicates that the perceived quality of an IoT-based guiding system, supported by location-aware sensing and mobile interaction technologies, can influence visitor experience and destination perception, which subsequently shape RV.

All four main structural paths were significant. The standardized path coefficients, standard errors, z values, and *p* values are shown in Table 5. H0 (SSQ → EXP), H1 (EXP → IM), H2 (IM

Table 4
Structural-model fit indices (Sample B).

Fit index	Value	Common threshold	Decision
chi-square (*df*), *p*	1474.943 (1426), 0.179	$p > 0.05$	Accepted
CFI	0.997	>= 0.90 (ideal >= 0.95)	Accepted
TLI	0.997	>= 0.90 (ideal >= 0.95)	Accepted
RMSEA	0.009	<= 0.08 (ideal <= 0.06)	Accepted
SRMR	0.031	<= 0.08	Accepted

Table 5
Structural path coefficients and hypothesis testing (Sample B).

Hypothesis	Path	beta	SE	*z*	*p*
H0	SSQ → EXP	0.622	0.032	19.216	<0.001
H1	EXP → IM	0.728	0.029	24.819	<0.001
H2	IM → RV	0.514	0.048	10.622	<0.001
H3	EXP → RV	0.243	0.049	4.939	<0.001

→ RV), and H3 (EXP → RV) were all supported. From a system-evaluation perspective, these results indicate that the perceived performance of the sensor-enabled IoT smart-guiding service system plays an important role in shaping visitor responses. In particular, the significant path from SSQ to EXP suggests that the operational quality of the guiding system—such as information accessibility, responsiveness, and interactive support—can directly influence visitors' experiential perceptions during on-site exploration. The subsequent significant relationships among EXP, IM, and RV further indicate that visitors' interactions with the guiding system can influence destination perception and ultimately affect behavioral outcomes. Overall, the structural-path results suggest that the effectiveness of IoT smart-guiding services supported by sensing technologies is reflected not only in system functionality but also in how visitors perceive and respond to the service in the heritage tourism environment.

To test the mediation proposed in H4, an effect-decomposition analysis was conducted. As shown in Table 6, the indirect effect of EXP on RV through IM was 0.374 ($p < 0.001$), the direct effect was 0.243 ($p < 0.001$), and the total effect was 0.617 ($p < 0.001$), indicating that IM played a partial mediating role in the relationship between EXP and RV. From a system-evaluation perspective, this finding suggests that visitors' experiential responses generated through interaction with the sensor-enabled IoT smart-guiding service system can influence behavioral outcomes both directly and indirectly through the formation of destination perception. In other words, the performance of sensing-supported guiding services affects not only the immediate visitor experience but also the cognitive evaluation of the destination. The partial mediation result indicates that part of the influence of EXP on RV operates through the formation of IM. This implies that when the smart-guiding system provides clear information delivery, stable access, and responsive interaction, visitors are more likely to develop a favorable perception of the destination environment, which subsequently strengthens RV. At the same time, the significant direct effect suggests that positive experiential responses produced during interaction with the guiding system can also directly enhance visitors' willingness to revisit or recommend the destination. Figure 3 shows the standardized estimates along the arrows, and the mediating role of IM corresponds to hypothesis H4.

Table 6
Effect decomposition and chained mediation (Sample B).

Effect	Path	Estimate	SE	*z*	*p*
Indirect	EXP → IM → RV	0.374	0.043	8.759	<0.001
Direct	EXP → RV	0.243	0.049	4.939	<0.001
Total	EXP → RV (total)	0.617	0.043	14.453	<0.001

Note: H4 (EXP → IM → RV mediation) was regarded as supported when the indirect effect was significant. The mediated proportion was approximately 60.6%.

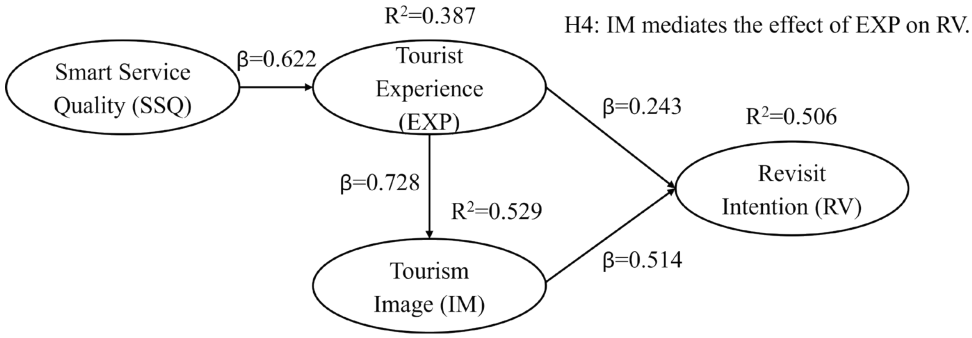

Fig. 3. Structural equation model with standardized path coefficients. Standardized estimates are shown along the arrows. The mediating role of IM corresponds to hypothesis H4.

4. Discussion

Taken together, the results in Tables 4–6 indicate that SSQ does not influence RV directly, but first activates EXP and then amplifies and stabilizes its subsequent effect through IM. From a sensor-enabled system evaluation perspective, this finding suggests that the effectiveness of an IoT smart-guiding system lies not merely in the deployment of sensing devices or digital interfaces, but in how these technological components are translated into visitor-perceived service performance, such as convenient information access, clear route guidance, accessible cultural content, and context-aware interaction. In heritage tourism environments, sensing-supported guiding services—such as location-triggered interpretation, mobile navigation, and interactive content delivery—become meaningful only when visitors perceive them as useful and reliable during on-site exploration. This interpretation is consistent with the emphasis on experiential value in the evolution of smart tourism information systems and digital services[14,15] and with the logic of layered IoT architectures and edge–cloud collaborative service design.[16,17]

Second, the path from EXP to IM showed the largest coefficient ($\beta = 0.728$), indicating that in a cultural heritage destination such as Xixi Heritage Village, IM is better understood as a cognitive accumulation of experience rather than a purely abstract previsit impression. In the context of IoT-supported tourism services, visitors continuously interact with the guiding system through mobile interfaces and sensing-based triggers while moving through different POIs.[18–20] These interactions gradually connect fragmented heritage information into a coherent narrative structure. When the guiding system supports a visit rhythm in which tourists can understand cultural content while walking, interact with contextual information, and cognitively connect dispersed sites, IM is more likely to form as a stable perception of the destination rather than a temporary evaluation of a single attraction.

Third, Table 6 shows that the mediating proportion of IM between EXP and RV reached 60.6%, indicating that RV is formed more through stable evaluations internalized from experience than through short-term affective responses alone. From a system-design perspective, this result implies that the value of IoT smart-guiding services is not limited to providing immediate informational assistance but also lies in supporting the gradual formation of a coherent DIM through continuous interaction with the guiding system. For heritage village managers and system designers, these findings suggest that the design of IoT smart-guiding services should move beyond technological novelty or isolated interactive functions. Instead, sensing-enabled guiding systems should help visitors construct a more integrated place perception by clarifying historical narratives, improving route legibility, visualizing relationships among heritage sites, and maintaining consistent interpretation and service delivery across different contexts. When the guiding system successfully integrates sensing technologies, mobile interfaces, and cultural interpretation into a coherent service experience, it becomes more likely to enhance both destination perception and RV.

The results indicate that the effectiveness of an IoT smart-guiding system in a heritage tourism environment depends not simply on the deployment of sensing technologies or digital devices, but also on whether these technological functions are translated into visitor-perceived service value. In the case of Xixi Heritage Village, the results show that SSQ significantly improved EXP, which subsequently strengthened IM and increased RV. This suggests that the perceived operational quality of the smart-guiding system—such as information accessibility, route clarity, interaction responsiveness, and system reliability—plays an important role in shaping visitors' experiential responses during on-site exploration. The strong relationship between EXP and IM further indicates that DIM in heritage tourism contexts is largely formed through accumulated on-site experiences rather than through purely abstract previsit impressions. When the guiding system supports a visit rhythm in which tourists can understand cultural content while walking, connect dispersed heritage sites through interpretation, and interact with contextual information, visitors are more likely to form a coherent perception of the destination.

The mediation analysis also showed that IM partially mediated the relationship between EXP and RV, accounting for approximately 60.6% of the total effect. This finding suggests that revisit intention is not driven solely by immediate experiential satisfaction but is largely shaped by the stable DIM formed through the experience process. In this sense, the value of sensor-enabled IoT guiding services lies in supporting experiential engagement and helping visitors construct an integrated perception of the heritage environment. From a practical perspective, these results imply that the design of smart-guiding systems in heritage villages should focus on information reliability, route interpretability, and interactive narrative integration. Systems that clearly present historical narratives, visualize relationships among sites, and provide timely navigation or contextual information are more likely to help visitors construct a coherent place perception. When sensing technologies, mobile services, and cultural interpretation are effectively integrated, the guiding system functions not only as an information tool but also as an experiential interface that enhances cultural understanding and memory formation.

5. Conclusions

The operational mechanism of IoT-enabled smart-guiding services in cultural heritage tourism environments is investigated using Xixi Heritage Village in Dongguan as the empirical case. A chained structural model (SSQ → EXP → IM → RV) is established to describe how the perceived performance of a sensor-enabled guiding system is translated into behavioral intention through experiential and cognitive processes. Using 700 valid responses to questionnaires and a split-sample strategy, EFA, CFA, and SEM are employed to ensure measurement robustness and structural validity. The results confirm that SSQ significantly enhances EXP, which subsequently strengthens IM and increases RV, while EXP also retains a direct effect on RV. In addition, IM exhibits a partial mediating role, indicating that revisit intention is primarily formed through a stabilized and accumulated destination image rather than immediate experiential responses alone. The main contribution does not lie in the directional relationships themselves, but in quantifying the hierarchical transformation mechanism linking sensor-enabled system performance with user-level behavioral outcomes. The findings demonstrate that the impact of IoT guiding systems is not directly realized at the behavioral level but is mediated through perception-based processes, with IM accounting for a substantial proportion (60.6%) of the total effect. This provides an important implication for sensor-system evaluation: the effectiveness of IoT services should be assessed not only in terms of technical deployment or sensing capability, but in terms of how sensing-supported functions are translated into coherent user experience and cognitive perception.

From an engineering perspective, a user-centric evaluation framework for multisensor IoT service systems is further supported, in which sensing components (e.g., location detection, proximity triggering, and interaction logging) are indirectly evaluated through their influence on experience, perception, and behavior. This contributes to bridging the gap between sensor-system deployment and human-centered service evaluation, which is often insufficiently addressed in existing IoT-related studies. Several limitations remain. The empirical setting is restricted to a single heritage village, and the generalizability of the findings requires further validation in other cultural heritage contexts. In addition, the analysis is primarily based on questionnaire data without incorporating objective behavioral indicators such as system logs, visitor trajectories, or crowd-sensing data. Although the measurement model shows acceptable reliability and validity, the *AVE* of IM remains marginal, suggesting that further refinement of destination-image measurement is needed. Future work might be to integrate objective IoT sensing data—including positioning records, dwell times, and interaction logs—with perception-based measurements to establish a hybrid evaluation framework. Cross-site comparisons and multigroup SEM analyses may also help determine whether the SSQ–EXP–IM–RV mechanism varies across different visitor segments or tourism environments. The findings indicate that in an IoT-enabled heritage tourism setting, the influence of smart-guiding systems on revisit intention is realized through a multistage perception-driven transformation mechanism rather than direct technological effects, providing a quantitative and system-oriented explanation of how sensor-enabled IoT services generate user-perceived value.

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