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An IoT Sensor-enabled Heritage Interpretation System: Empirical Validation through Servicescape–Stimulus–Organism–Response Structural Modeling

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To address the digital transformation needs of heritage interpretation services in smart tourism, in this study, we developed and evaluated an IoT sensor-enabled heritage interpretation system integrating environmental sensing, proximity detection, and mobile interactive interfaces within a unified IoT architecture. The system includes a sensing layer (environmental sensors, Bluetooth beacons, and mobile sensing modules), a network transmission layer, and an application layer, where real-time sensor data are transmitted through IoT middleware and converted into adaptive servicescape cues for personalized content delivery. This framework demonstrates how heterogeneous sensor signals—such as proximity detection, node identification, and spatial positioning—can be integrated to support context-aware interpretation services in heritage environments. Within this sensor-integrated framework, we validated a serial mechanism linking an IoT-enabled heritage servicescape (*I-SC*) and interpretation service quality (*ISQ*) to overall service quality (*OSQ*), positive affect (*PA*), perceived value (*PV*), and behavioral intention (*BI*) using a servicescape stimulus–organism–response (S–O–R) structural modeling approach. This approach provides a quantitative framework for evaluating how sensor-generated environmental signals affect human perception and behavioral outcomes, extending sensor-enabled systems beyond technical deployment toward human-centered effectiveness evaluation. Visitor perceptions were collected via questionnaire survey after interacting with the sensor-enabled system, followed by item analysis, exploratory factor analysis (EFA), confirmatory factor analysis (CFA), and structural equation modeling (SEM). The instrument showed strong reliability (Cronbach's α = 0.908). Sampling adequacy was excellent (Kaiser–Meyer–Olkin = 0.954; Bartlett's χ^2 = 17816.455, df = 1326, p < 0.001). EFA extracted 13 factors explaining 67.5% of the total variance. CFA indicated good model fit (χ^2/df = 0.942, Comparative Fit Index = 1.000, $RMSEA$ = 0.000, $SRMR$ = 0.023), with standardized loadings ranging from

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0.741 to 0.951, the composite reliability (*CR*) of 0.819–0.967, and the extracted average variance of 0.530–0.880, supporting convergent and discriminant validity. SEM supported all hypothesized paths: *I-SC→PA* (β = 0.539), *I-SC→OSQ* (β = 0.280), *ISQ→OSQ* (β = 0.465), *OSQ→PV* (β = 0.539), *PA→PV* (β = 0.273), *PV→BI* (β = 0.531), and *PA→BI* (β = 0.197). *PV* emerged as the most proximal driver of revisit and recommendation intentions. The results showed that sensor-integrated servicescape cues and real-time IoT data adaptation significantly enhance perceived service quality and affective responses. IoT sensor-enabled interpretation systems should thus prioritize intelligent sensing integration and dynamic content adjustment to increase *PV*, *OSQ*, *PA*, and *BI*. This study has some limitations. The sensing infrastructure mainly focused on location and interaction detection, and the empirical validation was conducted at a single heritage site, which may limit generalizability. Future research can incorporate additional sensor types and test the system across diverse cultural heritage environments.

1. Introduction

The advancement of smart tourism infrastructures has accelerated the deployment of IoT-based sensing systems in heritage environments. However, beyond hardware installation, a critical challenge lies in modeling how sensor-generated environmental signals are transformed into perceptible experiential stimuli and, subsequently, into measurable behavioral outcomes. In heritage interpretation contexts, IoT-enabled systems function as distributed sensing networks that continuously capture environmental and visitor-state data, including spatial position, proximity to exhibition nodes, dwell time, route progression, and interaction events. These real-time signals are transmitted through secured communication channels to backend platforms, where rule-based engines convert raw sensing inputs into adaptive interpretation triggers, content sequencing, and interaction prompts. Through this sensing–transmission–processing–actuation loop, the physical heritage environment is computationally reconstructed as a dynamic digital servicescape. In this study, the term "servicescape" refers to the perceptible environmental cues generated through the IoT sensing architecture, including spatial guidance signals, informational display triggers, and interaction prompts activated by sensor detection. In other words, servicescape represents the user-perceived environment formed by sensor-triggered interpretation cues rather than an abstract tourism-management concept. This definition is adopted to clarify how sensor-derived environmental signals are translated into structured perception variables that can be quantitatively modeled in the subsequent structural equation analysis.

Despite the increasing adoption of IoT sensing technologies, the effectiveness of such systems cannot be assumed solely from architectural deployment. A modeling framework is required to quantify how sensor-integrated environmental cues determine user cognition, affect, and *BI*. From a sensing-system perspective, the key problem is not technology presence, but signal translation: how contextual sensing inputs are mapped into perceived service quality, emotional response, and value assessment. Therefore, a sensor modeling approach must establish a measurable pathway linking environmental stimuli derived from sensing architecture to human-perception states and observable behavioral responses. In this study, the IoT sensor-enabled heritage interpretation system is abstracted into a reproducible multilayer architecture to ensure engineering clarity. The perception layer comprises positioning and proximity sensing modules [e.g., Bluetooth beacons, Quick Response (QR) Code/Near Field Communication (NFC) identifiers, Wi-Fi Round Trip Time (RTT), Global Navigation Satellite System (GNSS)], exhibition node recognition, and device status monitoring. These modules generate spatial-temporal signals that serve as primary stimulus inputs. The network layer ensures stable edge-to-cloud transmission and secure data access control.

The platform layer integrates a content management system (CMS) and a rule-based interpretation engine that converts location thresholds, dwell duration, and interaction frequency into adaptive content delivery logic. Simultaneously, interaction logs and feedback records are captured to close the sensing loop. The application layer executes smart interpretation interfaces, interactive modules, and adaptive routing recommendations. This layered architecture forms a closed-loop sensing–actuation system in which environmental data are continuously translated into user-facing interpretation stimuli. To model the transfer mechanism between sensor-derived stimuli and behavioral outcomes, we adopt the stimulus–organism–response (S–O–R) framework as a structured human-perception modeling tool. Previous studies on IoT sensor-enabled heritage interpretation systems have primarily focused on system design,(1) interface development, or the deployment of location-based interpretation technologies, such as Bluetooth beacon-based museum guides,(2) QR/NFC interactive interpretation systems,(3) and mobile augmented reality heritage guides.(4) These studies have demonstrated the feasibility of applying IoT sensing technologies to heritage interpretation and have highlighted their potential to improve visitor engagement and information accessibility. However, most prior research evaluates system performance using descriptive user feedback, usability testing, or qualitative observations, and relatively few studies quantitatively model how sensor-triggered environmental signals propagate through visitor perception and ultimately affect behavioral outcomes.

In contrast, we contribute to this research field by introducing a structural modeling approach that explicitly links IoT sensing inputs, perceived servicescape cues, and behavioral intention within a unified analytical framework. By IoT-enabled servicescape (*I-SC*), interpretation service quality (*ISQ*), and downstream perceptual constructs into a structural equation model, we provide quantitative evidence on how environmental sensing signals are translated into cognitive evaluation, affective responses, and value judgments that ultimately drive visitor behavior. The adoption of the S–O–R framework is particularly appropriate for validating sensor-enabled service systems because it provides a theoretical mechanism for describing how environmental stimuli generated by sensing architectures affect internal user states and behavioral responses. In the context of IoT-enabled heritage interpretation, the stimulus layer corresponds to environmental signals triggered by sensing technologies (e.g., location detection, proximity-based content activation, and interaction prompts).

The organism layer represents visitors' internal processing of these stimuli, including overall service evaluation and emotional responses. The response layer captures behavioral outcomes such as revisit intention and recommendation. Therefore, the S–O–R structural modeling approach enables the system to be empirically validated not only in terms of technical functionality but also in terms of its human-centered sensing effectiveness, revealing how sensor-generated environmental cues are translated into measurable behavioral impacts. Within this structure, *I-SC* and *ISQ* represent stimulus variables generated through sensor-triggered environmental orchestration. *I-SC* captures digitally enhanced ambient conditions, spatial functionality, informational/symbolic clarity, and socially coordinated interaction order, operationalized as a reflective–reflective second-order construct.[5,6] *ISQ* captures perceived the reliability, responsiveness, assurance, empathy, and tangibility of the interpretation service, extending SERVQUAL logic to IoT-enabled human–system collaboration contexts.[7,8]

The organism layer consists of overall service quality (*OSQ*), positive affect (*PA*), and perceived value (*PV*), representing internal evaluation states and affective processing outcomes. *OSQ* reflects holistic service system appraisal.[9,10] *PA* operationalizes affective activation consistent with Positive and Negative Affect Schedule (PANAS) constructs.[11,12] *PV* models the cognitive trade-off between experiential gains and resource expenditure, aligned with value theory and PERVAL logic.[13,14] *BI* constitutes the response variable, reflecting revisit and recommendation likelihood consistent with the established tourism and theory of planned behavior-based research.[9,15,16] Under the S–O–R sensor modeling paradigm, environmental signals captured and orchestrated through IoT architecture are hypothesized to propagate through affective and evaluative mediators before generating behavioral outcomes. Accordingly, the following hypotheses are formulated, and the conceptual model and hypothesized relationships are illustrated in Fig. 1.

H1: *I-SC* positively affects *PA*.
H2: *I-SC* positively affects *OSQ*.
H3: *ISQ* positively affects *OSQ*.
H4: *PA* positively affects *PV*.
H5: *PA* positively affects *BI*.
H6: *OSQ* positively affects *PV*.
H7: *PV* positively affects *BI*.

By integrating sensing architecture abstraction with structural equation modeling, we provide a quantitative validation of the signal translation pathway from IoT sensor-derived environmental stimuli to *BI*. The results contribute to sensor-enabled service system modeling

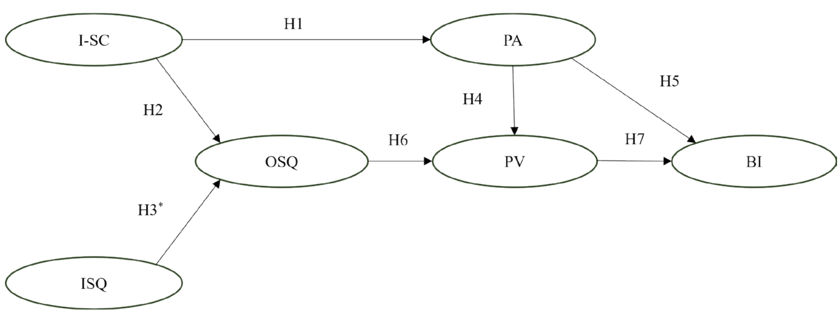

Fig. 1. Conceptual model and hypotheses: IoT-enabled heritage interpretation in a S–O–R framework (*I-SC* and *ISQ* as second-order constructs; *OSQ*, *PA*, *PV*, and *BI* as first-order constructs).

by demonstrating how distributed sensing inputs can be systematically linked to human-perception transfer mechanisms and measurable outcome variables within heritage interpretation environments.

2. Methods

2.1. System architecture and experimental context

The heritage tourism context of Jinshan Farmer Painting served as a real-world validation site for validating an IoT sensor-enabled heritage interpretation system. Rather than conceptualizing the system as a standalone device, it was implemented as a distributed sensing and service orchestration architecture designed to convert environmental and visitor-state signals into adaptive interpretation stimuli. The system consisted of a perception layer, a network layer, a platform layer, and an application layer operating as a closed-loop sensing–actuation structure. The perception layer integrated multiple contextual sensing modules, including Bluetooth proximity beacons, QR/NFC-based node identification, Wi-Fi RTT/GNSS-assisted positioning, and device status monitoring. Specifically, BLE beacons installed near exhibition nodes detected visitor proximity through Received Signal Strength Indicator (RSSI) signals, QR/NFC tags provided explicit node identification when scanned by visitors' mobile devices, and Wi-Fi RTT/GNSS signals supported approximate indoor/outdoor location estimation. These sensing devices generated raw environmental signals such as proximity detection, node identification codes, location coordinates, dwell-time records, and interaction timestamps. The collected sensor signals were transmitted through the network layer to the platform layer, where a rule-based processing engine converted them into interpretation triggers and interaction prompts. For example, when a visitor approached a beacon-equipped exhibit node or scanned a QR/NFC tag, the system automatically activated the corresponding interpretation content on the mobile interface. These sensing-triggered interactions formed the experiential stimuli that visitors perceived during the heritage tour.

The questionnaire survey was designed to measure visitors' perceptions and responses to these sensor-triggered interpretation services. Specifically, the survey items captured how users perceived the sensor-enabled servicescape cues (e.g., the clarity of location-based information, the usability of digital guidance, and interaction convenience), the perceived quality of the interpretation service delivered through the system, and the resulting experiential outcomes such as *PV*, affective response, and behavioral intention. In other words, the questionnaire did not measure the technical performance of sensors directly; rather, it evaluated how the sensing architecture translated environmental signals into perceivable interpretation experiences. To improve transparency and reproducibility, the questionnaire items used to operationalize each construct (*I-SC*, *ISQ*, *OSQ*, *PA*, *PV*, and *BI*) were developed on the basis of established measurement scales reported in the literature and adapted to the IoT-enabled heritage interpretation context, as described in Sect. 3.2. Each item was carefully contextualized to reflect visitors' experiences with sensor-triggered interpretation services, such as location-based content activation, digital guidance cues, and interactive information access.

The questionnaire therefore measures visitors' perceptions of how the sensing architecture translates environmental signals into interpretation experiences. The dataset used for the statistical analysis—including the anonymized response matrices for the pilot test (N = 150) and main survey (N = 700)—can be made available from the authors upon reasonable request. This clarification helps establish the connection between the IoT sensing architecture described in the system design and the perception-based measurement model employed in the structural analysis. The sensing infrastructure included (i) Bluetooth Low Energy (BLE) beacons installed near exhibition nodes to detect visitor proximity, (ii) QR/NFC identification tags attached to interpretation points for explicit content activation, and (iii) Wi-Fi RTT or GNSS positioning signals to estimate visitor location and movement trajectories within the heritage site. These modules continuously captured spatial-temporal signals such as visitor location, exhibition-node proximity, dwell duration, and interaction events.

The raw sensing data generated by these devices consisted primarily of beacon signal strength (RSSI), device identification codes from QR/NFC scanning, positioning coordinates or location zones, timestamped dwell-time records, and interaction-trigger logs. These sensor outputs were used as input signals for the interpretation system, enabling location-based content triggering, adaptive route guidance, and context-aware information delivery. In practice, when a visitor approached a beacon-equipped exhibition node or scanned a QR/NFC tag, the system detected the sensor signal and automatically activated the corresponding interpretation module. Sensing data were transmitted through secured mobile and on-site network infrastructure to backend servers (network layer), ensuring stable edge-to-cloud connectivity and access control. The collected sensor signals were transmitted in real time to the platform layer, where rule-based processing algorithms transformed the raw sensing inputs (e.g., proximity detection, dwell duration, or node identification) into interpretation triggers and interaction events. This data flow, from sensing acquisition to rule-based content activation, formed the core mechanism by which environmental sensing information was converted into visitor-facing interpretation services.

At the platform layer, a CMS and rule-based interpretation engine transformed sensor inputs into adaptive content triggers. Location thresholds, dwell-time conditions, and route progression logic were encoded as rule parameters. Interaction logs, event records, and feedback inputs were simultaneously recorded, forming a data capture loop for subsequent evaluation. At the application layer, mobile smart interpretation interfaces, interactive Q&A modules, personalized route recommendations, accessibility support functions, and satisfaction-reporting mechanisms executed real-time responses to sensor-triggered commands. Through this layered architecture, environmental sensing signals were computationally mapped into digitally mediated servicescape cues. Participants were on-site visitors who had interacted with this IoT-enabled interpretation system. A mixed sampling strategy combining on-site intercept surveys and online follow-up was adopted to improve the coverage of users exposed to the sensor-triggered interpretation process. All questionnaire items were measured on a seven-point Likert scale (1 = strongly disagree; 7 = strongly agree). A pilot test yielded 150 valid responses, and the main survey collected 700 valid responses from January to February 2026, including demographic and visit-related variables.

For the main sample ($N = 700$), questionnaires were primarily collected in the exhibition hall (58.29%), followed by the workshop (21.00%), cultural space (12.86%), and other areas (7.86%). Females accounted for 52.43% and males 45.57%. Age distribution was concentrated in the 21–30 (30.43%) and 31–40 (23.14%) groups. Most respondents had college/university education (51.29%). Nearly half were first-time visitors (47.43%), and typical visit duration was 1–2 h (34.29%) or 2–3 h (24.57%). The reported usage of the smart interpretation system ranged from low to moderate, with 19.86% indicating minimal interaction. These characteristics ensured exposure to various intensities of sensor-triggered interpretation stimuli. Standardized instructions were provided on-site to ensure response consistency, and missing values were checked immediately. The online follow-up employed the same instrument structure with mandatory-response settings and consistency validation to reduce invalid entries.

2.2 Measurement modeling and instrument development

The measurement model was constructed to quantify the signal translation pathway from IoT-enabled environmental stimuli to behavioral outcomes. Six latent constructs were included: *I-SC*, *ISQ*, *OSQ*, *PA*, *PV*, and *BI*. *I-SC* and *ISQ* were modeled as reflective–reflective second-order constructs, whereas *OSQ*, *PA*, *PV*, and *BI* were specified as first-order constructs. Scale development followed a structured modeling logic to ensure content validity and contextual alignment. Core construct meanings were derived from established theoretical foundations, including servicescape and expanded servicescape theory (*I-SC*), SERVQUAL (*ISQ*), *PA*, value tradeoff/PERVAL logic (*PV*), and *BI* frameworks in service and tourism research.(5–7,9, 12–15) Items were contextualized to reflect sensor-triggered interpretation features within the Jinshan Farmer Painting environment, such as location-based push notifications, interactive screens, QR/AR-assisted information access, and smart-tag identification mechanisms, thereby linking abstract constructs to observable sensing-enabled cues.(1,2) Translation–back translation procedures and pilot cognitive interviews were conducted to ensure semantic equivalence and reduce ambiguity. Prior to structural modeling, item analysis was performed to assess corrected item–total correlations and internal consistency. Refinement decisions prioritized theoretical coherence, factor structure stability, and error covariance diagnostics rather than relying solely on changes in Cronbach's α, thereby mitigating artificial inflation effects due to item-number expansion.(10,17–20) Table 1 shows the constructs, hierarchical relationships, scale sources, and contextualization strategy in the IoT-enabled heritage setting.

2.3 Data analysis procedure and structural validation

To validate the sensing-to-behavior translation mechanism, a sequential modeling workflow was adopted, consisting of item analysis, exploratory factor analysis (EFA), confirmatory factor analysis (CFA), and structural equation modeling (SEM), as illustrated in Fig. 2. All analyses were conducted using JASP, which is an open-source statistical software program based on R. R is an open-source statistical programming language widely used for data analysis and modeling. Reliability analysis was conducted for internal consistency testing, EFA was performed using

Table 1
Measurement constructs, scale sources, and contextualization strategy.

Construct	Measurement structure	No. of items	Primary scale source (s)	Contextualization in this study (IoT heritage tour)
I-SC	2nd-order reflective; 4 dimensions (*A*/*L*/*S*/*So*)	16	Servicescape/ expanded servicescape	Items anchored to Jinshan Farmer Painting visit; IoT cues specified (e.g., location-based push, QR/AR, interactive displays, smart-tag information access)
ISQ	2nd-order reflective; 5 dimensions (*TAN*/ *REL*/*RES*/ *ASS*/*EMP*)	20	SERVQUAL + service quality hierarchy	Wording adapted to the interpretation system and staff-assisted guidance (content accuracy, responsiveness, empathy) and to sensor-enabled service delivery (timeliness, stability)
OSQ	1st-order reflective	4	Overall quality/ service outcomes	General evaluation of the integrated tour service (system + on-site service); phrasing kept technology-neutral to reduce method bias
PA	1st-order reflective	4	PANAS (*PA*)	Affect items anchored to the on-site experience after using IoT interpretation and interaction features.
PV	1st-order reflective	4	Value trade-off/ PERVAL	Value framed as benefits vs time/effort; includes informational/experiential gains from IoT interpretation
BI	1st-order reflective	4	Service/ heritage tourism *BI* (revisit/ recommend)	Intention specified as revisit, recommend, and continued engagement with the attraction after the experience

Note. *TAN*: Tangibles; *REL*: Reliability; *RES*: Responsiveness; *ASS*: Assurance; *EMP*: Empathy.

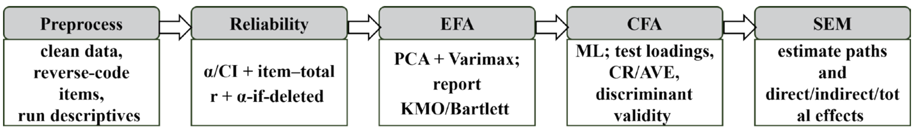

Fig. 2. Analysis pipeline used in this study: item analysis → EFA → CFA → SEM (implemented in JASP).

the factor module, and CFA/SEM estimations were carried out using the lavaan package in R. All hypothesis tests were two-tailed with significance level $p < 0.05$.

Because maximum likelihood (ML) estimation assumes multivariate normality, distribution diagnostics were performed prior to SEM estimation. When deviations from multivariate normality were detected, robust standard errors (e.g., MLR estimation) were applied to improve inferential robustness. Item analysis first evaluated internal consistency and discrimination capacity. Cronbach's α with 95% confidence intervals (*CI*), α-if-deleted, and corrected item–total correlations were examined to confirm construct representativeness.[21] EFA was conducted to explore the latent measurement structure. Principal component analysis with Varimax rotation was employed to enhance interpretability. Sampling adequacy was assessed using the Kaiser–Meyer–Olkin (KMO) measure and Bartlett's test of sphericity to confirm suitability for factor extraction.[22,23] Factor retention decisions were based on eigenvalues greater than 1 and the inspection of the scree plot. CFA was subsequently performed using ML estimation to validate the measurement model. Convergent validity was evaluated through standardized factor loadings (λ), composite reliability (*CR*), and average variance extracted (*AVE*). Discriminant validity was assessed using the Fornell–Larcker criterion ($\sqrt{AVE}$ exceeding interconstruct correlations).[21,22] Model fit was evaluated using χ^2/df, Comparative Fit Index (*CFI*), Tucker–Lewis Index (*TLI*), Root Mean Square Error of Approximation (*RMSEA*), and Standardized Root Mean Square Residual (*SRMR*), ensuring standardized reporting consistency. Finally, SEM was applied to estimate the structural model and test the proposed serial sensing mechanism linking environmental stimuli to *BI*. Standardized path coefficients (β), standard errors, test statistics, and p-values were reported for all hypothesized paths. Direct, indirect, and total effects were examined to validate the *I-SC*/*ISQ* → (*OSQ*/*PA*/*PV*) → *BI* signal propagation pathway.

3. Results

3.1 Item analysis and reliability

The initial reliability assessment was conducted to evaluate the internal consistency of the sensing-enabled measurement instrument. In the pilot sample (N = 150), the full instrument demonstrated high internal consistency (Cronbach's α = 0.908; 95% *CI*: 0.886–0.929), indicating stable construct representation across sensor-triggered experiential dimensions. The α-if-deleted values (0.905–0.908) suggest that the removal of any individual item would not materially improve reliability, implying the balanced contribution of items within the multiconstruct architecture. Most items exhibited acceptable discriminability (item–rest correlation ≥ 0.30). Three items (*PA*3, *I-SC*-So1, and *ISQ*-*EMP*1) fell below the conventional threshold; however, they were retained to preserve construct coverage related to affective activation and social/empathetic interaction under sensor-mediated conditions. These items were flagged for potential semantic refinement to enhance the clarity of scenario-specific IoT interpretation cues. From a sensing-system perspective, the high internal consistency indicates that environmental stimuli generated through the IoT architecture—such as location-triggered prompts, proximity-based interpretation activation, and interactive content delivery—were coherently perceived and cognitively structured by users. This supports the stability of the signal translation layer between sensor-generated inputs and latent experiential constructs.

All statistical analyses, including item analysis, EFA, CFA, and SEM, were conducted using the questionnaire response matrix as the primary modeling input. The responses were collected from visitors who interacted with the IoT-enabled smart interpretation service. The questionnaire instrument measured six constructs—*I-SC*, *ISQ*, *OSQ*, *PA*, *PV*, and *BI*—using a seven-point Likert scale ranging from 1 to 7. The IoT sensing components of the system, such as location-based triggers, proximity interactions, and node-based content delivery, were primarily used to operate the smart interpretation service and to generate the servicescape cues experienced by visitors. In contrast, the psychometric evaluation of measurement constructs and the subsequent hypothesis testing were based on visitors' post-experience perceptual survey responses. To clearly specify the datasets used at different stages of the analysis, two datasets were employed in this study. A pilot dataset (N = 150) was used exclusively for preliminary item analysis and reliability screening, including the examination of Cronbach's alpha, α-if-deleted values, and item–rest correlations, in order to evaluate item discrimination and refine questionnaire wording before conducting the main survey.

The main dataset (N = 700) was subsequently used for the full analytical pipeline consisting of EFA, CFA, and SEM, including the assessment of factorability through the KMO measure and Bartlett's test of sphericity, factor extraction, measurement model validation, and structural path estimation. In addition to reporting model estimation results, descriptive summaries of the questionnaire data were also examined to provide a clear overview of the raw survey evidence prior to the latent-variable analyses. Construct-level descriptive statistics, including the number of valid responses, missing values, mean, standard deviation, minimum and maximum values, skewness, and kurtosis, were calculated to assess the distributional characteristics of the survey responses. For the main survey dataset (N = 700), no missing values were observed for the construct scores owing to the enforced response settings during data collection. The mean and standard deviation of the constructs were as follows: ISQ = 4.712 ± 1.200, $I\text{-}SC$ = 4.889 ± 1.050, OSQ = 4.862 ± 1.515, PA = 4.766 ± 1.413, PV = 4.763 ± 1.574, and BI = 4.694 ± 1.668. These descriptive statistics provide an initial overview of the questionnaire responses and establish the empirical basis for the subsequent EFA, CFA, and SEM analyses.

3.2 Exploratory factor analysis

The quality and suitability of the questionnaire data were evaluated through a series of data-screening, reliability, and factorability assessments to ensure that the conclusions derived from the statistical analyses were supported by robust empirical evidence. The main survey dataset (N = 700) contained no missing values for the construct scores owing to the enforced response settings and completeness checks implemented during data collection, indicating that all questionnaires were fully completed. Prior to the main survey, a pilot sample (N = 150) was used to assess reliability and item discrimination. The pilot results demonstrated high internal consistency, with Cronbach's α = 0.908 (95% CI: 0.886–0.929) and a narrow range of α-if-deleted values (0.905–0.908), indicating a stable internal structure in which no single item disproportionately affected scale reliability.

Sampling adequacy and factorability were subsequently assessed to verify that the dataset was appropriate for latent-structure analysis. The KMO measure reached 0.954 and Bartlett's test of sphericity was highly significant (χ^2 = 17816.455, df = 1326, p < 0.001), confirming that the correlation matrix was suitable for factor analysis and subsequent latent-variable modeling. The high KMO value indicates substantial shared variance among variables, supporting the existence of a coherent latent structure underlying the measured constructs. Descriptive summaries of the questionnaire data were also examined to provide baseline evidence regarding the distributional properties of the raw survey responses. Construct-level descriptive statistics—including the number of valid responses, missing percentages, mean values, standard deviations, minimum and maximum values, skewness, and kurtosis—were calculated and are presented in

Table 2, allowing readers to evaluate the characteristics of the data prior to interpreting the model estimates.

EFA was conducted on the main sample (N = 700) by principal component analysis with Varimax rotation to obtain a parsimonious and interpretable factor structure. Factor retention followed the Kaiser criterion (eigenvalue > 1) and inspection of the scree plot, resulting in the extraction of 13 factors with eigenvalues ranging from 1.046 to 15.399. The rotated solution explained 67.5% of the total variance, with relatively balanced variance contributions across factors (approximately 4.9–5.7% each). Only salient loadings ($|\text{loading}| \geq 0.40$) were retained for interpretation. All retained items loaded strongly on their intended factors (0.664–0.793), and no substantial cross-loadings were observed, indicating a stable and interpretable simple structure. Item uniqueness ranged from 0.256 to 0.397 (communality ≈ 0.603–0.744), suggesting that a substantial proportion of item variance was captured by the extracted factors, and no items required removal owing to insufficient communality.

The extracted factor structure was also consistent with the predefined conceptual framework of the study. Specifically, the 13 factors corresponded to four first-order outcome constructs (*BI*, *PV*, *OSQ*, and *PA*) and nine first-order subdimensions underlying two second-order stimulus constructs (*ISQ*: *TAN*, *REL*, *RES*, *ASS*, *EMP*; and *I-SC*: *A*, *L*, *S*, *So*). This alignment between the theoretical operationalization and the empirical factor structure supports the validity of the measurement framework and provides a solid basis for proceeding to hierarchical CFA to validate the reflective–reflective second-order measurement model. Key outputs across the measurement validation pipeline are shown in Table 3. All subsequent statistical analyses—including item analysis, EFA, CFA, and SEM—were implemented using the open-source statistical platform JASP, with SEM estimation conducted through the lavaan engine. The analytical workflow followed a standardized procedure consisting of item analysis, EFA, CFA, and SEM, and the methodological description specifies the sequence of analytical steps and reported outputs at each stage to enhance the traceability and reproducibility of the analysis. In addition, a data-availability statement indicating that the anonymized questionnaire response matrices can be provided upon reasonable request for the independent verification or re-estimation of the models has been included.

Table 2
Descriptive statistics of questionnaire constructs (main survey, N = 700). Note: All constructs were measured on a 7-point Likert scale (1–7). Missing% is computed on construct scores.

Construct	No. of items	Mean	SD	Min	Max	Skewness	Kurtosis (excess)	Missing (%)
I-SC	16	4.889	1.050	2.312	7.000	−0.226	−0.749	0.0
ISQ	20	4.712	1.200	1.700	6.950	−0.246	−0.565	0.0
OSQ	4	4.862	1.515	1.000	7.000	−0.492	−0.583	0.0
PA	4	4.766	1.413	1.000	7.000	−0.354	−0.510	0.0
PV	4	4.763	1.574	1.000	7.000	−0.369	−0.792	0.0
BI	4	4.694	1.668	1.000	7.000	−0.291	−1.050	0.0

Table 3
Key outputs across the staged validation and SEM procedure.

Stage	Key statistics (this study)	Recommended criteria	Interpretation/decision
Item analysis (pilot, $N = 150$)	$\alpha = 0.908$ (95% *CI*: 0.886–0.929); α if deleted = 0.905–0.908; item–rest correlation mostly ≥ 0.30 (*PA*3, *I-SC*-So1, *ISQ-EMP*1 < 0.30)	$\alpha \geq 0.70$; item–rest correlation ≥ 0.30	Overall internal consistency was high. Three items were retained but flagged for wording/context refinement.
EFA (main sample, $N = 700$)	*KMO* = 0.954; Bartlett χ^2 = 17816.455, $df = 1326$, $p < 0.001$; 13 factors; cumulative variance = 67.5%; loadings = 0.664–0.793; communality ≈ 0.603–0.744	*KMO* ≥ 0.80; Bartlett $p < 0.05$; cumulative variance ≥ 50%; salient loadings ≥ 0.50	Sampling adequacy was excellent. The 13-factor solution matched the theorized first-order structure, supporting hierarchical CFA.
CFA (measurement model)	$\chi^2 = 1101.681$, $df = 1202$, $p = 0.987$; $\chi^2/df = 0.916$; *GFI* = 0.952; *SRMR* = 0.030; *RMSEA* = 0.000; *CFI* = 1.000; $\lambda = 0.741$–0.951; *CR* = 0.793–0.951; *AVE* = 0.548–0.768	*CFI*/*TLI* ≥ 0.90; *SRMR*/*RMSEA* ≤ 0.08; $\lambda \geq 0.70$; *CR* ≥ 0.70; *AVE* ≥ 0.50	Excellent fit and convergent validity; consistent with an engineering-style instrument validation pipeline
SEM (structural model)	$\chi^2 = 1236.510$, $df = 1257$, $p = 0.655$; $\chi^2/df = 0.984$; *GFI* = 0.938; *SRMR* = 0.037; *RMSEA* = 0.000; *CFI* = 1.000; key $\beta = 0.197$–0.539 (all 95% *CI*s exclude 0)	Fit: *CFI*/*GFI* ≥ 0.90; *SRMR*/*RMSEA* ≤ 0.08; significance: 95% *CI* excludes 0	Strong structural fit; results support the proposed S→O→R mechanism with significant direct and mediated effects

Note: *GFI* is Goodness-of-Fit Index.

Finally, the scope of generalizability of the findings was explicitly defined to avoid overstating the empirical implications of the study. The data were collected in a heritage tourism environment where visitors interacted with IoT-enabled interpretation services, including location-triggered information delivery, proximity-based interaction modules, and digital interpretation interfaces. Consequently, the findings are most directly applicable to comparable heritage or cultural tourism contexts in which similar IoT-based interpretation systems are deployed. This contextual boundary has been acknowledged in the discussion and limitations sections, and future cross-site studies are recommended to further examine the external validity and generalizability of the results.

3.3 Measurement model (CFA): structural stability and validity of the sensing–perception mapping

To ensure that the subsequent structural modeling reliably captures the translation of IoT sensor-generated environmental signals into perceptual constructs, the measurement model was evaluated through a sequential validation procedure. This included the assessment of multivariate normality, screening for improper solutions, the evaluation of overall model fit, and the verification of reliability, convergent validity, and discriminant validity. Such a procedure reduces risks of biased estimation and unstable inference in maximum likelihood-based SEM, and strengthens the credibility of the modeled sensing-to-perception transfer pathway.[24–27]

CFA and SEM were implemented in JASP, which operates on the R-based lavaan engine. Distributional assumptions and estimation stability were inspected prior to interpretation. When normality assumptions are not strictly satisfied, robust estimators such as MLR can be employed to enhance inferential robustness.(24–28) Before evaluating model fit, we screened for improper solutions that may indicate instability in the measurement structure, such as negative residual variances (Heywood cases) or λ approaching or exceeding unity.

The CFA results showed that all residual variances were positive (θ = 0.349–0.562), and standardized loadings (λ) were within acceptable ranges (0.662–0.807), with no values near problematic thresholds. This confirms that the measurement structure underlying the IoT-enabled stimulus constructs is statistically stable and free from estimation anomalies.(21,24) Using maximum likelihood estimation, the CFA demonstrated excellent model fit: χ^2 = 1101.681 (df = 1170, p = 0.923) and χ^2/df = 0.942. Absolute fit indices met or exceeded recommended thresholds (GFI = 0.945; $SRMR$ = 0.022; $RMSEA$ = 0.000), while incremental indices also indicated outstanding fit [Normed Fit Index (NFI) = 0.940; CFI = 1.000; Incremental Fit Index (IFI) = 1.004; Non-Normed Fit Index ($NNFI$) = 1.005; RFI = 0.932]. In cases of extremely high model fit and moderate-to-large sample sizes, indices such as IFI and $NNFI$ may slightly exceed 1 owing to computational rounding; such values are interpreted as approximately 1.00 and do not affect substantive conclusions. Parsimony and model stability were further supported by Parsimony Normed Fit Index ($PNFI$) = 0.829 and a critical N (CN) of 795.678. Collectively, these indices confirm that the measurement model satisfies established SEM criteria (e.g., $\chi^2/df < 3$; $CFI/NFI > 0.90$; $RMSEA < 0.08$; $PNFI > 0.50$; $CN > 200$), validating the structural integrity of the sensor-integrated construct architecture.(20–22)

Convergent validity was assessed through λ, CR, and AVE. All factor loadings were significant (λ = 0.662–0.807). CR values ranged from 0.792 to 0.872 and AVE ranged from 0.493 to 0.616. Although two subdimensions (*I-SC*-S: signage and symbolic cues and *I-SC*-So: social/operational order) exhibited AVE slightly below the 0.50 guideline (0.493), their CR values remained acceptable (0.802 and 0.792), and AVE values were very close to the threshold. From a sensing-system perspective, these dimensions capture informational-symbolic cues and social coordination under IoT mediation; slight AVE deviation likely reflects the inherently multidimensional perception of digitally augmented environmental cues rather than measurement instability. Therefore, convergent validity was considered acceptable.(17,27,28) The overall scale reliability was 0.952 and the overall CR was 0.972, indicating the strong internal coherence of the sensing-enabled stimulus–organism measurement structure. Discriminant validity was evaluated using the Fornell–Larcker criterion. For all constructs, the square root of AVE (0.702–0.785) exceeded interconstruct correlations, indicating adequate construct separability.(17,29) Although the correlation between ASS and EMP was relatively high (r = 0.707), it remained below the respective $\sqrt{AVE}$ values (ASS = 0.760; EMP = 0.767), supporting the distinctiveness of assurance and empathy perceptions within the IoT-enabled interpretation context. This confirms that sensor-triggered environmental cues and interpretation service attributes are cognitively differentiated rather than perceptually conflated. Overall, the CFA results validate the measurement layer as a stable representation of the sensing–perception mapping structure.(17,28–33)

3.4 SEM: Validation of the IoT sensing–behavior propagation mechanism

Before interpreting structural relations, SEM was screened for improper solutions. All endogenous constructs exhibited positive residual variances, and standardized path coefficients remained within plausible ranges, indicating no Heywood cases or convergence issues. The structural estimation was therefore considered stable for inference. The structural model demonstrated excellent fit: $\chi^2 = 1236.510$ ($df = 1257$, $p = 0.655$), with $\chi^2/df = 0.984$ (< 3). Absolute fit indices satisfied conventional thresholds ($GFI = 0.938$; $SRMR = 0.037$; $RMSEA = 0.000$), and incremental indices were similarly strong ($NFI = 0.932$; $CFI = 1.000$; $RFI = 0.929$). The slight exceedance of unity for *NNFI* (1.001) and *IFI* (1.001) is attributable to numerical rounding and is interpreted as approximately 1.00, indicating excellent model adequacy. These results confirm that the proposed S–O–R structural architecture provides a statistically coherent representation of the sensing-to-behavior propagation pathway.

Given the adequate model fit, we evaluated the hypothesized signal translation mechanism using standardized path coefficients (β) and their 95% *CI*. As summarized in Table 4, all primary paths from the stimulus layer (*I-SC*, *ISQ*) to the organism layer (*OSQ*, *PA*, *PV*) and from organism constructs to the response variable (*BI*) were positive and statistically significant, with *CI* excluding zero. These findings empirically support the proposed IoT sensing–perception–behavior mechanism. From a sensor modeling perspective, the structural results demonstrate that environmental signals orchestrated through the IoT architecture are not merely detected but effectively translated into evaluative and affective cognitive states, which subsequently propagate into *BI*. The validated pathway $I\text{-}SC/ISQ \rightarrow OSQ/PA \rightarrow PV \rightarrow BI$ represents a quantifiable transfer function linking distributed sensing inputs to measurable user outcomes. This confirms that the layered IoT data flow—perception, transmission, processing, and adaptive delivery—successfully generates structured experiential stimuli that affect downstream behavioral decisions.

Collectively, the structural results reveal a coherent S–O–R propagation chain that can be interpreted as a sensing-driven signal translation pathway from environmental stimuli to behavioral outcomes. Specifically, *I-SC*, representing sensor-orchestrated environmental cues,

Table 4
Structural path estimates of SEM.

Assumptions/paths	B	β	95% CI (β)
H1: $I\text{-}SC \rightarrow PA$	0.640	0.539*	[0.469, 0.609]
H2: $I\text{-}SC \rightarrow OSQ$	0.385	0.280*	[0.174, 0.387]
H3: $ISQ \rightarrow OSQ$	0.639	0.465*	[0.361, 0.569]
H4: $PA \rightarrow PV$	0.313	0.273*	[0.205, 0.342]
H5: $PA \rightarrow BI$	0.217	0.197*	[0.111, 0.283]
H6: $OSQ \rightarrow PV$	0.533	0.539*	[0.473, 0.604]
H7: $PV \rightarrow BI$	0.510	0.531*	[0.457, 0.604]

Note: B = unstandardized coefficient; β = standardized coefficient. *Significant effect when the 95% *CI* does not include zero.

exerts a significant positive effect on both *PA* (β = 0.539) and *OSQ* (β = 0.280). This indicates that environmental signals captured and processed through the IoT architecture—such as proximity-triggered interpretation, adaptive routing prompts, and interactive content activation—are effectively translated into affective responses and global quality appraisals. In parallel, *ISQ* strongly enhances *OSQ* (β = 0.465), suggesting that system reliability, responsiveness, and interaction design constitute a major evaluative channel through which sensor-triggered services are cognitively assessed in the smart heritage tour context. Within the organism layer, both the cognitive pathway (*OSQ* → *PV*, β = 0.539) and the affective pathway (*PA* → *PV*, β = 0.273) are statistically significant, demonstrating that *PV* emerges as a composite construct formed through dual processing routes.

From a sensor-system perspective, this implies that environmental sensing and service-execution signals are first encoded into quality judgments and emotional states, which are then integrated into a higher-order value assessment representing the overall utility of the interpretation experience. At the response stage, *PV* exerts a strong effect on *BI* (*PV* → *BI*, β = 0.531), while *PA* also contributes directly, though to a lesser extent (*PA* → *BI*, β = 0.197). The stronger effect of *PV* suggests that in IoT-enabled heritage environments, behavioral decisions such as revisit or recommendation are more proximally determined by integrated value evaluation than by affect alone. In engineering terms, this finding indicates that the sensing–processing–delivery loop does not directly translate into behavioral action; instead, its effectiveness is mediated through evaluative aggregation at the value layer. Taken together, the empirical estimates confirm a structured sensing–perception–behavior main chain: stimulus → (quality/affect) → value → *BI*. This chain can be interpreted as a validated transfer function linking distributed IoT sensing inputs to measurable behavioral outputs within a heritage interpretation context. Figure 3 visualizes the estimated SEM paths of the proposed S–O–R mechanism and is presented here to facilitate coefficient-to-path mapping prior to the mediation decomposition analysis.

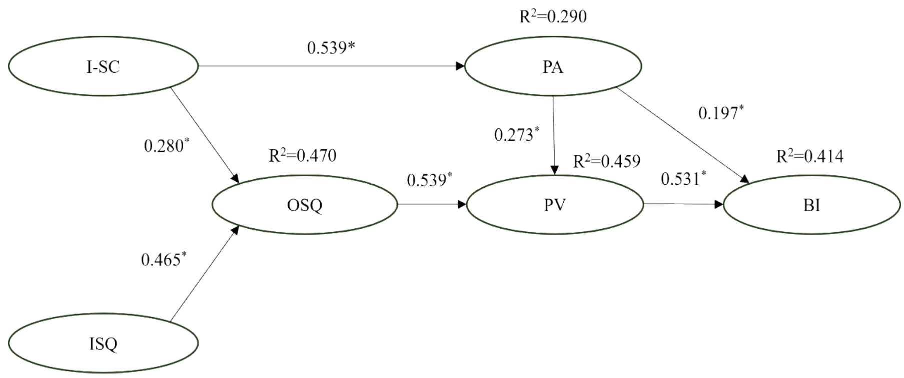

Fig. 3. SEM of the proposed S–O–R mechanism. Note: Solid arrows indicate hypothesized directional paths and * indicates significance (95% *CI* excludes zero).

3.5 Total effects and interpretation of the serial sensing mechanism

To further clarify how IoT sensor-derived stimulus constructs propagate through the modeled system, total and indirect effects were examined to determine whether *BI* is driven primarily through mediated organism states rather than direct stimulus activation. The results indicate that the effects of stimulus-layer variables on *BI* are predominantly transmitted via indirect pathways, consistent with the S–O–R signal propagation framework. Regarding total effects, *I-SC* demonstrates a significant overall effect on *BI* (β_{total} = 0.264, 95% *CI* [0.187, 0.342]). This suggests that environmental cues generated through sensor-triggered interpretation mechanisms do not directly convert into behavioral action; rather, their effect accumulates through downstream evaluative and affective processing layers. Similarly, *ISQ* exhibits a significant total effect on *BI* (β_{total} = 0.133, 95% *CI* [0.095, 0.171]). Notably, this effect is largely explained by its transmission through the quality–value pathway, indicating that system reliability and responsiveness function as upstream performance signals that must first be cognitively integrated before affecting decision outcomes.

Among the proximal determinants of *BI*, *PV* produces the strongest total effect (β_{total} = 0.531), confirming its role as the most immediate decision-level construct in the modeled architecture. *PA* shows a comparatively weaker overall effect (β_{total} = 0.342 when combining its direct and indirect components), reinforcing that affective activation alone is insufficient to drive behavioral commitment unless consolidated into value judgment. From a sensing-system perspective, this implies that emotional activation triggered by environmental signals must be structurally integrated into evaluative cognition before translating into stable *BI*. The decomposition of indirect effects further elucidates the internal propagation pathways. Three principal indirect chains originating from *I-SC* were statistically significant, with *CI* excluding zero. The first pathway, *I-SC* → *PA* → *BI* (β_{ind} = 0.106), reflects a direct affective transmission route in which sensor-orchestrated environmental cues evoke emotional activation that partially translates into *BI*. The second pathway, *I-SC* → *PA* → *PV* → *BI* (β_{ind} = 0.078), represents a serial affect-to-value conversion process, where affective responses are consolidated into *PV* before affecting behavior. The third pathway, *I-SC* → *OSQ* → *PV* → *BI* (β_{ind} = 0.080), illustrates a cognitive quality–value aggregation chain, emphasizing that environmental signals also operate through structured quality evaluation mechanisms.

In addition, the effect of *ISQ* on *BI* is fully transmitted through the canonical chain *ISQ* → *OSQ* → *PV* → *BI* (β_{ind} = 0.133). This indicates that interpretation service performance, as a system-execution attribute of the IoT architecture, affects behavioral outcomes only after being cognitively encoded into overall quality and subsequently integrated into value judgment. Collectively, these findings confirm that *PV* functions as the dominant proximal transfer node in the IoT sensing–behavior architecture. *I-SC* and *ISQ* do not directly trigger *BI*; instead, they propagate through sequential evaluative layers, *OSQ* and *PA*, which converge into value assessment before affecting revisit and recommendation decisions. From an engineering modeling perspective, the results validate a hierarchical transfer function in which distributed sensing inputs are progressively aggregated into higher-order cognitive states prior to generating measurable behavioral outputs.

4. Discussion

The present findings provide the empirical validation of how an IoT sensor-enabled heritage interpretation system translates environmental sensing inputs into measurable behavioral outcomes through a structured S–O–R pathway. Rather than treating smart interpretation as a mere technological deployment, the results demonstrate that the effectiveness of such systems depends on how sensing architecture is operationalized into perceptible servicescape cues and service-quality signals. First, *I-SC* functions as the primary front-end lever in the sensing–perception transfer chain. The significant effects of *I-SC* on both *PA* (β = 0.539) and *OSQ* (β = 0.280) indicate that distributed sensing inputs—such as proximity-triggered interpretation, adaptive routing prompts, interactive information nodes, and coordinated on-site social guidance—must be coherently integrated into an interpretable environmental structure. In engineering terms, the perception and rule-based processing layers of the IoT architecture must not only capture spatial-temporal signals but also transform them into structured, user-recognizable environmental cues. The data flow from sensor detection to adaptive content activation becomes meaningful only when it is cognitively encoded as atmosphere, layout functionality, informational clarity, and social coordination. Therefore, installing sensing devices alone does not guarantee experiential improvement; system integration across sensing, processing, and application layers is required to generate perceptible servicescape effects.

Second, *ISQ* operates as a key conversion interface between sensor-execution performance and global quality appraisal. The strong effect of *ISQ* on *OSQ* (β = 0.465) confirms that reliability, responsiveness, assurance, and empathy represent critical performance channels through which IoT-triggered services are cognitively evaluated. However, the structural results show that *BI* is not directly driven by perceived quality alone. Instead, intention formation depends primarily on *PV* and, to a lesser extent, affective activation (*PA*). This indicates that interpretation quality functions as an upstream performance signal within the IoT data-flow architecture, affecting behavioral outcomes through the quality → value → intention pathway rather than through a direct shortcut. From a sensing-system modeling perspective, this suggests that system responsiveness and content accuracy must ultimately be consolidated into user-perceived utility before affecting revisit or recommendation decisions.

Third, *PV* emerges as the dominant proximal mechanism linking the IoT sensing architecture to behavioral outcomes. The effect of *PV* on *BI* (β = 0.531) is substantially stronger than that of *PA* (β = 0.197), highlighting that decision-level responses are primarily governed by integrated value appraisal rather than emotion alone. In practical engineering and system-management terms, performance indicators for IoT-enabled interpretation systems should therefore emphasize measurable value gains, including time efficiency, reduced search or navigation effort, improved information accessibility, enhanced learning yield, and minimized cognitive load. These dimensions reflect how effectively sensor-derived environmental signals are transformed into tangible user benefits through the data processing and content delivery pipeline. Collectively, the findings validate a hierarchical sensing–evaluation–decision structure in which environmental signals captured at the perception layer propagate through affective and cognitive aggregation nodes before reaching behavioral output. Figure 3 visualizes this propagation structure, illustrating how stimulus-layer constructs (*I-SC* and *ISQ*) transmit through organism-layer mediators (*OSQ*, *PA*, and *PV*) to *BI*.

The model confirms that IoT sensing integration achieves behavioral effectiveness only when distributed data streams are coherently orchestrated into structured experiential signals and subsequently consolidated into value judgments. From a broader sensor-integration standpoint, the results indicate that the effectiveness of IoT-enabled heritage systems lies not only in their data acquisition capability but also in the stability and clarity of the sensing–processing–delivery loop. A well-designed architecture ensures that environmental sensing inputs remain distinguishable across perceptual channels while converging into higher-order evaluative constructs. This structured signal aggregation mechanism may inform the design of other sensor-enabled service systems beyond heritage tourism, including museum guidance, cultural exhibition platforms, and smart public information infrastructures.

From the perspective of sensing technology, we contribute to the application and evaluation of IoT-based sensing systems in cultural heritage environments. Specifically, the proposed IoT sensor-enabled interpretation system demonstrates how heterogeneous sensing technologies—such as proximity detection, location sensing, and node identification—can be integrated into a layered sensing–transmission–processing–application architecture to support context-aware heritage interpretation services. Through this architecture, raw environmental sensing signals are transformed into adaptive interpretation triggers and interactive information delivery mechanisms, enabling real-time sensing-driven visitor guidance and content activation. Beyond system deployment, we contribute to the sensing research domain by introducing a quantitative evaluation framework that links sensor-generated environmental signals with human perception and behavioral outcomes. By integrating sensing architecture with structural equation modeling, the proposed approach provides a reproducible method for analyzing how sensor-derived environmental cues affect service perception, emotional responses, and behavioral intentions. This framework demonstrates an important application of the sensing concept in human-centered environments, illustrating how sensor-enabled systems can extend beyond data acquisition to support intelligent service design and user-experience optimization in heritage tourism contexts.

5. Conclusions

In this study, we investigated an IoT sensor-enabled heritage interpretation system and empirically validated a structured S–O–R mechanism within a real-world heritage tourism setting. The findings demonstrate that the effectiveness of smart interpretation does not arise from technology deployment alone, but from how distributed sensing inputs are transformed into perceivable servicescape cues and service-quality signals, and subsequently consolidated into evaluative and behavioral outcomes. From a sensing perspective, we demonstrate a practical application of heterogeneous sensor technologies—such as proximity detection, node identification, and location-based sensing—within a unified IoT architecture to support context-aware interpretation services in heritage environments. By integrating sensing modules with a data-processing and content-delivery pipeline, the proposed framework illustrates how environmental sensing signals can be translated into meaningful user-centered interpretation experiences. The results confirm a hierarchical sensing–evaluation–decision pathway: *I-SC* and *ISQ* affect *OSQ* and *PA*, which are then integrated into *PV*, ultimately driving *BI*. Among these constructs, *PV* emerged as the most decision-proximal driver, indicating that behavioral impact is achieved primarily through value aggregation rather than affective activation alone. This finding highlights that the effectiveness of IoT sensing applications in cultural heritage services lies not only in data acquisition capabilities but also in the ability of sensing architectures to generate perceivable environmental cues that shape human perception and behavioral responses. The main contribution lies in establishing an engineering-oriented validation framework that links sensing architecture to human-factor outcomes through structural modeling. By abstracting the IoT system into a layered sensing–transmission–processing–application architecture and quantifying its signal propagation pathway, we provide a reproducible approach for evaluating how sensor-derived environmental inputs translate into measurable behavioral responses. In this regard, the study contributes to the application domain of sensors by demonstrating how sensing concepts can be integrated with human-centered system evaluation methods, providing a bridge between sensor-enabled infrastructure and user-perception modeling. From a system-design perspective, the coherent integration of servicescape cues and interpretation quality within the sensing data-flow pipeline is essential. System optimization should prioritize reliability, responsiveness, and structured content activation to enhance *PV* under real visitation conditions. Overall, the results indicate that the success of IoT-enabled interpretation systems depends on the stability and clarity of the sensing–processing–delivery loop that transforms environmental data into structured experiential signals. Nevertheless, several limitations remain. First, the sensing infrastructure employed in this study primarily focuses on location- and interaction-based sensing, while other sensing modalities—such as environmental monitoring sensors or user-state sensing—were not incorporated. Second, the empirical validation was conducted within a single heritage tourism site, which may limit the generalizability of the findings. Future research may address these issues by integrating additional sensor types and testing the sensing architecture across multiple cultural heritage environments to further explore the potential of sensor-enabled interpretation systems.

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