

Article

AI-Based Interpretation and Conservation-Oriented Visitor Response at World Heritage Sites: Authenticity, Parasocial Interaction, and Emotional Experience

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Abstract

AI-based interpretation is increasingly used in heritage tourism, yet its relationship with stewardship-relevant visitor responses remains insufficiently theorised. Drawing on the stimulus-organism-response framework, this study examines how visitor-perceived AI-based interpretation is associated with emotional experience and conservation-oriented behavioural intention at the Emei Mountain-Leshan Giant Buddha World Heritage Site in China. Survey data from 418 adult visitors collected in 2025 were analysed using partial least squares structural equation modelling. AI-based interpretation was positively associated with perceived authenticity ($\beta = 0.657$), parasocial interaction ($\beta = 0.530$), emotional experience ($\beta = 0.355$), and conservation-oriented behavioural intention ($\beta = 0.117$). The direct association with conservation-oriented behavioural intention was small. Approximately four-fifths of the total AII-CBI association was accounted for by statistically significant indirect pathways through authenticity, parasocial interaction, and emotional experience. Emotional experience was the strongest proximal predictor of conservation-oriented behavioural intention ($\beta = 0.422$). Supplementary indirect-effect and moderation analyses further indicate that authenticity-based and relation-based pathways link AI interpretation with stewardship-oriented intention, and that the AII-authenticity association is stronger among first-time visitors. These findings extend smart-tourism research beyond technology acceptance by showing how AI interpretation can operate as a heritage-communication resource when it is perceived as authentic, socially engaging, and emotionally meaningful.

Keywords: AI-based interpretation; World Heritage Sites; perceived authenticity; parasocial interaction; emotional experience; conservation behavioural intention; heritage tourism

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1. Introduction

Artificial intelligence is reshaping the communicative infrastructure of tourism. It allows destinations to personalise narrative content, respond conversationally to visitor enquiries, and adjust interpretation to different visitor needs (Samara et al., 2020; Xu et al., 2024). In heritage tourism, however, this shift cannot be understood as service optimisation alone. Interpretation is a symbolic practice through which heritage value is translated into visitor understanding, memory, identity, and ethical orientation toward the past (Poria et al., 2006; Ruan et al., 2024). When interpretation becomes algorithmically mediated, the central question is not only whether visitors find the system useful. It is also whether AI-mediated interpretation can support, rather than dilute, a meaningful heritage encounter. This study foregrounds that interpretive question.

This issue is particularly important at World Heritage Sites (WHSs), whose UNESCO designation places them within a global framework of preservation. WHS interpretation is expected to communicate outstanding universal value, foster intercultural understanding, and encourage public commitment to conservation. Unlike ordinary tourist attractions, these sites operate under a dual mandate of visitor experience and preservation. AI systems may extend interpretive reach, lower linguistic and cognitive barriers, and tailor narratives to heterogeneous audiences. Yet, if detached from the historical, religious, or ecological substance of a site, they may also produce superficial engagement, over-personalised narratives, or a loss of cultural authority. The legitimacy of AI as a heritage interpreter therefore depends on interpretive depth and cultural fidelity, not on technological novelty alone.

Existing AI-tourism research has produced substantial evidence on adoption, perceived usefulness, service quality, trust, and behavioural intention to use intelligent systems (Samara et al., 2020; Xu et al., 2024). This body of work is theoretically important, but it remains largely anchored in utilitarian and transactional frames, especially technology-acceptance and service-quality logics. It has also had limited engagement with two adjacent bodies of literature that are central to heritage settings. Critical heritage scholarship views interpretation as an authorised discourse that selects, frames, and legitimises meanings of the past (Smith, 2006). Critical-AI scholarship warns that machine-generated narration can encode bias, obscure provenance, and produce fluent but unfounded content (Crawford, 2021; Bender et al., 2021). Read together, these bodies of literature suggest that algorithmic interpretation at heritage sites raises questions of cultural authority and credibility, not merely usability. Heritage-tourism research therefore needs an analytic lens that can connect digitally mediated interpretation with authenticity appraisals, quasi-social engagement with technological agents, emotional experience, and conservation-oriented response (Li et al., 2024; Weng et al., 2020).

This study addresses that gap by positioning perceived authenticity (PA) and parasocial interaction (PSI) as two theoretically distinct organismic mechanisms within a stimulus-organism-response (S-O-R) framework. PA captures whether AI-mediated narratives are perceived as credible, place-grounded, and faithful to heritage meanings, building on Wang's (1999) object-related and existential distinction and later heritage-tourism elaborations (Yi et al., 2019; Domínguez-Quintero et al., 2019). PSI captures the socially vivid, one-sided sense of companionship that visitors may develop with a conversational or anthropomorphised AI interpreter, drawing on media studies and recent AI-tourism research (Horton & Wohl, 1956; Xu et al., 2024; Ye et al., 2021). Together, PA and PSI help explain why similar intelligent interfaces may be experienced either as a thin digital layer added to the visit or as an affectively engaging route into heritage meaning. The study asks whether these two organismic pathways link AI-based interpretation with conservation-oriented behavioural intention, and whether emotional experience functions as the proximal affective bridge in that relationship.

The study makes four contributions. First, it relocates AI-based interpretation from a service-efficiency frame to the domain of heritage communication, cultural translation, and meaning-making (Ham, 2013; Tilden, 1977). Second, it develops a dual-mechanism account that integrates authenticity-based appraisal with parasocial relational engagement. Third, it links emotional experience with conservation-oriented behavioural intention, extending smart-tourism research from acceptance-centred outcomes toward stewardship-relevant responses (Li et al., 2024; Ruan et al., 2024). Fourth, it examines these relationships in the Emei Mountain-Leshan Giant Buddha WHS, a mixed-heritage context where sacred mountain landscape, monumental Buddhist carving, and conservation sensitivity coexist. Figure 1 summarises the study's innovation architecture.

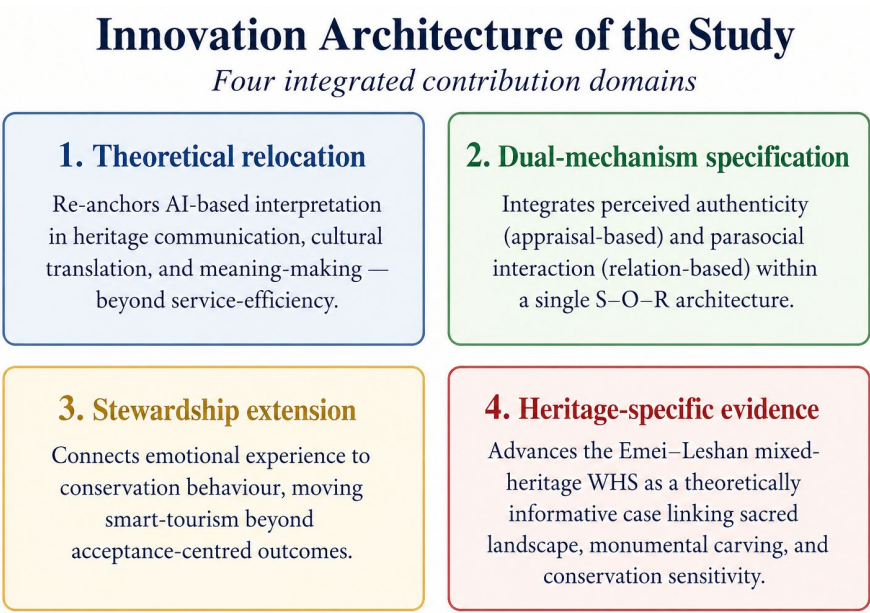


Figure 1. Innovation architecture of the study. Note. The figure summarises the four contribution domains of the study: (i) repositioning AI interpretation within heritage communication; (ii) specifying perceived authenticity and parasocial interaction as parallel mechanisms; (iii) extending behavioural attention from technology acceptance to stewardship-relevant outcomes; and (iv) situating the model in a mixed-heritage WHS case context.

2. Literature Review and Research Gap

AI has become increasingly visible in tourism and hospitality, reshaping destination communication, service personalisation, visitor analytics, recommendation systems, and conversational assistance (Samara et al., 2020; Xu et al., 2024). This literature has clarified why tourists adopt intelligent technologies and how such systems improve convenience, responsiveness, and perceived service quality. Heritage interpretation, however, is not service delivery in the conventional sense. Its purpose is not only to reduce uncertainty, but to translate cultural and ecological significance into visitor understanding (Poria et al., 2006; Weng et al., 2020). A heritage-sensitive account of AI must therefore ask whether AI interpretation supports meaning, credibility, and preservation-oriented awareness, not only whether it is accepted, used, or enjoyed.

Emotional experience occupies a central position in tourism scholarship because travel is valued through affective resonance, memory, and self-relevance as well as through information acquisition (De Rojas & Camarero, 2008; Prayag & Del Chiappa, 2023). In heritage contexts, affective response is intensified by symbolic landscapes, historical depth, sacred associations, and collective identity (Domínguez-Quintero et al., 2019; Yi et al., 2019). Prior research shows that interpretation can turn factual knowledge into personally meaningful understanding, and that emotional experience is linked with satisfaction, place attachment, and revisit intention. The emotional implications of AI-mediated interpretation nevertheless remain under-theorised. Existing AI-tourism studies have tended to treat AI mainly as a stimulus for trust, ease of use, or satisfaction (Xu et al., 2024), leaving its affective and existential implications less clearly specified.

Conservation-oriented behavioural intention is a second outcome that warrants closer attention. The sustainability of WHSs depends partly on whether visitors translate appreciation into responsible conduct, willingness to protect site values, and support for preservation norms (Weng et al., 2020). Recent research links authenticity, cultural experience, place attachment, and affectively rich interpretation with conservation-oriented intention (Li et al., 2024; Ruan et al., 2024). What remains less clear is whether AI-based in-

terpretation is associated with such pro-conservation responses, or whether its behavioural relevance is limited to convenience, novelty, and adoption. The theoretical link is likely to run through organismic states. AI interpretation appraised as authentic may provide credible heritage meanings on which moral responsibility for preservation can rest. Interpretation experienced as socially present may embed conservation messages within a personally addressed, quasi-social frame.

Authenticity remains a foundational construct in tourism and heritage research. Wang's (1999) distinction between object-related and existential authenticity is especially relevant here because AI interpretation does not alter the material authenticity of a heritage object. It may, however, shape whether visitors experience the encounter as meaningful, credible, and self-relevant. Subsequent work has further differentiated authenticity into objective, constructive, and existential dimensions (Yi et al., 2019; Domínguez-Quintero et al., 2019). This work shows that mediated interpretation can support authenticity when it is perceived as historically grounded and culturally faithful. Parasocial interaction (PSI) provides a complementary relational lens. Originating in media studies (Horton & Wohl, 1956), PSI explains how audiences form socially meaningful but one-sided relationships with mediated personae. As conversational AI becomes more socially responsive, PSI has been extended into AI-tourism research to explain why visitors may respond to AI interpreters as more than neutral information channels (Xu et al., 2024; Ye et al., 2021).

Human-computer interaction (HCI) and communication research provide further theoretical grounding for parasocial responses to AI agents. Reeves and Nass's (1996) Media Equation and Nass and Moon's (2000) work on social responses to computers show that humans often apply social schemata to technological agents. Sundar's (2008) MAIN model explains how agency, modality, interactivity, and navigability heuristics shape the perceived credibility of machine-mediated content. Mori et al.'s (2012) uncanny-valley thesis also cautions that excessive anthropomorphism can turn relational warmth into discomfort. These perspectives clarify why AI heritage interpreters may elicit relational engagement, while also delimiting when such engagement is likely to remain constructive.

Taken together, these observations reveal a heritage-specific research gap with both theoretical and ethical significance. Smart-tourism research remains largely anchored in adoption-centred outcomes and has paid comparatively less attention to AI's experiential, affective, and stewardship-relevant implications. Heritage-interpretation research, although rich in authenticity and emotion, has rarely examined intelligent or conversational interpretive agents. Parasocial-interaction research has demonstrated the relational salience of mediated communication, but it has only recently entered heritage-interpretation debates. Heritage ethics and critical AI scholarship further caution that algorithmic interpretation is not a neutral delivery mechanism: if it is not governed through expert review and cultural accountability, it may amplify cultural authority, simplify contested meanings, or reproduce biased and unverifiable narratives (Smith, 2006; Bender et al., 2021; Crawford, 2021). Accordingly, this study is organised around one core theoretical proposition: in WHS contexts, AI-based interpretation is associated with conservation-oriented visitor response when it is perceived as culturally credible, relationally engaging, and emotionally meaningful. This proposition integrates the empirical sub-issues of direct association, mediation, and affective transmission within a single heritage-specific S-O-R framework.

3. Theoretical Framework

This study adopts the stimulus-organism-response (S-O-R) perspective (Mehrabian & Russell, 1974) as its meta-framework and integrates it with authenticity theory and parasocial interaction theory. S-O-R is appropriate for this question for three reasons. First, the research interest lies in internal appraisal and affective processing, namely au-

thenticity, relational engagement, and emotion, which intervene between an external interpretive stimulus and behavioural response. Second, S-O-R accommodates parallel organismic mechanisms, which is necessary for testing whether authenticity and parasocial interaction operate as complementary pathways. Third, S-O-R is well established in heritage- and emotion-focused tourism research, providing a comparable theoretical baseline. Within this architecture, AI-based interpretation functions as the external stimulus. Perceived authenticity and parasocial interaction are conceptualised as organismic states that translate the interpretive stimulus into cognitive-evaluative appraisal of heritage meaning and relational involvement with the interpretive agent. Emotional experience and conservation behavioural intention represent the response stratum, with emotional experience theorised as the proximal affective bridge between interpretive engagement and stewardship-oriented intention.

This theoretical framing departs from the assumption that AI is merely a functional channel for efficient information delivery. In heritage settings, an AI interpreter may operate as a technologically mediated co-interpreter whose narrative accuracy, cultural sensitivity, dialogic responsiveness, and social presence shape how visitors understand the destination. The construct is therefore treated not simply as a digital service feature, but as an ethically constrained form of heritage mediation. Authenticity and parasocial interaction are specified as explanatory mechanisms rather than as ancillary covariates. Authenticity captures whether interpretive content is culturally credible and place-grounded, whereas PSI captures whether the interpretive form is relationally engaging and socially present. The central proposition is that interpretive credibility and relational involvement together help explain whether AI-supported interpretation is experienced as culturally convincing, emotionally engaging, and behaviourally relevant. The proposed conceptual model is presented in Figure 2.

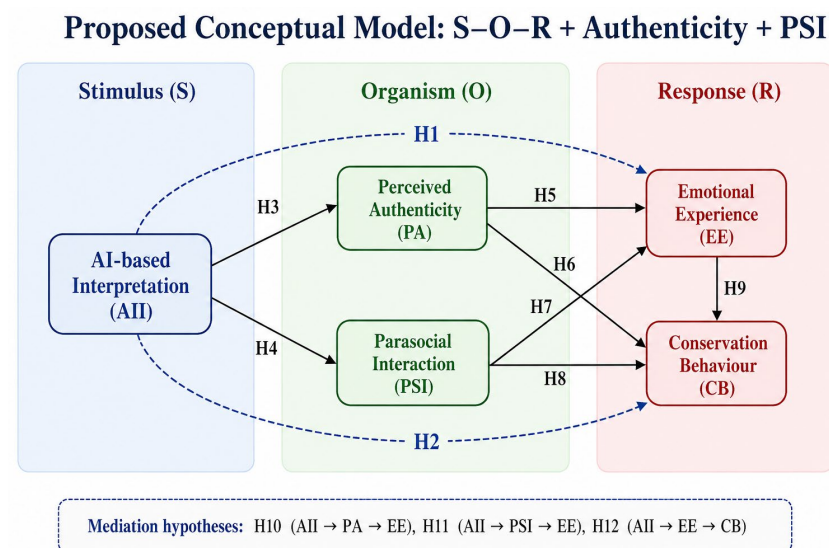


Figure 2. Proposed conceptual model of the study. Note. The model positions AI-based interpretation as a stimulus (S) linked with visitors through two parallel organismic mechanisms (O): perceived authenticity (PA), an appraisal-based mechanism, and parasocial interaction (PSI), a relation-based mechanism. These mechanisms are modelled as antecedents of emotional experience (EE) and conservation behavioural intention (CBI), with EE additionally serving as the proximal affective bridge between AI interpretation and CBI.

4. Hypotheses Development

AI-based interpretation may be associated with a richer visitor experience when it turns a static informational supply into responsive, personalised, and context-sensitive

communication. When an intelligent interpreter explains symbolic meanings, links visible site features to historical and religious narratives, and adapts interpretive depth to visitors' knowledge needs, it may be linked with greater attention, curiosity, and affective resonance (Liu, 2020; Xu et al., 2024). In WHS contexts, such interpretation may also be associated with conservation-oriented response because it clarifies the site's outstanding value, vulnerability, and the visitor's relational responsibility toward preservation (Weng et al., 2020). Consistent with S-O-R logic and the cross-sectional design, the study hypothesises positive associations rather than strict causal effects.

Perceived authenticity constitutes the first explanatory mechanism. In heritage tourism, authenticity is not confined to the material originality of objects. It also concerns whether interpretation is experienced as credible, culturally grounded, and connected to place (Wang, 1999; Yi et al., 2019). AI-based interpretation may be associated with stronger authenticity appraisals when its narratives are historically accurate, locally sensitive, and aligned with the site's cultural logic, conditions that recent heritage-tourism studies identify as important for authentic experience (Domínguez-Quintero et al., 2019; Li et al., 2024). An authentic interpretive encounter is, in turn, expected to be linked with deeper emotional experience because visitors are more likely to be moved by meanings they regard as genuine. It is also expected to be linked with conservation behavioural intention because credible heritage meanings can strengthen moral responsibility toward preservation (Ruan et al., 2024).

Parasocial interaction constitutes the second explanatory mechanism. Conversational AI can provide a socially vivid sense of being addressed, guided, and accompanied by an interpretive agent. Such relational cues invite visitors to experience the system as responsive, attentive, and companionable, echoing foundational PSI mechanisms identified by Horton and Wohl (1956) and recent evidence from AI-mediated tourism services (Xu et al., 2024; Ye et al., 2021). This mediated companionship is especially relevant in heritage environments, where visitors often require narrative guidance to connect material features with cultural meanings. PSI is therefore theorised to be positively associated with emotional experience by increasing the vividness and addressivity of interpretation, and with conservation behavioural intention by embedding preservation messages within a quasi-relational frame.

The downstream pathways involving authenticity and parasocial interaction are theorised to be both affective and behavioural. Authenticity is expected to be associated with stronger emotional experience by rendering the encounter meaningful and place-grounded. PSI is expected to be associated with stronger emotional involvement by making interpretation feel vivid, addressed, and relationally proximate. Both organismic mechanisms are also expected to be positively associated with conservation behavioural intention because credible meanings and relationally engaging messages can make heritage protection more salient and personally meaningful. The dual-mechanism specification integrates appraisal-based and relation-based explanations within a heritage-specific S-O-R architecture.

Emotional experience is further specified as a proximal correlate of conservation behavioural intention. In WHS tourism, emotionally meaningful encounters are associated with the conversion of abstract awareness of heritage value into personal attachment, moral concern, and stewardship-oriented intention (Prayag & Del Chiappa, 2023; Ruan et al., 2024). Visitors who feel moved, inspired, or connected during interpretation are therefore expected to be more likely to support protective behaviours during and after the visit. By the same logic, emotional experience is theorised as the affective conduit through which AI interpretation is linked with appraisal, relational engagement, and behavioural response. Because perceived authenticity and parasocial interaction are also theorised to be

linked with both emotional experience and conservation behavioural intention, the model additionally implies complementary indirect pathways from AII to CBI through PA and PSI, and sequential pathways through PA/PSI and EE.

The strength of the appraisal-based pathway from AI-based interpretation to perceived authenticity is expected to vary with visitors' prior anchoring of the site. First-time visitors arrive with relatively weak pre-formed authenticity beliefs and may therefore rely more heavily on AI-supported interpretation when constructing perceptions of credibility, historical grounding, and cultural meaning. Repeat visitors, by contrast, may possess established authenticity schemata that leave less room for the interpretive stimulus to shift appraisal. Visit frequency is therefore theorised as a boundary condition on the AII → PA association, with the association expected to be stronger among first-time visitors.

Accordingly, the study proposes the following hypotheses:

- H1.** *AI-based interpretation is positively associated with tourists' emotional experience.*
- H2.** *AI-based interpretation is positively associated with tourists' conservation-oriented behavioural intention.*
- H3.** *AI-based interpretation is positively associated with perceived authenticity.*
- H4.** *AI-based interpretation is positively associated with parasocial interaction.*
- H5.** *Perceived authenticity is positively associated with tourists' emotional experience.*
- H6.** *Perceived authenticity is positively associated with tourists' conservation-oriented behavioural intention.*
- H7.** *Parasocial interaction is positively associated with tourists' emotional experience.*
- H8.** *Parasocial interaction is positively associated with tourists' conservation-oriented behavioural intention.*
- H9.** *Emotional experience is positively associated with conservation-oriented behavioural intention.*
- H10.** *Perceived authenticity mediates the relationship between AI-based interpretation and emotional experience.*
- H11.** *Parasocial interaction mediates the relationship between AI-based interpretation and emotional experience.*
- H12.** *Emotional experience mediates the relationship between AI-based interpretation and conservation behavioural intention.*
- H13.** *Visit frequency moderates the association between AI-based interpretation and perceived authenticity, such that the positive association is stronger for first-time visitors than for repeat visitors.*

5. Materials and Methods

5.1. Research Design

This study uses a quantitative, cross-sectional visitor survey to examine associations among AI-based interpretation, perceived authenticity, parasocial interaction, emotional experience, and conservation behavioural intention at a WHS. A survey design is appropriate because the model centres on latent psychological constructs whose relationships require

simultaneous estimation. PLS-SEM was selected because the study is prediction-oriented, includes multiple indirect paths, and estimates a relatively complex nomological network of reflective constructs. This choice is methodological and does not imply that PLS-SEM is universally superior to covariance-based SEM. Because the data are cross-sectional and visitor-reported, the model is interpreted as evidence of theory-consistent association and mediation patterns rather than as proof of temporal ordering, strict causality, or exclusion of all third-variable explanations.

5.2. Case Context

The Emei Mountain-Leshan Giant Buddha WHS in Sichuan Province, China, provides a theoretically informative empirical context because it is a mixed heritage landscape rather than a single-monument destination. The property was inscribed on the UNESCO World Heritage List in 1996 under criteria (iv), (vi), and (x), with a property area of 15,400 ha and a buffer zone of 46,900 ha ([UNESCO World Heritage Centre, n.d.](#)). Its outstanding universal value joins Buddhist sacred geography, traditional temple architecture, the 71 m Leshan Giant Buddha carved in the eighth century, and exceptionally diverse mountain vegetation. The site's visitor-service actions also provide institutional context for examining digital and intelligent guide functions ([Leshan Giant Buddha Scenic Area Administrative Committee, 2021](#)). This combination makes the site suitable for examining how AI-based interpretation is associated with visitor-level authenticity appraisal, relational engagement, emotion, and conservation behavioural intention.

The case is also analytically valuable because interpretation at Emei-Leshan must bridge several meaning systems at once, including tangible monumentality, living religious tradition, ecological sensitivity, crowd movement, and rules for responsible visitation. In such a setting, AI interpretation is more than a digital convenience. It can function as a curatorial interface that selects, sequences, and personalises cultural explanation while guiding tourists through a conservation-sensitive landscape.

Within this case site, AI-based interpretation was operationalised as visitors' perceived encounter with the destination's heterogeneous mobile intelligent interpretation ecology rather than with a single proprietary platform. For this study, AI-based interpretation refers to visitor-facing interpretive systems that combine heritage content with one or more intelligent functions, such as algorithmic matching, adaptive sequencing, conversational responsiveness, location-sensitive delivery, or intelligent retrieval. This makes it conceptually and operationally distinct from a general digital audio guide. A conventional digital audio guide primarily delivers pre-recorded linear narration, whereas AI-based interpretation adds adaptive, data-mediated, or interactive functions that shape how heritage meanings are selected, sequenced, and personalised. The realised sample used six versioned AI-interpretation systems across five system types: a smart-guide mobile application ($n = 190$, deployed in three sequential versions, v2.1/v2.2/v2.3); a structured AI audio guide embedded in the intelligent interpretation ecology ($n = 121$); a WeChat scenic-area mini-programme ($n = 66$); on-site intelligent kiosks ($n = 28$); a beta AR heritage guide ($n = 11$); and a small residual category ($n = 2$). The system name, version label, system type, survey site, and on-site exposure duration were recorded for every respondent and are reported in Tables S3, S5 and S6. Mean exposure was 18.9 min ($SD = 6.7$; range 4–41), indicating that the construct refers to a substantive interpretive encounter rather than a fleeting interface exposure. This heterogeneous operationalisation strengthens ecological validity within the site's interpretive ecology and allows system-type reproducibility checks, while also delimiting the study as an analysis of visitor-perceived AI-mediated interpretation across a realised system mix rather than the internal architecture of a single proprietary or generative-AI engine.

Table 1 and Figures 3 and 4 summarise the case-site logic. Together, they position Emei-Leshan as a dense interpretive environment in which AI-mediated explanation may be associated with perceived authenticity, parasocial interaction, emotional experience, and conservation behavioural intention.

Table 1. Case-site profile and analytical relevance.

Dimension	Case-Site Evidence	Analytical Relevance to This Study
Official property	Mount Emei Scenic Area, including Leshan Giant Buddha Scenic Area	A mixed WHS where natural, cultural, religious, and managerial meanings are simultaneously salient.
UNESCO status	Inscribed in 1996 under criteria (iv), (vi), and (x); property area 15,400 ha; buffer zone 46,900 ha.	Supports a case design centred on outstanding universal value, authenticity, integrity, and conservation communication.
Heritage configuration	Sacred mountain landscape, Buddhist temple architecture, Leshan Giant Buddha, and diverse vegetation.	Requires interpretation that connects material evidence, symbolic meaning, ecological sensitivity, and visitor responsibility.
Digital interpretation context	Mobile smart-guide services, QR/audio explanation, route navigation, and online interpretive content are part of the visitor-service ecology.	Makes AI-based interpretation a plausible stimulus within the on-site visitor journey rather than an abstract technology-use scenario.
Research implication	The site combines high symbolic density with conservation pressure and mass-tourism visitation.	Provides a strong empirical setting for testing whether AI interpretation activates PA, PSI, EE, and CBI.

Note. WHS = World Heritage Site; PA = perceived authenticity; PSI = parasocial interaction; EE = emotional experience; CBI = conservation behavioural intention. UNESCO facts are drawn from the official World Heritage Centre property page.

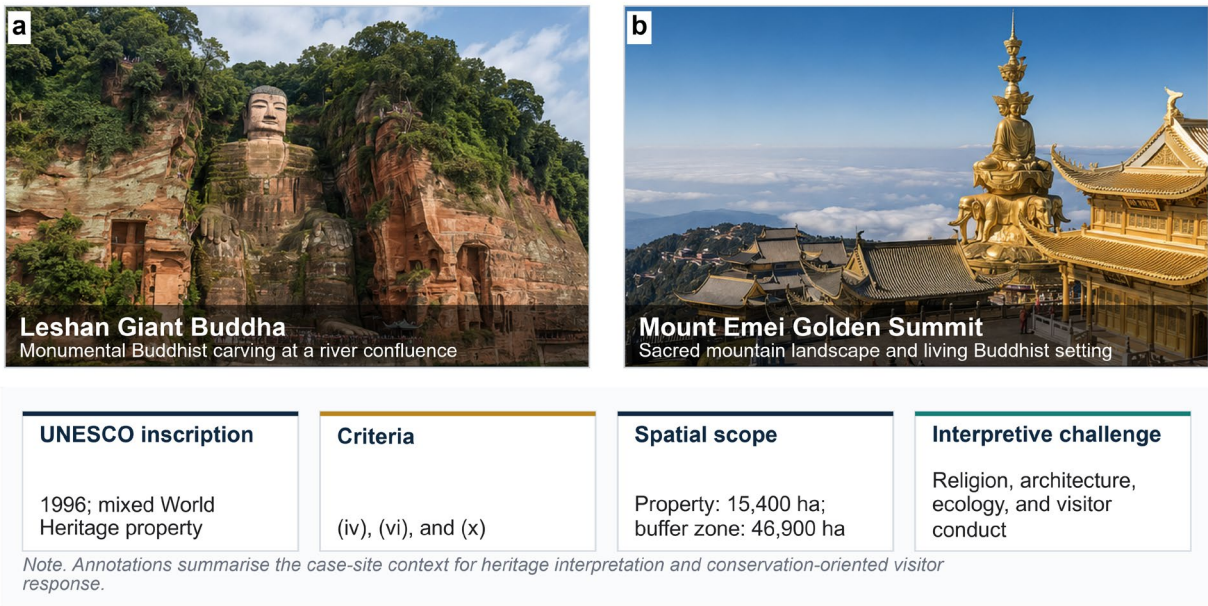


Figure 3. Case-site context of Emei Mountain-Leshan Giant Buddha World Heritage Site. (a) Leshan Giant Buddha; (b) Mount Emei Golden Summit. Photo credits: Wang Ji, Wikimedia Commons, CC BY 2.5; analytical annotations and layout are the authors’ own. Full image-source URLs and licence details should be retained in the submission’s figure-permission documentation.

AI-mediated heritage interpretation ecology

From site materiality to stewardship-oriented conservation intention

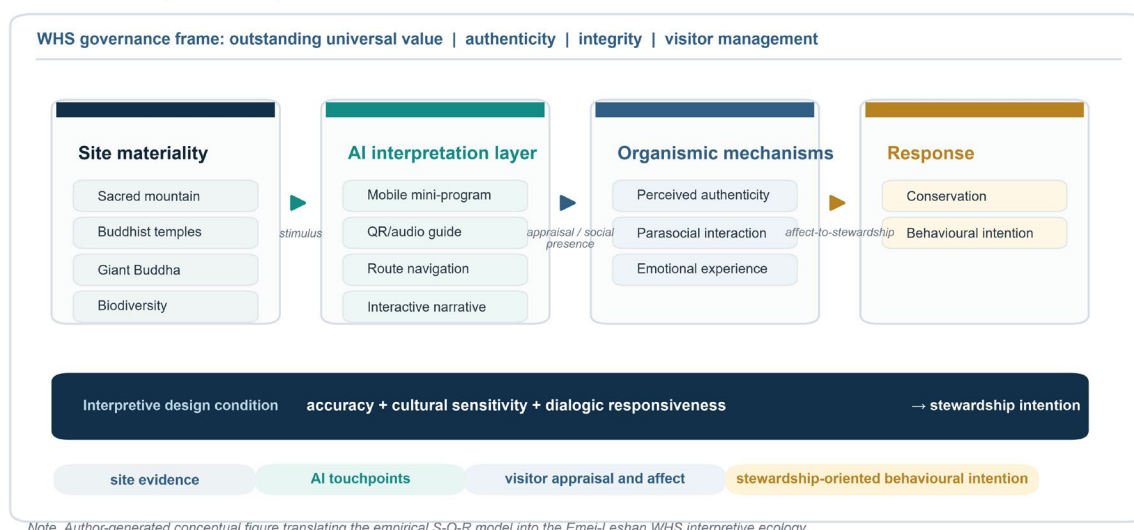


Figure 4. AI-mediated heritage interpretation ecology at the Emei-Leshan WHS. Note. The figure translates the empirical S-O-R model into the case-specific interpretive ecology linking site materiality, AI interpretation, organismic mechanisms, and stewardship-oriented response.

5.3. Sampling and Data Collection

Data were collected through on-site convenience-intercept sampling at the primary visitor zones of the Emei-Leshan property. Fieldwork was conducted between July and September 2025, after the institutional ethics waiver had been granted, spanning peak and shoulder visitation periods. Eligible respondents were adult visitors (≥ 18 years) who had completed at least 30 min of the on-site visit and confirmed use of the smart-guide or intelligent interpretation service during the current visit. Trained research assistants approached visitors at exit nodes and primary viewing platforms, explained the study purpose, obtained informed consent, and administered the questionnaire via tablet device. No personally identifiable or sensitive information was collected. Of 510 visitors approached, 460 agreed to participate. After screening for response completeness, attentional consistency, and exposure verification, 418 valid cases were retained, yielding a participation rate of 90.2% and an analytic retention rate of 82.0%. Demographic characteristics of decliners were not retained in the anonymised dataset, so a formal respondent-versus-decliner comparison could not be implemented. The retained auxiliary administration data nevertheless allowed early-versus-late respondent comparison and a three-wave temporal stability check. These diagnostics are reported in Section 5.3 and Tables S1 and S2 as partial safeguards against observable non-response bias, while the absence of decliner-level information is retained as a limitation. A pilot test ($n = 32$) with a comparable visitor sample was used to refine wording, instructions, and Mandarin-English translation/back-translation procedures (Brislin, 1970); no items were dropped after the pilot.

Data were obtained through a structured visitor questionnaire developed around the five focal constructs: AI-based interpretation, perceived authenticity, parasocial interaction, emotional experience, and conservation behavioural intention. Items were adapted from established scales in heritage interpretation, authenticity, parasocial interaction, and conservation-behaviour research, then linguistically calibrated to the WHS interpretive context. Following screening for response completeness, attentional consistency, and response-pattern integrity, 418 valid responses were retained for analysis. The retained sample exceeds conventional minimum thresholds for PLS-SEM estimation with the present

model complexity and is sufficient to support stable bootstrap-based inference for the indirect effects of interest.

Potential non-response bias was assessed using an early-versus-late respondent comparison following [Armstrong and Overton's \(1977\)](#) procedure. The 418 retained cases were partitioned into the first half ($n = 209$, early) and second half ($n = 209$, late) of the fieldwork window. Welch's t -tests for continuous variables and Pearson χ^2 tests for categorical variables were applied to age, gender, education, region of residence, AI-system type, on-site AI exposure duration, prior visit history, and the four marker-variable items. None of the fourteen comparisons reached significance (all $p \geq 0.124$; all Cohen's $d \leq 0.15$; all Cramér's $V \leq 0.11$), indicating no observable difference between early and late respondents on the recorded characteristics. The full results are reported in Table S1. As an additional robustness check, the sample was partitioned into three sequential fieldwork waves (Wave 1: $n = 155$; Wave 2: $n = 155$; Wave 3: $n = 108$). One-way ANOVAs on the same set of variables again returned no significant wave-level differences (all $p \geq 0.091$; Table S2), supporting the temporal stability of the sampling frame across the July–September 2025 fieldwork window.

5.4. Analytical Strategy

The analytical sequence followed established guidance for reflective-measurement PLS-SEM in tourism research ([do Valle & Assaker, 2016](#)). The analysis first reports respondent profile, descriptive statistics, and inter-construct correlations. It then evaluates indicator reliability, internal consistency, convergent validity, and discriminant validity using the HTMT criterion ([Henseler et al., 2015](#)). Finally, it assesses predictor collinearity, explained variance, standardised path coefficients, indirect effects, moderation, effect sizes, predictive relevance, and approximate fit. The model was estimated in SmartPLS 4.0 (SmartPLS GmbH, Oststeinbek, Germany), with 5000-resample bootstrapping for path, mediation, and moderation inference. Bias-corrected 95% confidence intervals are reported for indirect and interaction effects. The final analytic sample contained complete responses only after screening, so no imputation was applied. To reduce dependence on a single dichotomous coding of visit frequency, the H13 boundary-condition test was handled at two levels. The primary structural test retained the theoretically motivated first-time-versus-repeat contrast, because the hypothesis concerns whether visitors with no prior on-site authenticity anchors differ from visitors with prior site experience. In addition, exact prior-visit counts and last-visit recency were retained in the auxiliary dataset and reported as continuous-variable diagnostics: $\log(\text{prior visits before this trip} + 1)$, based on the recorded count (range 0–8; $M = 1.11$, $SD = 1.67$), and a recency-weighted index defined as $1/(1 + \text{last-visit-months-ago}/12)$. These continuous measures are used to contextualise and check the robustness of the moderation interpretation rather than to present a separate causal claim. Procedural and statistical safeguards against common method bias are reported in Section 5.5, while recognising that post hoc tests cannot eliminate the limitations of single-source cross-sectional data.

5.5. Procedural and Statistical Safeguards Against Common Method Bias

Because all focal constructs were measured through a single self-administered questionnaire, procedural and statistical safeguards were implemented against common method bias (CMB), consistent with current hospitality and tourism PLS-SEM discussions of CMB practice ([Castillo et al., 2026](#)). Procedurally, items were separated into construct blocks; respondents were assured of anonymity; predictor and outcome items were framed with psychological-separation cues; and the questionnaire embedded an attention-check item that all 418 retained respondents passed. As a marker-variable safeguard, the questionnaire included a theoretically unrelated four-item marker measuring evaluations of consumer-

packaging design (e.g., “the packaging colour is appealing”), captured on the same 1–7 Likert format. The marker showed acceptable internal consistency (Cronbach’s $\alpha = 0.766$) and was essentially uncorrelated with the auxiliary measures ($|r| \leq 0.051$ with age, AI exposure duration, prior visits, and last-visit recency), satisfying the unrelatedness condition required for marker-based CMB diagnostics (Lindell & Whitney, 2001). The marker is used downstream both as a Lindell-Whitney partial-correlation adjustment and as an unmeasured-latent-method construct in the PLS-SEM (Williams et al., 2010). Harman’s single-factor test, full-collinearity VIFs, and marker-variable diagnostics are reported as convergent screens rather than as proof that CMB is absent. For design transparency, 14.4% of the sample ($n = 60$) was recruited through an online follow-up after the on-site visit; an onsite-versus-online-follow-up comparison returned uniformly null differences on demographics, AI exposure, prior visit history, and marker items (all $p \geq 0.238$; Table S4). These safeguards reduce, but cannot eliminate, single-source and social-desirability concerns.

6. Results

6.1. Respondent Profile

The respondent profile was relatively balanced by gender. Among the 418 respondents, 184 were male (44.0%), 224 were female (53.6%), and 10 selected other or preferred not to answer (2.4%). Respondents ranged from 18 to 63 years old ($M = 34.6$, $SD = 10.1$). The sample was therefore concentrated in young and middle-adult visitor groups, with sufficient age dispersion for auxiliary robustness checks but without respondents above 63 years old.

Regarding educational background, most respondents held a bachelor’s degree or above, consistent with the tech-literate profile expected among users of mobile and intelligent interpretation systems. In the retained demographic summary, 187 respondents held a bachelor’s degree, 58 held a master’s degree, and 7 held a doctoral degree; 105 reported high-school education, and 61 selected another education category. In terms of visit history, the auxiliary visit-history data indicate that 225 respondents were first-time visitors with no prior on-site visits before the current trip, accounting for 53.8% of the sample. The exact prior-visit count before the current trip ranged from 0 to 8 ($M = 1.11$, $SD = 1.67$), providing the basis for the count-based and recency-weighted robustness specifications reported in the analytical strategy and supplementary diagnostics. Overall, the sample reflects a relatively diverse respondent profile in terms of gender, age, education, residence region, AI-system exposure, and prior visit history.

AI-System Exposure and Fieldwork Composition

The realised AI-interpretation exposure is summarised in Tables S5 and S6. The five system types covered mobile smart-guide application (45.5%), AI audio guide (28.9%), WeChat mini-programme (15.8%), on-site intelligent kiosk (6.7%), and AR heritage-guide beta (2.6%). These categories reflect the actual interpretive ecology of the Emei-Leshan property rather than a single platform. Mean exposure duration was 18.9 min ($SD = 6.7$), with the AR system attracting the longest median engagement (median = 23 min) and the standard mobile app the shortest (median = 18 min). Across the five primary collection sites, namely, Mount Emei entrance (30.4%), Leshan Giant Buddha area (27.0%), Visitor Centre (16.5%), online follow-up (14.4%), and the Cable Station (11.7%), the demographic and exposure profile remained statistically homogeneous. This supports integrated analysis across the heterogeneous interpretive ecology.

6.2. Descriptive Statistics and Correlations

Table 2 reports means, standard deviations, and inter-construct correlations for the five focal variables. Construct means ranged from 4.038 to 4.089 on a 5-point scale, indicating positive but not ceiling-bound evaluations. AI-based interpretation correlated positively with perceived authenticity ($r = 0.657$), parasocial interaction ($r = 0.530$), emotional experience ($r = 0.626$), and conservation behavioural intention ($r = 0.576$). Emotional experience was also strongly associated with conservation behavioural intention ($r = 0.673$). These bivariate associations are directionally consistent with the proposed model and provide preliminary evidence that AI interpretation, its theorised organismic mechanisms, and the affective-behavioural outcomes co-vary in the expected manner.

Table 2. Means, Standard Deviations and Correlation Coefficients of Variables.

Construct	M	SD	AII	PA	PSI	EE	CBI
AII	4.08	0.88	1.000	0.657	0.530	0.626	0.576
PA	4.04	0.73	0.657	1.000	0.430	0.559	0.541
PSI	4.05	0.81	0.530	0.430	1.000	0.516	0.525
EE	4.07	0.92	0.626	0.559	0.516	1.000	0.673
CBI	4.09	0.91	0.576	0.541	0.525	0.673	1.000

Note. Diagonal values equal 1.000; off-diagonal cells report inter-construct Pearson correlations. The pattern—particularly the strong AII–PA ($r = 0.657$) and EE–CBI ($r = 0.673$) associations—is directionally consistent with the proposed appraisal–relation–affect–behaviour sequence and provides preliminary, theory-aligned evidence prior to structural estimation.

6.3. Measurement Model Assessment

The measurement assessment yielded uniformly satisfactory reliability and convergent validity across all five constructs. Cronbach’s α values ranged from 0.915 to 0.947, composite reliability (CR) values from 0.936 to 0.960, and average variance extracted (AVE) values from 0.746 to 0.827. All indices exceed conventional thresholds for reflective constructs ($\alpha \geq 0.70$; $CR \geq 0.70$; $AVE \geq 0.50$), supporting indicator reliability, internal consistency, and convergent validity. Discriminant validity was evaluated via the HTMT criterion (Henseler et al., 2015); all HTMT values fell below the recommended 0.90 cutoff, supporting empirical distinctness among the focal constructs. Tables 3 and 4 present the measurement-model and discriminant-validity results, respectively.

Table 3. Reliability and Validity Assessment.

Construct	Item	Loading	Alpha	CR	AVE
AII	AII1	0.891	0.938	0.953	0.801
	AII2	0.891			
	AII3	0.910			
	AII4	0.897			
	AII5	0.886			
PA	PA1	0.865	0.915	0.936	0.746
	PA2	0.854			
	PA3	0.874			
	PA4	0.860			
	PA5	0.864			
PSI	PSI1	0.891	0.929	0.946	0.778
	PSI2	0.880			
	PSI3	0.865			
	PSI4	0.889			
	PSI5	0.887			
EE	EE1	0.899	0.942	0.956	0.811

Table 3. *Cont.*

Construct	Item	Loading	Alpha	CR	AVE
EE	EE2	0.901			
EE	EE3	0.896			
EE	EE4	0.907			
EE	EE5	0.901			
CBI	CB1	0.903	0.947	0.960	0.827
CBI	CB2	0.916			
CBI	CB3	0.897			
CBI	CB4	0.919			
CBI	CB5	0.911			

Note. All standardised loadings exceeded conventional thresholds (≥ 0.70), and the reliability and convergent validity indices (Cronbach's α , composite reliability, AVE) satisfied recommended cutoffs ($\alpha \geq 0.70$; CR ≥ 0.70 ; AVE ≥ 0.50), jointly supporting the reflective measurement model for the five focal constructs.

Table 4. Discriminant validity assessment (HTMT).

Construct	AII	PA	PSI	EE	CBI
AII	1.000	0.710	0.567	0.666	0.611
PA	0.710	1.000	0.467	0.603	0.582
PSI	0.567	0.467	1.000	0.552	0.559
EE	0.666	0.603	0.552	1.000	0.712
CBI	0.611	0.582	0.559	0.712	1.000

Note. Discriminant validity is assessed via the heterotrait–monotrait (HTMT) criterion (Henseler et al., 2015); all HTMT values remained below the recommended 0.90 cutoff, supporting the empirical distinctness of authenticity and parasocial interaction as two non-redundant organismic mechanisms.

6.4. Structural Model Assessment

Before structural-path estimation, predictor collinearity was inspected to ensure the interpretability of path coefficients. As reported in Table 5, variance inflation factor (VIF) values ranged from 1.413 to 2.266, below the conservative cutoff of 3.0. The structural diagnostics in Table 6 show that the model explained 43.2% of the variance in perceived authenticity, 28.1% in parasocial interaction, 46.8% in emotional experience, and 52.8% in conservation behavioural intention. These R^2 values indicate that the model captures substantial variance in the focal constructs, especially in the stewardship-oriented outcome.

Table 5. Collinearity assessment.

Predictor Path	VIF
AII $\rightarrow$ EE	2.029
PA $\rightarrow$ EE	1.791
PSI $\rightarrow$ EE	1.413
AII $\rightarrow$ CBI	2.266
PA $\rightarrow$ CBI	1.887
PSI $\rightarrow$ CBI	1.513
EE $\rightarrow$ CBI	1.878

Note. All variance inflation factor (VIF) values fall below the conservative cutoff of 3.0, indicating that multicollinearity among predictors is not a substantive concern and that the subsequent path coefficients can be interpreted with confidence.

Table 6. Structural model diagnostics.

Endogenous Construct	R^2	Comment
PA	0.432	Explained variance
PSI	0.281	Explained variance

Table 6. Cont.

Endogenous Construct	R ²	Comment
EE	0.468	Explained variance
CBI	0.528	Explained variance

Note. R² values denote the proportion of variance explained in each endogenous construct: 43.2% (PA), 28.1% (PSI), 46.8% (EE), and 52.8% (CBI). The >50% R² for the focal stewardship outcome indicates that the appraisal-relation-affect-behaviour sequence captures substantial variance in heritage visitor response.

6.4.1. Additional Structural Diagnostics: Effect Size, Predictive Relevance, and Model Fit

Following Hair et al. (2021), three additional structural diagnostics were examined: Cohen's f^2 effect sizes for each predictor, Stone-Geisser's Q^2 predictive relevance obtained via blindfolding (omission distance = 7), and the standardised root mean square residual (SRMR) as an approximate model-fit index. Because PLS-SEM is a variance-based and prediction-oriented approach, covariance-based global fit indices such as chi-square, CFI, or RMSEA are not treated as decisive model-acceptance criteria here. SRMR is therefore reported as a descriptive approximate-fit diagnostic alongside R^2 , Q^2 , f^2 , collinearity, and bootstrapped path evidence. Effect sizes for the principal AII paths were substantively meaningful: AII → PA produced a large f^2 ($f^2 = 0.762$), AII → PSI produced a large f^2 ($f^2 = 0.391$), and AII → EE produced a medium f^2 ($f^2 = 0.175$). Effect sizes for the organism-to-response paths were small to medium (f^2 range = 0.041–0.246), and the direct AII → CBI path produced a near-negligible f^2 ($f^2 = 0.018$). This pattern is consistent with the structural coefficients, in which behavioural response is predominantly mediated. Q^2 values were positive for all four endogenous constructs ($Q^2_{PA} = 0.319$; $Q^2_{PSI} = 0.205$; $Q^2_{EE} = 0.346$; $Q^2_{CBI} = 0.418$), supporting predictive relevance. The estimated model produced an SRMR of 0.058, below the conventional 0.08 cutoff and indicating acceptable approximate fit. Together, these diagnostics support the structural-path interpretation without implying causal identification from the cross-sectional model.

Turning to the direct paths, AI-based interpretation was positively associated with emotional experience ($\beta = 0.355$, $t = 6.960$, $p < 0.001$), supporting H1. Its direct association with conservation behavioural intention was also significant but smaller in magnitude ($\beta = 0.117$, $t = 2.304$, $p = 0.021$), supporting H2 while indicating that behavioural response is only partly carried by the direct stimulus channel. AI-based interpretation was further positively associated with perceived authenticity ($\beta = 0.657$, $t = 17.798$, $p < 0.001$) and parasocial interaction ($\beta = 0.530$, $t = 12.737$, $p < 0.001$), supporting H3 and H4, respectively. These paths indicate that intelligent interpretation is linked with both the appraisal-based and relation-based organismic channels specified in the conceptual model.

Perceived authenticity was positively associated with emotional experience ($\beta = 0.226$, $t = 4.706$, $p < 0.001$) and conservation behavioural intention ($\beta = 0.151$, $t = 3.252$, $p = 0.001$), supporting H5 and H6. Parasocial interaction showed comparable positive associations with emotional experience ($\beta = 0.230$, $t = 5.404$, $p < 0.001$) and conservation behavioural intention ($\beta = 0.180$, $t = 4.326$, $p < 0.001$), supporting H7 and H8. The close magnitude of the PA and PSI paths indicates that interpretive credibility and relational involvement operate as complementary mediators in the WHS interpretive context. Finally, emotional experience showed the strongest direct association with conservation behavioural intention ($\beta = 0.422$, $t = 9.107$, $p < 0.001$), supporting H9 and highlighting the importance of affective engagement in stewardship-oriented response.

6.4.2. Mediation Analysis

Bootstrapped indirect-effect analysis (5000 resamples; bias-corrected 95% confidence intervals) supported the proposed mediation logic. Perceived authenticity mediated the AII → EE relationship ($\beta = 0.149$, $t = 4.826$, $p < 0.001$, 95% CI [0.089, 0.210]), supporting

H10. Parasocial interaction also mediated the AII $\rightarrow$ EE relationship ($\beta = 0.122$, $t = 4.951$, $p < 0.001$, 95% CI [0.076, 0.172]), supporting H11. Emotional experience mediated the AII $\rightarrow$ CBI relationship ($\beta = 0.150$, $t = 5.834$, $p < 0.001$, 95% CI [0.101, 0.202]), supporting H12. The total AII-CBI association estimate was 0.576 (direct = 0.117; total indirect = 0.459), so approximately 79.7% of AII's association with conservation behavioural intention was accounted for by statistically significant indirect pathways. Decomposed by pathway, the specific indirect associations accounted for approximately 17.2% of the total estimate via PA $\rightarrow$ CBI (0.099/0.576), 16.5% via PSI $\rightarrow$ CBI (0.095/0.576), 26.0% via EE alone (0.150/0.576), 10.9% via PA $\rightarrow$ EE $\rightarrow$ CBI (0.063/0.576), and 9.0% via PSI $\rightarrow$ EE $\rightarrow$ CBI (0.052/0.576). Because a significant but small direct path coexists with stronger indirect transmission, the pattern is best characterised as complementary partial mediation rather than full mediation. Four additional pathways are therefore reported as supplementary indirect effects rather than primary hypotheses: AII $\rightarrow$ PA $\rightarrow$ CBI, AII $\rightarrow$ PSI $\rightarrow$ CBI, AII $\rightarrow$ PA $\rightarrow$ EE $\rightarrow$ CBI, and AII $\rightarrow$ PSI $\rightarrow$ EE $\rightarrow$ CBI. These estimates were positive and directionally consistent with the theoretical claim that AI interpretation is associated with stewardship-oriented intention through both credibility-based and relation-based organismic channels.

Read holistically, the results provide theory-consistent evidence for the proposed dual-mechanism S-O-R model. AI-based interpretation is associated with both authenticity-based appraisal and parasocial relational engagement. These organismic mechanisms are, in turn, associated with emotional experience and conservation behavioural intention. Emotional experience emerges as the strongest proximal predictor of stewardship-oriented response. The pattern of direct and indirect associations is consistent with the argument that intelligent interpretation in a WHS setting is better understood as a meaning-generating and relationship-inducing communicative resource than as a neutral informational interface.

6.4.3. Moderation Analysis

Moderation by visit history was first examined by grouping respondents into first-time and repeat visitors and introducing the AII $\times$ visit-history product term into the structural model. This binary coding was selected because the focal hypothesis concerns whether visitors with weak prior authenticity anchors respond more strongly to intelligent interpretation than visitors with prior on-site experience. Coefficients were estimated via 5000-resample bootstrapping with bias-corrected 95% confidence intervals. The interaction term was significant and negative ($\beta = -0.135$, $t = 2.78$, $p = 0.005$, 95% CI [-0.231, -0.040]), supporting H13. Simple-slopes inspection indicated that the AII $\rightarrow$ PA association was stronger for first-time visitors ($\beta = 0.712$, $p < 0.001$) than for repeat visitors ($\beta = 0.532$, $p < 0.001$), although both groups showed significant positive associations. To avoid treating visit history as a purely binary construct, the auxiliary data were further examined through exact prior-visit counts and last-visit recency (Table S9). These continuous diagnostics support the same substantive interpretation: AI-based interpretation appears especially salient as an authenticity-construction resource when visitors have weaker prior interpretive anchors, while still remaining relevant for repeat visitors. The moderation result should therefore be read as a boundary-condition pattern rather than as evidence of a deterministic causal difference between visitor groups.

7. Discussion

This study reframes AI-based interpretation in WHSs as a meaning-generating, relational, and stewardship-relevant form of communication rather than as a neutral informational channel. The most important finding is that AI-based interpretation is strongly associated with perceived authenticity ($\beta = 0.657$), whereas its direct association with conservation behavioural intention is small ($\beta = 0.117$). Approximately four-fifths of the total

AII-CBI association is carried indirectly, predominantly through emotional experience. In other words, AI interpretation is linked with conservation-oriented intention less through information exposure alone than through emotionally meaningful heritage experience. The central theoretical implication is that AI interpretation should not be evaluated only by usefulness or ease of use. It should also be evaluated by whether it supports authentic, socially engaging, and emotionally meaningful heritage communication.

The empirical model received coherent support across direct and indirect paths (Tables 6–10). AI-based interpretation was positively related to perceived authenticity, parasocial interaction, emotional experience, and conservation behavioural intention. Authenticity and parasocial interaction each contributed positively to emotional experience and conservation behavioural intention, while emotional experience showed the strongest direct association with conservation behavioural intention ($\beta = 0.422$; Table 8). The supported mediation paths in Table 9 substantiate the central proposition that AI-based interpretation is associated with stewardship-oriented visitor response through credibility-based appraisal, quasi-social engagement, and affective resonance. The pattern is consistent with earlier heritage-interpretation evidence that affectively rich and credibility-laden communication is associated with stronger visitor response than purely informational delivery (De Rojas & Camarero, 2008; Weng et al., 2020). The present study extends this argument to an AI-mediated, conversational interpretation context.

Table 7. Additional structural diagnostics: f^2 effect sizes, Q^2 predictive relevance, and model fit.

Structural Path/Construct	f^2	Effect-Size Interpretation	Q^2 (Predictive Relevance)
AII → PA	0.762	Large	$Q^2_{PA} = 0.319$
AII → PSI	0.391	Large	$Q^2_{PSI} = 0.205$
AII → EE	0.175	Medium	—
AII → CBI (direct)	0.018	Negligible (mediated path dominates)	—
PA → EE	0.082	Small	—
PA → CBI	0.041	Small	—
PSI → EE	0.087	Small	—
PSI → CBI	0.062	Small	—
EE → CBI	0.246	Medium	$Q^2_{EE} = 0.346$; $Q^2_{CBI} = 0.418$
Model fit	—	SRMR = 0.058 (<0.08 conventional cutoff)	—

Note. f^2 thresholds follow Cohen (1988): 0.02 = small, 0.15 = medium, 0.35 = large; these generic thresholds are used for comparability and interpreted alongside heritage-tourism context. Q^2 values were obtained via blindfolding with omission distance = 7; $Q^2 > 0$ indicates out-of-sample predictive relevance. SRMR is reported as an approximate descriptive fit index for PLS-SEM rather than as a covariance-based global-fit test. AII = AI-based interpretation; PA = perceived authenticity; PSI = parasocial interaction; EE = emotional experience; CBI = conservation behavioural intention.

Table 8. Structural model and hypothesis testing.

Hyp.	Path	Beta	t-Value	p-Value	Decision
H1	AII → EE	0.355	6.960	<0.001	Supported
H2	AII → CBI	0.117	2.304	=0.021	Supported
H3	AII → PA	0.657	17.798	<0.001	Supported
H4	AII → PSI	0.530	12.737	<0.001	Supported
H5	PA → EE	0.226	4.706	<0.001	Supported
H6	PA → CBI	0.151	3.252	=0.001	Supported
H7	PSI → EE	0.230	5.404	<0.001	Supported
H8	PSI → CBI	0.180	4.326	<0.001	Supported
H9	EE → CBI	0.422	9.107	<0.001	Supported

Note. Path estimates are reported as standardised coefficients with bootstrapped t-values and p-values (5000 resamples). The close magnitudes of the PA → EE/CBI and PSI → EE/CBI paths indicate that interpretive credibility (PA) and relational involvement (PSI) operate as complementary—rather than competing—organismic mechanisms within the WHS interpretive context.

Table 9. Mediation analysis results.

Hyp.	Indirect Path	Beta	t	p	95% CI
H10	AII → PA → EE	0.149	4.826	<0.001	[0.089, 0.210]
H11	AII → PSI → EE	0.122	4.951	<0.001	[0.076, 0.172]
H12	AII → EE → CBI	0.150	5.834	<0.001	[0.101, 0.202]
S1	AII → PA → CBI	0.099	3.20	=0.001	[0.039, 0.160]
S2	AII → PSI → CBI	0.095	4.10	<0.001	[0.050, 0.141]
S3	AII → PA → EE → CBI	0.063	4.06	<0.001	[0.032, 0.093]
S4	AII → PSI → EE → CBI	0.052	4.35	<0.001	[0.028, 0.075]

Table 10. Moderation analysis results.

Test	Path/Group	β	p	Interpretation
Interaction	AII × visit frequency → PA	−0.135	0.005	Negative interaction; H13 supported
Simple slope	AII → PA, first-time visitors	0.712	<0.001	Stronger association
Simple slope	AII → PA, repeat visitors	0.532	<0.001	Weaker but significant association

These findings sharpen the distinction between instrumental and interpretive value. From an instrumental perspective, AI improves access to information and lowers the cost of visitor guidance, outcomes already documented in AI-tourism research (Samara et al., 2020; Xu et al., 2024). From an interpretive perspective, AI matters when it helps organise narrative attention, personalise cultural explanation, and make heritage significance emotionally available to visitors. The positive AII → EE path ($\beta = 0.355, p < 0.001$) is therefore theoretically meaningful because it links intelligent interpretation with affective depth, not only with digital convenience. This finding is broadly consistent with Liu (2020) and Domínguez-Quintero et al. (2019), who report that high-quality interpretation is associated with emotional engagement. The present evidence extends that regularity to AI-mediated interpretation in a mixed WHS setting.

Perceived authenticity emerged as a particularly influential explanatory mechanism, both as an organismic state associated with AI interpretation ($\beta = 0.657$; Table 8) and as a mediator of its affective and behavioural outcomes (Table 9). The strong positive AII → PA path qualifies the concern that technological mediation necessarily erodes the genuine quality of heritage experience. The evidence supports a conditional view: AI can be associated with heightened authenticity when it conveys historically grounded, culturally respectful, and context-sensitive narratives, conditions that resonate with constructive and existential authenticity scholarship (Wang, 1999; Yi et al., 2019). This result also connects with Li et al. (2024), who find that digital cultural-heritage experiences are linked with conservation intention through authenticity and place attachment. The present study extends that argument by positioning visitor-perceived AI-based interpretation as an upstream interpretive stimulus within the same explanatory chain.

A noteworthy pattern is the asymmetry between the two organismic pathways. AI-based interpretation is more strongly associated with perceived authenticity ($\beta = 0.657$) than with parasocial interaction ($\beta = 0.530$). Although both associations are large and statistically significant, the difference suggests that credibility-based appraisal may be the more salient route of organismic activation in WHS interpretive contexts. This is consistent with the ethical economy of heritage interpretation, in which cultural credibility and historical fidelity take priority over relational warmth. It also contrasts with acceptance-focused AI service contexts, where parasocial and anthropomorphic cues may be more central (Xu et al., 2024; Ye et al., 2021). The practical implication is that WHS interpretation governance should prioritise content fidelity, co-produced with heritage experts and custodian communities, before relational design choices are optimised.

Parasocial interaction adds a complementary layer of explanation (Table 8). Visitors respond not only to what an AI interpreter says, but also to how socially present, responsive, and companion-like the system feels. In heritage settings, this relational quality may sustain attention, reduce interpretive distance, and encourage more personal processing of conservation messages. The positive $PSI \rightarrow EE$ ($\beta = 0.230$) and $PSI \rightarrow CBI$ ($\beta = 0.180$) paths indicate that relational design is part of the mechanism through which AI communication becomes meaningful. This finding is consistent with Xu et al. (2024) and Ye et al. (2021), who report the experiential salience of parasocial cues in AI-mediated tourism. It also suggests that PSI can contribute to stewardship-oriented outcomes in WHSs, not only to service-encounter responses.

The strong path from emotional experience to conservation behavioural intention ($\beta = 0.422$; Table 8) clarifies the affective basis of stewardship. Conservation intention is unlikely to arise from information exposure alone (Ruan et al., 2024). Visitors must also experience the site as meaningful, fragile, and worthy of protection. By modelling the AII-CBI association through emotional experience, the analysis shows how digital interpretation may contribute to heritage sustainability without displacing human or material modes of interpretation. Its value lies in helping visitors translate understanding into affective commitment. This affective-bridge argument is consistent with the broader literature on emotion-driven conservation behavioural intention (Prayag & Del Chiappa, 2023; Weng et al., 2020), while specifying the underexplored case in which the upstream interpretive stimulus is AI-mediated.

Taken together, the discussion contributes to theory in three ways. First, it connects smart-tourism technology to authenticity, parasocial interaction, and conservation psychology within a unified S-O-R architecture. Second, it shows that authenticity and parasocial interaction are complementary rather than redundant mechanisms. Third, it cautions against a purely novelty-driven view of AI deployment in heritage settings. In WHSs, the value of AI depends less on digital spectacle itself than on whether AI-mediated interpretation can support cultural credibility, affective engagement, and responsible visitor conduct.

Positioning Against Prior Studies

To clarify how the present model relates to earlier work, Table 11 positions the study against representative contributions on AI-mediated tourism, heritage interpretation, authenticity, parasocial interaction, and conservation behavioural intention. The comparison highlights three patterns. First, prior AI-tourism studies have focused chiefly on adoption, satisfaction, or service quality, leaving stewardship-oriented outcomes under-examined. Second, heritage-interpretation studies have established the authenticity-emotion-behaviour chain but have typically treated the interpretive agent as human or place-based rather than algorithmic. Third, parasocial-interaction work has illuminated relational dynamics in AI service encounters but has not yet been fully integrated with WHS conservation outcomes. The present study sits at the intersection of these streams by jointly modelling AII, PA, PSI, EE, and CBI within a heritage-specific S-O-R architecture.

Synthesising the empirical and theoretical strands above, the findings support the study's core proposition: AI interpretation in WHS contexts is best understood not only through acceptance or efficiency metrics, but through the joint operation of interpretive credibility, quasi-social engagement, and affective resonance. AI-based interpretation is associated with both emotional experience and conservation behavioural intention, but its direct behavioural association is modest compared with the indirect transmission through perceived authenticity, parasocial interaction, and emotional experience. Perceived authenticity and parasocial interaction operate as parallel and complementary mechanisms, with authenticity remaining the stronger credibility-based pathway. Emotional experience

functions as the proximal affective bridge through which AI interpretation is linked with upstream appraisal, relational engagement, and stewardship-oriented response. This framing consolidates the earlier sub-questions into a single proposition while retaining the empirical distinctions among direct, mediating, and affective pathways.

Table 11. Positioning against representative prior studies.

Study	Focus/Theoretical Lens	Method	Key Finding	This Study's Extension
Xu et al. (2024)	Tourist acceptance of ChatGPT in travel services; TAM × PSI	PLS-SEM	PSI mediates the relationship between AI service cues and acceptance.	Extends PSI from service-acceptance outcomes to stewardship-oriented conservation behavioural intention in a WHS context.
Li et al. (2024)	Digital cultural heritage; authenticity, cultural experience, place attachment	PLS-SEM	Authenticity and place attachment are associated with tourists' conservation intentions.	Adds AI-based interpretation as the upstream stimulus and PSI as a parallel relational mechanism.
Ruan et al. (2024)	Heritage tourism interpretation content; knowledge-based vs affection-based	Experimental/survey	Affection-based interpretation is more effective for heritage willingness than knowledge-based interpretation.	Empirically validates the affection-priority logic for an AI-mediated interpretive agent and links it to conservation behavioural intention.
Domínguez-Quintero et al. (2019)	Cultural heritage destination; authenticity → emotion → satisfaction	PLS-SEM	Authenticity intensifies emotional experience and feeds destination satisfaction.	Replaces satisfaction with conservation behavioural intention as the downstream outcome, reorienting the chain toward heritage sustainability.
Weng et al. (2020)	Tour interpretation and perceived heritage values	Comparative survey (guided vs. unguided)	Interpretation enhances perceived heritage values and conservation-relevant cognition.	Tests the same explanatory logic where the interpretive agent is algorithmic rather than human-guided.
Liu (2020)	Digital interpretation and presentation technologies at a heritage site	Mixed-method case study	Digital interpretation can enhance visitor experience when culturally embedded.	Moves from descriptive evidence to a fully specified structural model with stewardship-oriented mediation paths.
Ye et al. (2021)	Parasocial interaction on tourism companies' social media	Survey + PLS-SEM	PSI is linked with engagement and behavioural outcomes in mediated tourism communication.	Transposes PSI from marketing communication to heritage interpretation and links it to conservation behavioural intention.
This study	AI-based interpretation at a mixed-heritage WHS; integrated S-O-R + authenticity + PSI	PLS-SEM with bootstrapped mediation ($n = 418$)	AII activates PA and PSI; both feed EE and CBI; EE is the strongest proximal predictor of CBI.	Integrates smart-tourism, heritage-interpretation, and PSI streams into one heritage-specific model.

Note. AII = AI-based interpretation; PA = perceived authenticity; PSI = parasocial interaction; EE = emotional experience; CBI = conservation behavioural intention; WHS = World Heritage Site. The comparison illustrates how the present study integrates three previously separate streams—smart-tourism research, heritage-interpretation research, and parasocial-interaction research—within a single heritage-specific S-O-R architecture.

The evidence reported above does not imply that AI-based interpretation will be beneficial in every heritage context. Several conditions may attenuate, or even reverse, the dual-mechanism pathways documented here. First, in highly sacred or ritually charged contexts, technologically mediated narration may be experienced as intrusive on the contemplative atmosphere, eroding perceived authenticity. Second, visitors with deep prior domain expertise may perceive AI-generated narratives as superficial or formulaic, dampening both PA and PSI activation. Third, anthropomorphised AI voices that exceed visitors' acceptance thresholds may elicit the uncanny-valley response (Mori et al., 2012), converting intended relational warmth into discomfort. Fourth, generative AI systems prone to factual hallucination or culturally insensitive output may erode interpretive credibility. These boundary conditions frame AII deployment in WHSs as a conditional, governance-dependent intervention rather than a universally beneficial technological upgrade.

8. Implications

The theoretical contribution can be summarised in four messages. First, AI interpretation in WHSs is a communicative and curatorial mechanism rather than a neutral interface. Second, authenticity and parasocial interaction represent complementary and empirically distinguishable pathways. One concerns interpretive credibility and cultural meaning; the other concerns relational involvement and social presence. Third, emotionally rich interpretation operates as a proximal affective bridge linking visitor experience with stewardship-oriented intention. Fourth, the study advances an integrated smart-heritage perspective in which intelligent technologies are theoretically linked with heritage authenticity, visitor emotion, and stewardship psychology.

Managerially, the findings suggest that destination managers should design AI interpretation around narrative depth, cultural credibility, emotional pacing, and relational voice. Effective AI deployment at WHSs is not primarily a question of usability or automation. It is also a curatorial question of how to translate heritage value into visitor meaning, emotional salience, and protective intention. Three operational priorities follow. First, narrative content should be co-produced with heritage experts, conservation managers, and local cultural stakeholders to support historical accuracy and cultural resonance. Second, conversational design should cultivate a relationally engaging voice that is responsive, attentive, and culturally registered, without descending into anthropomorphic spectacle. Third, conservation messages should be embedded within emotionally meaningful narrative arcs rather than appended as standalone directives. These priorities frame AI interpretation as a curatorial investment in the communicative capacity of the heritage destination.

Policy Implications for UNESCO and WHS Management

Beyond destination-level managerial guidance, the findings have implications for WHS management and heritage-governance practice. Several of these implications can be translated into the quantifiable indicators summarised in Table 12. First, AI interpretation should be treated as a curatorial and communicative instrument, not merely an ICT procurement item. Second, because authenticity emerged as the strongest organismic mechanism, site authorities should develop content-governance protocols co-produced with heritage experts, site managers, and relevant cultural stakeholders. They should also establish an AI-content ethical-audit mechanism with four minimum components: pre-release expert verification of historical, religious, and ecological claims; periodic sampling of generated or adaptive outputs; documentation of factual errors, cultural-sensitivity concerns, and corrective actions; and assignment of an accountable curator or review committee. Third, the PSI → CBI pathway suggests that relational design should be engaging but ethically restrained, avoiding anthropomorphic spectacle, narrative oversimplification, or displacement of human guides. Fourth, the EE → CBI pathway suggests that conservation messaging should be embedded within emotionally meaningful narrative arcs rather than appended as standalone behavioural directives. These implications should be read as case-based managerial guidance for local AI-interpretation governance, not as a general policy prescription beyond the study setting.

Table 12. Quantifiable management indicators for AI-based heritage interpretation.

Priority Area	Recommended Action	Quantifiable Indicator/Target
Content authenticity	Co-author narratives with heritage experts and custodian communities; require expert sign-off before release	100% of historical/religious statements verified against authoritative sources; documented expert approval per content module
Hallucination & ethics audit	Establish a standing ethical-audit mechanism with quarterly expert review of randomly sampled AI-generated historical, religious, and ecological narratives	≥200 generated outputs reviewed per quarter; factual-error rate < 2%; named accountable curator and audit trail
Emotional pacing	Embed conservation messages within emotionally framed narrative arcs rather than standalone directives	≥1 emotionally framed stewardship prompt per major interpretive node; visitor-rated emotional resonance monitored
Relational-design restraint	Tune anthropomorphism below the uncanny-valley threshold; preserve human-guide options	Visitor discomfort/uncanny rating tracked; design flagged for revision if >10% report discomfort
Access & inclusivity	Provide multilingual, adaptive-depth narration	≥5 languages; ≥2 adaptive depth levels (novice/expert)
Credibility-first sequencing	Verify content fidelity before adding relational/anthropomorphic features	Authenticity QA completed and signed off prior to release of conversational/relational layer

Note. The indicators translate the study’s mechanism-level findings into auditable management targets. Because perceived authenticity is the strongest organismic mechanism and emotional experience is the strongest proximal predictor of conservation behavioural intention, content fidelity and emotional pacing are prioritised, while relational and anthropomorphic design is constrained and ethically audited.

9. Limitations and Future Research

The limitations and future research directions can be grouped into four categories. First, model-structure limitations: the variance-based model captures average linear associations and cannot represent asymmetric, equifinal, conjunctural, or reciprocal patterns among organismic states. Future studies should therefore complement PLS-SEM with fuzzy-set qualitative comparative analysis (fsQCA), longitudinal cross-lagged modelling, or experimental designs. Second, causal-design limitations: the cross-sectional design enables only contemporaneous association and statistical mediation, not strict causal inference. The supplementary auxiliary dataset strengthens robustness checks but cannot establish temporal ordering. Future replications should separate AII-stimulus appraisal and CBI outcomes temporally, or experimentally manipulate AI interpretation exposure and narrative design. Third, research-method limitations: all focal constructs are visitor-reported. Although a four-item marker variable was embedded for Lindell-Whitney and Williams-ULMC adjustment (Section 5.5), early-versus-late and three-wave checks returned uniformly null differences (Tables S1 and S2), and visit frequency was operationalised under binary, count-based, and recency-weighted rules (Section 5.4), residual limitations remain. These include the absence of behavioural-trace data on actual conservation conduct, the absence of decliner-level demographic records, and the self-reported nature of the continuous visit-history measures. Fourth, data-and-technology limitations: the on-site intercept method naturally favoured tech-literate and highly educated visitors, with about three-fifths holding a bachelor’s degree or above. This may marginally elevate baseline values of perceived authenticity and AI acceptance. The single mixed-heritage WHS case constrains generalisability, and the July–September 2025 data window is technologically

time-sensitive given the rapid evolution of generative AI. The AI-system mix observed in the sample comprised six versioned platforms across five system types (Tables S5 and S6), supporting reproducibility within the realised interpretive ecology while limiting claims about any single AI engine. Future work should benchmark sample composition against scenic-area visitor statistics, compare cultural, natural, and mixed WHSs across cultural regions, combine survey data with system logs and interface documentation, and experimentally isolate AI voice, anthropomorphism, narrative depth, and interaction modality.

Future studies could combine survey modelling with interviews, ethnographic observation, and interaction-log analysis to examine how visitors engage with AI interpreters in situ. Such work could identify the moments at which interpretive credibility, relational engagement, or affective resonance break down. Mixed-method evidence would help clarify when AI interpretation complements human-guided and place-based modes of heritage communication, and when it risks simplifying complex cultural meanings. Further work should also examine cross-cultural and intergenerational heterogeneity in parasocial responses to AI heritage interpreters, given that expectations of social presence and authority are culturally and generationally inflected.

Configurational analysis is also promising because visitor response to AI interpretation may arise from multiple sufficient combinations rather than from one uniform net-association pathway. For example, high conservation behavioural intention may emerge from strong authenticity and moderate emotional resonance for some visitors, but from relational engagement and strong emotional resonance for others. A dual-method strategy combining PLS-SEM with fsQCA would clarify whether appraisal-based and relation-based routes are substitutable, complementary, or jointly necessary under different visitor and site conditions.

10. Conclusions

A central finding anchors this study: although AI-based interpretation is strongly associated with perceived authenticity, its direct association with conservation behavioural intention is small ($\beta = 0.117$). Roughly four-fifths of its total association with stewardship-oriented intention is accounted for by indirect pathways through authenticity, parasocial interaction, and, above all, emotional experience. This counterintuitive pattern suggests that AI interpretation is linked with conservation intention less through technology exposure itself than through the meanings, relationships, and emotions that interpretation helps activate. By integrating perceived authenticity and parasocial interaction into an S-O-R framework and testing the model with 418 visitors at the Emei Mountain-Leshan Giant Buddha WHS, the study shows that intelligent interpretation is linked to visitors through complementary appraisal-based and relation-based pathways. Emotional experience operates as the proximal affective bridge to stewardship-oriented intention. These conclusions are bounded. They are most defensible for mixed Asian World Heritage Sites comparable to Emei-Leshan that use moderately intelligent, smartphone-based mobile interpretation systems. They should not be generalised without qualification to single-monument sites, fully immersive or robot-embodied AI, or cultural settings with markedly different expectations of social presence and interpretive authority. Practically, the findings point to credibility-first AI heritage governance: expert-verified content, periodic hallucination and cultural-sensitivity audits, emotionally paced stewardship prompts, restrained relational voice design, multilingual and adaptive access, and preservation of human-guide alternatives. Because the evidence is cross-sectional and visitor-reported, the conclusions should be read as theoretically grounded associations rather than causal estimates. Future work should test the model longitudinally and experimentally, validate visitor intention

against behavioural traces, audit the generative components of interpretation systems for hallucination and cultural bias, and compare across heritage types and cultural regions.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/tourhosp7070208/s1>, Table S1. Early-versus-late respondent comparison on demographic, exposure, visit-history, and marker variables; Table S2. Three-wave robustness check (one-way ANOVA across Wave 1, Wave 2, Wave 3); Table S3. Survey-site distribution of the 418 retained respondents; Table S4. Onsite ($n = 358$) versus online-follow-up ($n = 60$) respondent comparison; Table S5. AI-system name $\times$ system-type matrix; Table S6. AI-exposure duration (minutes) by AI-system type; Table S7. Marker variable item descriptives; Table S8. Marker variable inter-item correlation matrix; Table S9. Continuous visit-history descriptives; Table S10. Demographic profile summary used for the control-variable robustness check.

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Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The data presented in this study are available on request from the corresponding author due to ethical and privacy considerations related to participant consent. Additional materials, including the anonymised questionnaire (provided in Appendix A), SmartPLS outputs, screening information, and documentation of the destination's digital/intelligent guide functions, may also be made available upon reasonable request, subject to institutional and ethical data-sharing requirements.

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Appendix A. Measurement Items

All items were rated on a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree) and were adapted from established scales, then linguistically calibrated to the AI-mediated WHS interpretation context. Source families are indicated next to each construct.

A1. AI-based Interpretation (AII)—adapted from Liu (2020); Xu et al. (2024); Samara et al. (2020).

AII1. The AI interpretation system provides culturally rich explanations of the heritage site.

AII2. The AI interpretation responds to my questions in a context-sensitive way.

AII3. The AI interpretation adapts its narrative depth to my interests and prior knowledge.

AII4. The AI interpretation connects visible site features to historical and religious narratives.

AII5. The AI interpretation gives me a personalised understanding of the heritage site.

A2. Perceived Authenticity (PA)—adapted from Wang (1999); Yi et al. (2019); Domínguez-Quintero et al. (2019).

PA1. The interpretation I received feels historically accurate.

PA2. The interpretation I received feels culturally faithful to this site.

PA3. The interpretation conveys a genuine sense of the site's heritage value.

PA4. The interpretive content feels connected to the place and its living traditions.

PA5. The interpretation communicates the site's meaning credibly.

A3. Parasocial Interaction (PSI)—adapted from Horton and Wohl (1956); Xu et al. (2024); Ye et al. (2021).

PSI1. I feel that the AI interpreter is attentive to my needs.

PSI2. I feel that the AI interpreter is responsive when I ask questions.

PSI3. I feel as if the AI interpreter is accompanying me through the visit.

PSI4. The AI interpreter feels like a knowledgeable companion at the site.

PSI5. The AI interpreter seems to address me personally.

A4. Emotional Experience (EE)—adapted from De Rojas and Camarero (2008); Prayag and Del Chiappa (2023); Domínguez-Quintero et al. (2019).

EE1. The interpretation moved me emotionally.

EE2. The interpretation gave me a sense of awe.

EE3. I felt deeply involved in the heritage encounter.

EE4. The interpretation made me feel inspired.

EE5. The interpretation produced a personal sense of connection to the site.

A5. Conservation Behavioural Intention (CBI)—adapted from Weng et al. (2020); Li et al. (2024); Ruan et al. (2024).

CB1. I am willing to support efforts to protect this heritage site.

CB2. I intend to behave responsibly during my visit to heritage sites.

CB3. I would encourage other visitors to protect heritage sites.

CB4. I would willingly comply with conservation rules and guidelines at heritage sites.

CB5. I would contribute, in some form, to heritage preservation in the future.

Note. Item wording shown above reflects the English-language reporting version; the field questionnaire was administered in Mandarin following translation/back-translation procedures. All five reflective constructs satisfied conventional reliability and validity thresholds ($\alpha \geq 0.915$; $CR \geq 0.936$; $AVE \geq 0.746$), and HTMT values fell below 0.90 (see Tables 3 and 4).

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