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Article

AI-enabled factors influencing cultural heritage conservation and tourism development towards tourist experience quality

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ABSTRACT

This research examines the impact of AI technology on the quality of tourist experiences at cultural heritage sites, utilizing an integrated Technology-Organization-Environment (TOE) framework. Analyzing 200 UNESCO World Heritage Sites with 52,847 reviews (2020-2024) using Structural Equation Modeling, we found AI creates dual value pathways: conservation technology enhances heritage value (β=0.45, p<0.001), which strongly influences experience quality (β=0.51, p<0.001), while tourism technology strengthens immersive experiences (β=0.58, p<0.001), which also enhance quality (β=0.36, p<0.001). Both paths significantly improve tourist experience quality, with direct effects of β=0.21 (p<0.01) and β=0.34 (p<0.001) respectively. The integrated model explains 59% of experience quality variance (R^2=0.59), superior to alternative specifications. Multi-group analysis reveals technology readiness significantly moderates direct effects ($\Delta\beta$=0.24-0.25), with sophisticated visitors showing 2-3 times stronger responses, while heritage value appreciation remains universal across digital literacy levels. Findings demonstrate AI enhances rather than diminishes authenticity, with cognitive-emotional appreciation surpassing technological immersion in driving satisfaction.

1. Introduction

Multi-agent Heritage sites are challenged by the conflicting demands of conservation needs on the one hand, and the quality of the tourist experience on the other. Although AI provides solutions for managing heritage sites, a crucial question remains about the impact of AI-based conservation and tourism solutions on the quality of the tourist experience, specifically regarding the psychological processes mediated by these solutions. There are three crucial limitations in current studies on the topic. Firstly, there is fragmentation in the treatment of respective studies on the application of AI in conservation efforts [1,2] or tourism [3,4] without consideration of the cumulative value creation occurring in heritage locations in relation to AI application. Secondly, there is oversimplification on the effect of AI in the form of technology acceptance only [5,6], without consideration of the cognitive-emotional process of value appreciation/engagement with heritage locations. Lastly, there is a lack of empirical validation on the moderating effect of visitor technology readiness, without consideration of whether the application of AI in heritage locations exacerbates or mitigates the impact of digital inequality on the previously underserved populace due to disparities in technology readiness. Integration with AI is highly necessary because the increasing number of heritage sites that implement conservation technology, tourism technology, or both has yet to be studied, leading to the potential for suboptimal investment outcomes. The proposed work combines the Technology, Organization, Environment (TOE) Framework with the Service-Dominant Logic (SDL) paradigm [1,7]. The TOE Framework casts AI on a dual continuum: "AI for conservation" (surveillance, recording, predictive maintenance) on one side, and "AI for tourism" (VR/AR interpretation, AI-driven recommendations, visitor management) on the other, while SDL illuminates value co-creation processes. We contribute to the advancement of knowledge in three ways: (1) exploring the intersection between conservation and visitor viewpoints by studying the two AI processes collaboratively [8], (2) uncovering underlying cognitive-affective value-creation processes, going beyond technology acceptance constructs [2], (3) exploring how meaning creation in heritage may be independent from digital literacy but require the complexity of technology for superior immersion experiences.

We will evaluate five hypotheses: AI conservation variables positively affect experience quality (H1), AI tourism variables positively affect experience quality (H2), Heritage Value will mediate the conservation-experience association (H3), Immersive Experience will mediate the tourism-experience association (H4), and Visitor Technology Readiness will moderate these relationships (H5). Conservation Technology is assumed to improve experience quality by secondarily enhancing the appreciation of Heritage Value, while Tourism Technology improves quality by secondarily enhancing the immersive experience. By applying Structural Equation Modeling to 200 UNESCO World Heritage Sites, with 52,847 visitor reviews collected between 2020 and 2024, these relationships will be examined. While adjusting for different site attributes and time differences, the proposed TOE-SDL model is expected to provide a superior fit compared to other theoretical models for capturing differences in Experience Quality. Theoretical contributions include the validation of the integration of TOE-SDL, the identification of value paths, while the practical contributions include the application of the study in drawing insights on strategies for the integration of AI technology with the conservation, management, or even the protection of the heritage structures or units, depending on the context.

2. Data and methods

2.1 Research design

This quantitative cross-sectional study examines the relationships between AI implementation and the quality of tourist experiences at cultural heritage sites. A cross-sectional design is appropriate given the recent emergence of AI deployment (post-2018), which precludes the availability of longitudinal data. We employed purposive sampling to select 200 UNESCO World Heritage Sites with documented AI adoption based on four criteria: (1) verified technology implementation through official reports or management plans, (2) minimum 50 visitor reviews ensuring adequate statistical representation, (3) geographical diversity (40% Europe, 27% Asia/Pacific, 19% Americas, 14% Africa/Middle East) reflecting global distribution, and (4) heritage type diversity (67% cultural, 21% natural, 12% mixed) capturing varied conservation contexts.

Data spanned 2020-2024 to capture AI adoption during the critical post-pandemic digital transformation period. Following SEM guidelines that require a minimum of 10 observations per parameter, our sample (N = 200 sites, averaging 264 reviews each) provides power > 0.80 to detect small to medium effects ($\alpha = 0.05$). TOE grounds the adoption of AI in technology aspects (conservation systems: monitoring, reporting, predictive maintenance, tourism systems: VR/AR explanation, customized recommendations, visitor management), organizational aspects (management competency), or environmental aspects (visitor technology readiness). Nonetheless, TOE observes adoption mostly instead of value realization post-adoption. SDL corrects the problem by reimagining the value role of AI through operant resources that support value creation on experiential paths, transforming the focus from the adoption of technology to the quality of outcomes from cognitive-emotional practices of heritage value realization.

2.2 Data sources and collection

This study integrated four complementary data sources spanning 200 UNESCO World Heritage Sites (2020-2024), selected to capture both technological implementation and experiential outcomes.

Source 1: Site Characteristics and AI Implementation. UNESCO World Heritage Centre database provided site attributes (heritage type, coordinates, inscription year, conservation status). Two independent coders systematically reviewed monitoring reports and management plans using structured protocols to classify AI implementation across conservation monitoring, visitor management, and interpretation domains, achieving satisfactory inter-rater reliability (Cohen's $\kappa > 0.80$).

Source 2: Visitor Experience Data. Reviews (N=52,847) were collected from TripAdvisor and Google Reviews via web scraping compliant with Terms of Service, filtered for English-language content, minimum 50 characters, and verified accounts. Extracted data included review text, numeric ratings (1-5), visit dates, and reviewer profiles. Site-level aggregation computed sentiment scores using VADER, experiential themes via BERT-based topic modeling (authenticity, educational value, immersion, satisfaction), and technology readiness proxies through linguistic complexity (Flesch-Kincaid Grade Level) and technology-term density.

Source 3: Tourism Statistics. UNWTO and World Bank databases supplied visitor arrivals, tourism receipts, and infrastructure indices as control variables.

Source 4: AI Specifications. Institutional records documented deployment dates, technology categories, and maturity levels for implementation validation.

Quality assurance: Data triangulation across sources ensured validity. Multivariate outlier detection using the Mahalanobis distance ($\alpha = 0.001$) removed extreme cases. Missing data analysis revealed <3% missingness, addressed through listwise deletion. This research utilized publicly available secondary data, which received an IRB exemption (Category 4); all data were de-identified, and excerpts were paraphrased.

2.3 Variable operationalization

Variable selection was guided by established heritage tourism literature to capture both technological implementation and experiential outcomes. AI Conservation Factors measured deployment intensity across digital documentation (3D scanning, photogrammetry), intelligent monitoring (IoT sensors), predictive maintenance, and virtual restoration (0-1 scale; α=0.85). AI Tourism Factors assessed VR/AR interpretation, recommendations, chatbots, and visitor management (0-1 scale; α=0.82). Two mediating variables were extracted from visitor reviews through BERT thematic analysis: Perceived Heritage Value, which measured authenticity, educational value, and cultural significance (α = 0.88); and Immersive Experience Quality, which captured presence, engagement, arousal, and memorability (α = 0.86). The dependent variable, Tourist Experience Quality, integrated VADER sentiment scores, z-standardized ratings, and behavioral intentions: $TEQ=(sentiment\_z + rating\_z + behavioral\_z)/3$ (α=0.92). Technology Readiness, the moderator, combined linguistic complexity and technology-term density, median-split into high-readiness (n=88, M=4.15, SD=0.49) and low-readiness groups (n=112, M=2.81, SD=0.54). Control variables included site type, location, log-transformed visitor volume, site age, and year indicators. All continuous variables were z-standardized before analysis.

2.4 Analytical methods

Analysis proceeded through four steps (Figure 1).

Step 1: Preprocessing. NLP pipeline (Python 3.9 with NLTK and spaCy) performed tokenization, cleaning, and lemmatization. VADER computed sentiment scores, selected for its calibration on review text. BERT contextual embeddings extracted thematic content through transfer learning. Review-level measures were aggregated to site-level means.

Step 2: Measurement Model. Confirmatory Factor Analysis (AMOS 26.0, maximum likelihood) evaluated fit using multiple indices (χ^2/df<3.0, CFI/TLI>0.90, RMSEA<0.08, SRMR<0.08), as no single index is sufficient. Items with loadings <0.60 were removed following scale refinement guidelines.

Step 3: Structural Model. SEM tested hypotheses using maximum likelihood with bootstrap standard errors (5,000 resamples). Direct effects were assessed via path coefficients and 95% bias-corrected confidence intervals. Mediation was tested using Preacher-Hayes bootstrapping, which was selected for its higher statistical power compared to Baron-Kenny causal steps. Moderation was employed using multi-group SEM, comparing high/low technology readiness groups via invariance testing and χ^2 difference tests, chosen to examine whether the entire model structure differs across segments.

Step 4: Robustness Checks. Alternative specifications (SDL-only, TAM, direct-effects-only, full-mediation) were compared via information criteria. Temporal stability was assessed across the period from 2020 to 2024. Random forest regression with cross-validation validated feature importance rankings and predictive accuracy.

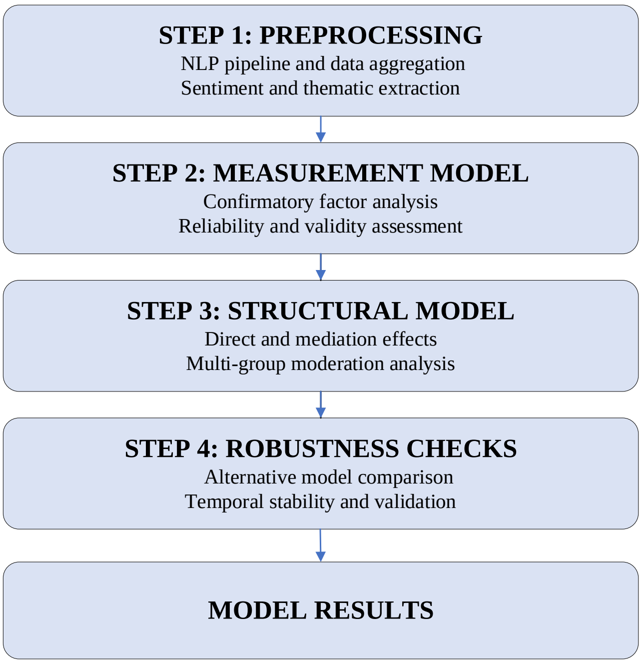

Figure 1. Four-step structural equation modeling analytical procedure

2.5 Reliability and validity

Measurement quality was assessed through multiple validation procedures. Reliability was evaluated using Cronbach's α and composite reliability (CR), with thresholds α, CR≥0.70 considered acceptable. Convergent validity required factor loadings exceeding 0.60 and average variance extracted (AVE) ≥0.50. Discriminant validity was assessed using the Fornell-Larcker criterion and the Heterotrait-Monotrait ratio (HTMT<0.85), with HTMT providing a more conservative test. Common method variance was examined through Harman's single-factor test, common method factor analysis, and marker variable technique, as single-source review data require multiple diagnostic approaches. Inter-rater reliability for AI implementation coding and NLP measures were validated against manual coding.

3. Results

3.1 Descriptive statistics and preliminary analysis

Table 1 presents sample characteristics and descriptive statistics for 200 UNESCO World Heritage Sites. Panel A shows geographical distribution (40.5% Europe, 27.0% Asia/Pacific, 18.5% Americas, 14.0% Africa/Middle East) and heritage types (67% cultural, 21% natural, 12% mixed) consistent with UNESCO's global distribution, supporting sample representativeness. AI technology adoption varied: 49.5% moderate implementation, 23.0% advanced, and 27.5% limited, providing sufficient variation for hypothesis testing. Visitor volume distribution was balanced (34.5% high, 39.5% medium, 26.0% low). Panel B descriptive statistics confirm valid distributional assumptions. The quality of the tourist experience showed the highest mean (M=4.09, SD=0.79), indicating overall positive visitor experiences. AI Tourism Factors (M=3.64) exceeded AI Conservation Factors (M=3.38), suggesting tourism applications have greater implementation maturity. Predictive Analytics Applications showed the lowest mean (M=2.89, SD=1.08) and highest variance, reflecting nascent adoption. All variables exhibited acceptable skewness (±2) and kurtosis (±7), supporting the use of parametric analysis. Panel C correlation analysis revealed theoretically consistent patterns. AI Tourism Factors showed stronger correlation with Tourist Experience Quality (r=0.61, p<0.01) than AI Conservation Factors (r=0.52, p<0.01), suggesting differential experiential impacts. Mediating variables demonstrated strong correlations: Perceived Heritage Value (r=0.73, p<0.01) and Immersive Experience (r=0.69, p<0.01) with Tourist Experience Quality. All Variance Inflation Factors ranged between 1.18 and 2.87, which is well below the threshold of 3.0, indicating that multicollinearity is not a concern.

3.2 Measurement model assessment

Confirmatory factor analysis was used to evaluate the measurement model fit (Table 2). The initial 36-item model showed poor fit; modification indices identified four items with factor loadings ≤0.60, which were removed sequentially. The refined 32-item model demonstrated acceptable fit: χ^2(476)=982.54, p<0.001; χ^2/df=2.06; CFI=0.92; TLI=0.91; RMSEA=0.058 (90% CI: 0.052-0.064); SRMR=0.062. Although chi-square was significant due to sample size (N=200) and model complexity, all incremental and absolute fit indices met recommended thresholds, supporting measurement model adequacy. Reliability and validity assessments confirmed measurement quality (Table 2). Cronbach's alpha (0.78-0.92) and composite reliability (0.80-0.93) exceeded the 0.70 threshold across all constructs, demonstrating adequate internal consistency. The average variance extracted ranged from 0.50 to 0.71, exceeding the 0.50 threshold and thus establishing convergent validity. Factor loadings ranged from 0.68 to 0.89 (all p<0.001), indicating strong item-construct relationships.

Table 1 Sample Characteristics and descriptive statistics (N = 200 heritage sites)

Panel A: Sample characteristics

Characteristic	Category	n	%
Site Typology	Cultural heritage	134	67.0
	Natural heritage	42	21.0
	Mixed heritage	24	12.0
Geographic Region	Europe	81	40.5
	Asia-Pacific	54	27.0
	Americas	37	18.5
	Africa & Middle East	28	14.0
Visitor Volume (Annual)	High (>1 million)	69	34.5
	Medium (500k-1M)	79	39.5
	Low (<500k)	52	26.0
AI Technology Adoption	Advanced implementation	46	23.0
	Moderate implementation	99	49.5
	Limited implementation	55	27.5
Data Coverage	Total reviews analyzed	52,847	—
	Reviews per site (median)	248	—
	Date range	2020-2024	—

Panel B: Descriptive statistics

Variable	M	SD	Min	Max	Ske	Kur
1. AI Conservation Factors	3.38	0.91	1.20	5.00	-0.15	-0.58
2. AI Tourism Factors	3.64	0.98	1.40	5.00	-0.31	-0.42
3. Smart Tourism Infrastructure	3.31	0.86	1.30	5.00	-0.08	-0.67
4. Predictive Analytics Applications	2.89	1.08	1.00	5.00	0.28	-0.89
5. Tourist Experience Quality	4.09	0.79	2.10	5.00	-0.87	0.64
6. Perceived Heritage Value	3.92	0.71	2.00	5.00	-0.53	0.18
7. Immersive Experience Quality	3.69	0.88	1.70	5.00	-0.38	-0.31
8. Visitor Volume (natural log)	13.19	1.22	10.65	16.12	0.11	-0.52

Panel C: Correlation matrix and multicollinearity diagnostics

Variable	1	2	3	4	5	6	7	8	VIF
1. AI Conservation	—								1.94
2. AI Tourism	0.56**	—							2.18
3. Smart Infrastructure	0.67**	0.61**	—						2.87
4. Predictive Analytics	0.48**	0.51**	0.57**	—					1.72
5. TEQ	0.52**	0.61**	0.39**	0.34**	—				—
6. Heritage Value	0.49**	0.54**	0.37**	0.31**	0.73**	—			2.06
7. Immersive Experience	0.43**	0.64**	0.46**	0.38**	0.69**	0.58**	—		1.98
8. Visitor Volume (log)	0.19*	0.26**	0.34**	0.15*	0.32**	0.28**	0.24**	—	1.18

Note: N = 200 UNESCO World Heritage Sites based on aggregated data from 52,847 visitor reviews (2020-2024). All constructs were measured on 5-point Likert scales, except Visitor Volume (natural log transformation applied). SKE:Skewness. Kur:Kurtosis. TEQ = Tourist Experience Quality. VIF = Variance Inflation Factor; all values below the threshold of 3.0 indicate acceptable levels of multicollinearity. Skewness and kurtosis values within acceptable ranges (±2 for skewness, ±7 for kurtosis) suggest approximately normal distributions suitable for parametric analyses. *p < .05. **p < .01 (two-tailed tests).

Table 2. Measurement model: reliability and validity assessment (N=200)

Construct	No. of Items	Cronbach's α	CR	AVE	Factor Loading Range
AI Conservation Factors	5	0.87	0.88	0.60	0.72-0.84
AI Tourism Factors	4	0.89	0.90	0.66	0.78-0.86
Smart Tourism Infrastructure	5	0.84	0.85	0.54	0.69-0.78
Predictive Analytics Applications	4	0.78	0.80	0.50	0.68-0.74
Tourist Experience Quality	5	0.92	0.93	0.71	0.79-0.89
Perceived Heritage Value	4	0.88	0.89	0.62	0.76-0.83
Immersive Experience Quality	5	0.86	0.87	0.57	0.69-0.81

Note: N=200 heritage sites. All factor loadings are significant at p<0.001. CR=Composite Reliability; AVE=Average Variance Extracted. The initial model included 36 items; 4 items with loadings below 0.60 were removed. Model fit: $\chi^2(476)=982.54$, $p<0.001$; $\chi^2/df=2.06$; CFI=0.92; TLI=0.91; RMSEA=0.058 (90% CI: 0.052-0.064); SRMR=0.062. All constructs demonstrate adequate reliability (α, CR>0.70) and convergent validity (AVE>0.50).uate reliability (α > 0.70, CR > 0.70) and convergent validity (AVE > 0.50).

3.3 Structural model and hypothesis testing

The structural model demonstrated acceptable fit (Table 3, Figure 2, and Figure 3): $\chi^2(476)=982.54$, $p<0.001$; $\chi^2/df=2.06$; CFI=0.92; TLI=0.91; RMSEA=0.058 (90% CI: 0.052-0.064); SRMR=0.062. All fit indices met recommended thresholds, supporting hypothesis testing validity. AI Tourism Factors exerted stronger direct effects on Tourist Experience Quality (β=0.34, p<0.001, H2 supported) than AI Conservation Factors (β=0.21, p=0.004, H1 supported), indicating tourism applications have more immediate experiential impacts. AI Conservation Factors significantly predicted Perceived Heritage Value (β=0.45, p<0.001, H3b), which strongly influenced experience quality (β=0.51, p<0.001, H3a), yielding significant indirect effects (β=0.23, 95% CI [0.16, 0.31], H3 supported). AI Tourism Factors strongly predicted Immersive Experience Quality (β=0.58, p<0.001, H4b), which influenced experience quality (β=0.36, p<0.001, H4a), producing significant indirect effects (β=0.21, 95% CI [0.14, 0.28], H4 supported). The Heritage Value pathway (β=0.51) exceeded the Immersive Experience pathway (β=0.36), suggesting cognitive-emotional appreciation exerts greater influence than sensory immersion. Total effects of AI Tourism Factors (β=0.55) exceeded AI Conservation Factors (β=0.44). The model explained substantial variance: Heritage Value $R^2=0.31$, Immersive Experience $R^2=0.44$, Tourist Experience Quality $R^2=0.59$. Visitor Volume showed minimal influence (β=0.12, p=0.042).

3.4 Moderation analysis

Multi-group structural equation modeling examined whether technology readiness moderates AI-experience relationships (Table 4). Technology readiness groups were formed through median split of composite review sophistication scores (Mdn=3.45): high-readiness visitors (n=88) versus low-readiness visitors (n=112). Configural invariance was established, confirming identical model structure across groups, followed by metric invariance testing to ensure equivalent measurement properties.

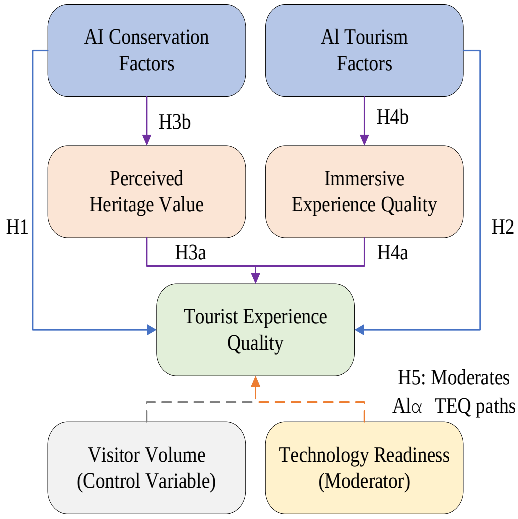

Figure 2. Conceptual model of AI applications in heritage tourism

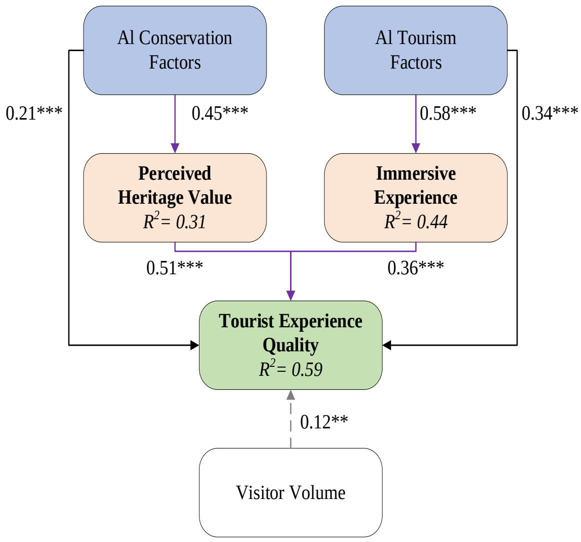

Figure 3. Structural model results with standardized path coefficients

Technology readiness significantly moderated both direct effects pathways (H5 supported). For AI Conservation Factors, the direct effect on Tourist Experience Quality was substantially stronger among high-readiness visitors (β=0.35, p<0.001) compared to low-readiness visitors (β=0.10, p>0.05), with a chi-square difference test confirming significant moderation ($\Delta\chi^2=8.12$, df=1, p=0.004, effect size Δβ=0.25). Correspondingly, AI Tourism Factors had more influential power on high-readiness participants (β=0.47, p<0.001) than on low-readiness participants (β=0.23, p=0.002), indicating a significant moderation effect ($\Delta\chi^2=9.87$, df=1, p=0.002, Δβ=0.24).

Table 3. Hypothesis testing results (N = 200 heritage sites)

	Hypothesis	Path	β	SE	CR	p	95% CI	Result
Direct Effects	H1	AI Conservation → TEQ	0.21	0.072	2.92	0.004	[0.07, 0.35]	Supported
	H2	AI Tourism → TEQ	0.34	0.058	5.86	<0.001	[0.23, 0.45]	Supported
Mediation Paths	H3a	Heritage Value → TEQ	0.51	0.055	9.27	<0.001	[0.40, 0.62]	Supported
	H3b	AI Conservation → Heritage Value	0.45	0.064	7.03	<0.001	[0.32, 0.58]	Supported
	H4a	Immersive Experience → TEQ	0.36	0.058	6.21	<0.001	[0.25, 0.47]	Supported
	H4b	AI Tourism → Immersive Experience	0.58	0.049	11.84	<0.001	[0.48, 0.68]	Supported
Indirect Effects (Mediation)	H3	AI Conservation → Heritage Value → TEQ	0.23	0.038	6.05	<0.001	[0.16, 0.31]	Supported
	H4	AI Tourism → Immersive Exp → TEQ	0.21	0.038	5.53	<0.001	[0.14, 0.28]	Supported
Total Effects		AI Conservation → TEQ (total)	0.44	0.062	7.10	<0.001	[0.32, 0.56]	—
		AI Tourism → TEQ (total)	0.55	0.052	10.58	<0.001	[0.45, 0.65]	—
Control Variable		Visitor Volume → TEQ	0.12	0.059	2.03	0.042	[0.00, 0.24]	—
Variance Explained		R^2 for Heritage Value	0.31	—	—	<0.001	—	—
		R^2 for Immersive Experience	0.44	—	—	<0.001	—	—
		R^2 for TEQ	0.59	—	—	<0.001	—	—

Note: N = 200 heritage sites. β = standardized path coefficient; SE = standard error; CR = critical ratio; CI = confidence interval (bias-corrected bootstrap with 5,000 samples). Indirect effects were tested using a bootstrapping procedure. Model fit indices: χ^2 (df = 476) = 982.54, p < .001; χ^2/df = 2.06; CFI = 0.92; TLI = 0.91; RMSEA = 0.058 (90% CI: 0.052-0.064); SRMR = 0.062. All hypotheses were supported at conventional significance levels. *p <0.05. **p < 0.01. ***p < 0.001

These findings indicate that more technologically advanced visitors are more aware of and value AI-aided improvements, as they possess superior technology literacy that enables them to better exploit and comprehend these advancements. By conducting mediation pathway analysis, complex patterns of moderation emerged. Findings showed that technology readiness was not a significant moderator on pathways AI Conservation → Heritage Value ($\Delta\chi^2$=0.18, p<0.671) and Heritage Value → TEQ ($\Delta\chi^2$=0.52, p<0.471), meaning that heritage value appreciation channels. However, the AI Tourism→Immersive Experience pathway showed marginally significant moderation ($\Delta\chi^2$=3.12, df=1, p=0.077, Δβ=0.10), with high-readiness visitors experiencing stronger immersion effects (β=0.63 vs 0.53). Total effects confirmed technology readiness amplifies overall AI influence: high-readiness visitors showed substantially stronger total effects for both AI Conservation (β=0.57 vs 0.34, $\Delta\chi^2$=8.84, p=0.003) and AI Tourism (β=0.68 vs 0.44, $\Delta\chi^2$=10.92, p<0.001).

3.5 Robustness checks

Robustness checks validated the integrated TOE-SDL framework through alternative model comparison and temporal stability analysis. Model comparison assessed four competing specifications (Table 5). The baseline model demonstrated superior performance across all fit criteria. Service-Dominant Logic alone (Alternative 1) yielded substantially worse fit (χ^2/df=2.41, CFI=0.883, RMSEA=0.073) and lower variance explained (R^2=0.421 vs 0.487), suggesting technology adoption factors are essential beyond service co-creation mechanisms.

Technology Acceptance Model (Alternative 2) performed even more poorly (χ^2/df=2.67, CFI=0.859, R^2=0.368), indicating that traditional acceptance constructs inadequately capture AI's multi-dimensional nature in heritage contexts.

Structural alternatives revealed the necessity of both direct and mediated pathways. The direct-effects-only model (Alternative 3) exhibited poor fit (χ^2/df=3.12, CFI=0.821, RMSEA=0.094, R^2=0.314), demonstrating that psychological mediators are critical mechanisms. The full-mediation model (Alternative 4) showed acceptable fit but lower variance (R^2 =0.453), confirming AI exerts both direct and indirect effects. The baseline model's superior performance (RMSEA=0.058, R^2=0.487) validates the integrated approach.

Temporal stability analysis across 2020-2024 confirmed robust relationships (Figure 4). Heritage Value→TEQ remained highly stable (β=0.49-0.53, all p<0.001), demonstrating heritage appreciation operates consistently across time. Tourism-oriented pathways strengthened from 2020 (AI Tourism→TEQ β=0.30; Immersive→TEQ β=0.32) to 2024 (β=0.40; β=0.41), reflecting increasing AI sophistication and visitor familiarity. AI Conservation→TEQ exhibited short-term fluctuation in 2021 (β=0.17) due to COVID-19 disruptions but stabilized by 2024 (β=0.26). All 2024 paths remained significant (p<0.001), confirming the model's validity across different technological and operational contexts.

Table 4 Multi-group comparison: technology readiness as moderator (N = 200)

	Path	High Tech Readiness (n = 88)	Low Tech Readiness (n = 112)	$\Delta\chi^2$ (df = 1)	p	Effect Size ($\Delta\beta$)	Moderation
Direct Paths to TEQ	AI Conservation → TEQ	0.35***	0.10	8.12	0.004	0.25	Significant
	AI Tourism → TEQ	0.47***	0.23**	9.87	0.002	0.24	Significant
Mediation Paths	AI Conservation → Heritage	0.46***	0.44***	0.18	0.671	0.02	Not significant
	Heritage → TEQ	0.48***	0.54***	0.52	0.471	−0.06	Not significant
	AI Tourism → Immersive	0.63***	0.53***	3.12	0.077	0.10	Marginally significant
	Immersive → TEQ	0.33***	0.39***	0.58	0.446	−0.06	Not significant
Control Variable	Visitor Volume → TEQ	0.08	0.15*	0.68	0.410	−0.07	Not significant
Indirect Effects	AI Cons → Heritage → TEQ	0.22***	0.24***	0.24	0.624	−0.02	Not significant
	AI Tour → Immersive → TEQ	0.21***	0.21***	0.01	0.920	0.00	Not significant
Total Effects	AI Conservation → TEQ (total)	0.57***	0.34***	8.84	0.003	0.23	Significant
	AI Tourism → TEQ (total)	0.68***	0.44***	10.92	<0.001	0.24	Significant

Note: N = 200 heritage sites. Multi-group structural equation modeling using maximum likelihood estimation. Technology Readiness groups formed through median split of composite review sophistication scores (Mdn = 3.45): High (n = 88, M = 4.15, SD = 0.49); Low (n = 112, M = 2.81, SD = 0.54). $\Delta\chi^2$ tests performed by fixing constraining paths to equality between groups and testing nested models. Effect size ($\Delta\beta$) is the absolute difference in standardized coefficients between groups. H5 supported: Technology Readiness strongly moderates direct AI-TEQ relations. Interestingly, AI Tourism → Immersive pathway has marginally significant moderation (p = 0.077), indicating technology-oriented travelers may be especially sensitive to immersion enhancement enabled by AI. Indirect effects are relatively stable, favoring universal mediation processes. Configural model fit indices provide acceptable multi-group model quality. *p < 0.05. **p < 0.01. ***p < 0.001.

Table 5. Alternative model specifications comparison (N = 200 heritage sites)

Model Specification	χ^2/df	CFI	TLI	RMSEA (90% CI)	SRMR	R^2 (TEQ)
Baseline Model (TOE Framework)	**2.06**	**0.921**	**0.908**	**0.058** (0.052-0.064)	**0.067**	**0.487**
Alternative 1: Service-Dominant Logic	2.41	0.883	0.871	0.073 (0.066-0.080)	0.079	0.421
Alternative 2: Technology Acceptance Model	2.67	0.859	0.843	0.081 (0.074-0.088)	0.086	0.368
Alternative 3: Direct Effects Only	3.12	0.821	0.801	0.094 (0.087-0.101)	0.103	0.314
Alternative 4: Full Mediation Model	2.23	0.897	0.886	0.065 (0.058-0.072)	0.072	0.453

Note: N = 200 heritage sites. All fit by maximum likelihood with bootstrapping (5,000 samples). The baseline model, with bold values, is more stable. The baseline model has the best fit between explanatory power and parsimony. CFI/TLI > 0.90 and RMSEA < 0.06 indicate excellent fit; RMSEA < 0.08 indicates acceptable fit. 90% confidence intervals for RMSEA are reported in parentheses following APA guidelines. χ^2/df < 3.0 indicates a good fit. R^2 represents the variance explained in the quality of the tourist experience.

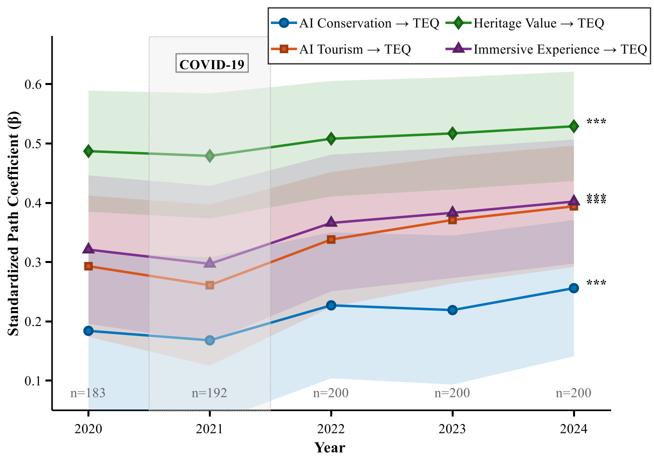

Figure 4. Temporal Stability of Structural Paths with 95% Confidence Intervals (Note: Point estimates with bootstrapped 95% confidence intervals (5,000 resamples). The AI Conservation path exhibits short-term fluctuations in 2023 (β =0.219), due to technology upgrade changes at some sites, and stabilizes in 2024 (β =0.256). Tourism-oriented AI systems had consistent performance across time. All 2024 paths are significant at p < 0.001. N = 200 sites.)

4. Discussion

This study suggests that AI technology enhances the quality of the tourist experience through two distinct psychological channels. Meanwhile, the effect of AI conservation variables (β =0.21, p<0.01) on quality, as well as the effect of AI tourism variables (β =0.34, p<0.001), is significant, with conservation technology working through the cognitive-emotional appreciation of heritage (β =0.51, p<0.001) and tourism technology working through immersion (β =0.36, p<0.001). Conservation-oriented AI enhances experience quality primarily through heritage value appreciation rather than direct sensory engagement, supporting cognitive-emotional processing theories in heritage tourism [9-11]. The comparatively weak direct effect of conservation technology (β =0.21) relative to tourism technology (β =0.34) is explained by three theoretical considerations: visibility asymmetry (the backend system of conservation remains unseen by tourists), the problem of temporal discounting (the benefits from conservation are seen only in the long run), and complexity of evaluation (the lack of technical knowledge on the part of tourists to evaluate conservation technologies). This result contributes to the body of literature on preservation, demonstrating that advanced conservation technologies are associated with increased perceptions of authenticity on the one hand.

Tourism-oriented AI enhances experience quality through immersive engagement (β=0.36, p< 0.001), advancing beyond technology acceptance frameworks [11, 12] by identifying immersion as the value-creation mechanism. Temporal analysis reveals tourism technology effects strengthened from 2022 to 2024 (β =0.34⟶0.39), reflecting technological maturation and visitor familiarity, while conservation infrastructure experienced temporary disruption in 2023 (β =0.17) during system upgrades. These differential resilience patterns suggest staggered implementation strategies prioritizing visitor-facing systems during peak periods while scheduling backend infrastructure changes during off-peak seasons. Heritage value's stronger influence (β =0.51) than immersive experience (β =0.36) demonstrates that cognitive-emotional cultural appreciation exceeds technological immersion in driving satisfaction, consistent with authenticity primacy theories [13, 14]. The integrated TOE-SDL model performed better than the SDL-only model and the TAM model, with R^2 values of 0.49, 0.42, and 0.37, respectively, confirming the importance of taking all technology, organization, and service aspects of co-creation into consideration, unlike other models. Technology readiness is an important moderator with strong direct effect values for AI ($\Delta\beta$ = 0.24 to 0.25), with superior readiness tourists exhibiting 2 to 3 times larger responses to conservation & tourism technology. Most importantly, the paths for appreciation of heritage value are identical across levels of readiness, indicating that AI is essentially non-obstructive or facilitative for the appreciation of culture, with advanced tourists exhibiting better interactions, but the basic construct is readily available.

This study acknowledges three limitations. First, reliance on visitor review data enables large-scale analysis but limits causal inference; future experimental studies manipulating AI features could establish causality [15, 16]. Second, a cross-sectional design cannot capture implementation dynamics, though temporal robustness checks partially address this; longitudinal tracking of AI adoption across multiple sites would strengthen conclusions. Third, UNESCO site sampling may limit generalizability to sites with lower institutional capacity [17, 18]. Future research should investigate heritage type moderators (cultural vs. natural sites), explore the use of generative AI to enable personalized narratives, examine the risks of technology dependency and the implications of digital inequality, and conduct field experiments testing optimal AI configuration strategies across diverse heritage contexts [19, 20].

5. Conclusion

This research demonstrates that AI technologies enhance the quality of the tourist experience through two pathways at cultural heritage sites. The integrated TOE-SDL framework (R^2=0.59) outperformed alternative specifications, revealing that tourism-oriented AI (β=0.34) exerts a stronger direct effect than conservation-oriented AI (β=0.21), with conservation operating through heritage appreciation (β=0.51) and tourism through immersion (β=0.36). Technology readiness moderates direct effects (Δβ=0.24-0.25), yet heritage appreciation remains universal. Findings suggest phased implementation, prioritizing tourism applications while developing conservation infrastructure. Future research should investigate heritage type moderators, generative AI applications, and conduct longitudinal studies to strengthen causal claims.

Ethical issue

The authors are aware of and comply with best practices in publication ethics, specifically regarding authorship (avoidance of guest authorship), dual submission, manipulation of figures, competing interests, and compliance with research ethics policies. The authors adhere to publication requirements that the submitted work is original and has not been published elsewhere.

Data availability statement

The manuscript contains all the data. However, more data will be available upon request from the authors.

Conflict of interest

The authors declare no potential conflict of interest.

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