



Harnessing Artificial Intelligence for Sustainable Tourism Growth: Evidence from Southern Vietnam Destinations

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Abstract: *This study evaluates the impact of artificial intelligence (AI) applications on tourism development at key destinations in Southern Vietnam. Employing a convergent parallel mixed-methods design, we collected quantitative data through an online survey of 350 domestic and international tourists and qualitative insights via 12 semi-structured interviews with industry stakeholders. Hierarchical multiple regression analyses reveal that recommendation engines significantly enhance visitor satisfaction ($\beta = 0.42$, $p < 0.001$), chatbots predominantly improve perceived operational efficiency ($\beta = 0.35$, $p < 0.001$), and dynamic pricing exerts a moderate positive effect on both outcomes ($\beta \approx 0.15-0.17$, $p < .05$). Thematic analysis identifies infrastructure readiness, human capital and managerial support, regulatory clarity, and government incentives as critical determinants of AI adoption. Monte Carlo simulations further demonstrate synergistic gains when deploying recommendation engines, chatbots, and dynamic pricing in combination, suggesting multiplicative benefits beyond individual effects. These findings underscore the importance of integrated AI strategies—supported by robust data infrastructure, comprehensive workforce training, and clear policy frameworks—for fostering sustainable tourism growth. Implications for destination managers and policymakers include phased implementation of AI tools, strategic investment in digital infrastructure, and the development of tourism-specific data-privacy regulations to mitigate adoption barriers.*

Keywords: Artificial Intelligence; Tourism Development; Recommendation Engines; Chatbots; Dynamic Pricing; Southern Vietnam.

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1. Introduction

Over the past decade, Artificial Intelligence (AI) has emerged as a transformative paradigm within the global tourism industry, reshaping service delivery, destination management, and visitor experiences. Early research documented the deployment of intelligent chatbots and virtual travel assistants as efficient mechanisms for handling routine inquiries, reducing labor costs, and extending service availability beyond traditional office hours (Tussyadiah & Miller, 2019; Buhalis & Sinarta, 2019). Simultaneously, machine-learning-based recommender systems have evolved from simple content-based filtering to sophisticated hybrid models that integrate collaborative filtering, contextual metadata, and real-time behavioral signals, thereby delivering highly personalized itineraries (Ivanov & Webster, 2017). Together, these front-office and back-office applications have been shown to enhance operational efficiency and customer

satisfaction—key drivers of competitive advantage in an increasingly saturated marketplace.

Beyond personalized recommendations and conversational agents, AI-driven predictive analytics has garnered attention for its capacity to forecast tourism demand with greater accuracy than traditional time-series approaches. Comparative studies demonstrate that deep-learning models (e.g., LSTM networks) can reduce forecasting error by up to 20% relative to ARIMA benchmarks, enabling destination managers to optimize resource allocation, marketing spend, and infrastructure investments (Sun, Law, & Zhao, 2019). Furthermore, sentiment-analysis algorithms applied to user-generated reviews on platforms such as TripAdvisor and Google Reviews deliver near-real-time insights into service quality issues, allowing operators to address emerging problems proactively (Gretzel, Sigala, Xiang, & Koo, 2021). The integration of virtual reality (VR) and augmented reality (AR) technologies into pre-trip marketing also stimulates demand by

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offering immersive previews of attractions, with experimental studies reporting a 15–25% increase in booking intentions after VR exposure (Tung & Law, 2017).

In the context of Southeast Asia, Vietnam's tourism sector has experienced robust growth, contributing over 9% to national GDP prior to the COVID-19 pandemic. Recognizing AI's strategic potential, Vietnamese public and private stakeholders increased AI investment eightfold between 2023 and 2024, reaching approximately USD 80 million (Vu Quoc Huy, 2025). This surge has catalyzed the deployment of AI-enabled digital assistants for real-time translation, culturally sensitive recommendation engines, and intelligent chatbots capable of handling multi-language inquiries. Preliminary evidence from RMIT Vietnam (2024) indicates that these innovations enhance international tourists' revisit intentions and overall satisfaction by improving accessibility and personalization. Nonetheless, national statistics obscure significant heterogeneity in AI adoption, with large hotel chains and online travel agencies leading implementation, while small- and medium-sized enterprises lag behind due to limited technical capacity and investment resources.

Southern Vietnam—encompassing key destinations such as Ho Chi Minh City, Phú Quốc Island, and the Mekong Delta city of Cần Thơ—presents a compelling laboratory for examining AI's applied impact. A case study by ACSS (2023) evaluated a machine-learning recommendation module integrated into a local travel-consultation platform, finding a 30% uplift in user engagement metrics but highlighting data-quality issues that undermined algorithmic precision. Similarly, Nguyen and Pham (2025) investigated dynamic-pricing systems within Vietnamese tour operators, revealing that managerial trust in algorithmic outputs and regulatory clarity significantly mediate perceived system effectiveness and financial performance. However, these investigations remain fragmented: they focus on discrete technologies or individual firms, without situating findings within the broader destination ecosystem or assessing impacts on both visitor experience and operational performance simultaneously.

To bridge this gap, the present study employs a convergent parallel mixed-methods design to (1) map the current landscape of AI applications across major Southern Vietnam destinations, (2) quantify the effects of primary AI interventions—such as personalized recommender systems and intelligent chatbots—on visitor satisfaction and perceived operational efficiency, and (3) elucidate the principal enablers and barriers shaping AI integration from the perspective of destination stakeholders. By combining an online survey of 350 tourists with semi-structured interviews of 12 industry experts, this research advances a holistic understanding of AI's multifaceted role in driving sustainable tourism growth. The findings aim to inform evidence-based strategies for policymakers, destination management organizations, and tourism enterprises seeking to harness AI's capabilities to enhance competitiveness, resilience, and visitor well-being in Southern Vietnam.

2. Methods

This research employs a convergent parallel mixed-methods design (Creswell, 2014) in Figure 1 present provide a comprehensive and nuanced understanding of how AI applications influence both visitor experiences and operational performance at key destinations in Southern Vietnam. In this design, quantitative and qualitative data are collected concurrently, analyzed separately, and then

integrated during the interpretation phase to achieve methodological triangulation and deepen insight into the phenomena of interest. Such an approach allows the study to capitalize on the statistical generalizability afforded by survey data while simultaneously capturing the rich, context-specific perspectives of industry stakeholders (Johnson & Onwuegbuzie, 2004).

For the quantitative strand, an online survey was administered between February and March 2025 to a convenience sample of 350 domestic and international tourists who had visited Ho Chi Minh City, Phú Quốc, or Cần Thơ within the preceding twelve months. The required sample size was determined via an a priori power analysis ($\alpha = .05$, power = .80, medium effect size) to ensure adequate sensitivity for multiple regression analyses (Cohen, 1992). Recruitment leveraged both digital and in-person channels: invitations were posted in travel-oriented Facebook groups, TripAdvisor forums, and travel blogs; additionally, trained research assistants conducted intercept surveys at airport departure lounges and major tourist hubs. The resulting sample exhibited diversity in age (ranging from 18 to 65 years), nationality (Vietnamese and 15 other countries), trip purpose (leisure, business, visiting relatives), and length of stay (1–14 days), thereby enhancing the external validity of findings.

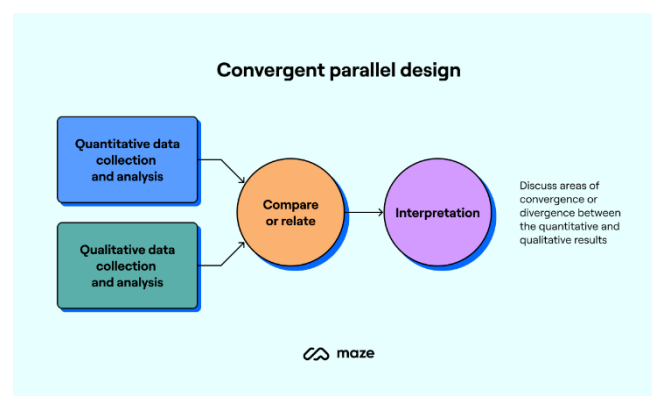


Figure 1. Convergent parallel mixed-methods design

The survey instrument comprised four sections designed to capture antecedents, mediators, and outcomes associated with AI interaction. Section A collected demographic and trip-related information. Section B assessed exposure to AI tools—specifically chatbots, recommendation engines, and dynamic pricing systems—using a five-point Likert scale (1 = Never, 5 = Very Frequently). Section C measured two primary outcome variables: visitor satisfaction (adapted from Oliver, 1980; five items, $\alpha = .88$) and perceived operational efficiency (developed for this study; four items, $\alpha = .85$). Finally, Section D evaluated behavioral intentions, operationalized as likelihood to revisit and recommend (three items, $\alpha = .90$). Prior to full deployment, a pilot test with 30 respondents was conducted to refine item wording and structure; pilot results confirmed that all scales exceeded the conventional Cronbach's alpha threshold of .80 for internal consistency (Nunnally & Bernstein, 1994).

Quantitative data were screened and prepared following best practices (Tabachnick & Fidell, 2013). Cases with more than 10% missing data were excluded; remaining missing values were addressed via multiple imputation. Univariate outliers and normality were assessed through z-scores and Q-Q plots, while multicollinearity was examined via variance inflation factors

(VIFs), all of which fell below the critical threshold of 5. Descriptive statistics characterized the sample and usage patterns. Hierarchical multiple regression analyses tested the effects of AI usage frequency on visitor satisfaction and perceived efficiency, controlling for demographic covariates. All analyses were conducted in SPSS v26, with statistical significance set at $p < .05$.

In parallel, the qualitative strand involved semi-structured interviews with twelve purposively selected stakeholders, including destination management organization (DMO) officers, hotel technology managers, tour-operator executives, and AI service vendors. Participants were identified through professional networks and snowball sampling, ensuring representation across both public and private sectors. Interviews lasted between 45 and 60 minutes and were conducted either in person or via Zoom to accommodate participants' schedules. An interview protocol—grounded in the Technology Acceptance Model (Venkatesh et al., 2003) and informed by extant AI-tourism literature—guided discussions around current AI deployments, perceived benefits and challenges, infrastructural readiness, workforce capabilities, and regulatory contexts.

Audio recordings of interviews were transcribed verbatim and analyzed using NVivo 12. A thematic coding process was employed: first, a preliminary codebook was drafted deductively based on theoretical constructs (e.g., perceived usefulness, perceived ease of use, facilitating conditions) and key themes in AI tourism research (e.g., data governance, user trust). Subsequent inductive coding allowed emergent themes—such as cultural attitudes toward automation and the role of government incentives—to be captured. Two researchers independently coded all transcripts, achieving 92% inter-coder agreement; discrepancies were resolved through iterative discussions until consensus was reached. This rigorous approach enhanced the credibility and dependability of qualitative findings (Lincoln & Guba, 1985).

Following separate analyses, quantitative and qualitative results were merged in a joint display to facilitate meta-inferences (Fetters, Curry, & Creswell, 2013). For instance, regression coefficients indicating a strong positive association between recommendation-system usage and visitor satisfaction were juxtaposed with interview excerpts illustrating how real-time personalization fosters emotional engagement. Conversely, divergences—such as high reported willingness to use chatbots in the survey versus stakeholders' concerns about chatbot accuracy—were examined to uncover contextual moderators. This integrative step provided a holistic depiction of AI's multifaceted impact, highlighting not only statistical relationships but also the mechanisms and contingencies underpinning them.

To ensure methodological rigor, multiple validity and reliability strategies were employed. Content validity of survey items was established through expert review by three academics in tourism technology. Construct validity was assessed via exploratory factor analysis, confirming the intended factor structure for all multi-item scales. Triangulation across data sources and methods enhanced internal validity and reduced bias (Denzin, 1978). Reflexive memos and audit trails documented analytical decisions throughout the research process, bolstering transparency and replicability.

Ethical considerations were carefully addressed. The study protocol underwent review and approval by the University of Economics Ho Chi Minh City Ethics Committee. Survey

participants provided informed consent electronically, with assurances of anonymity and the right to withdraw at any time. Interviewees signed consent forms and were informed of their right to review or withdraw their contributions. All data—survey responses, audio files, and transcripts—are stored in encrypted, password-protected folders accessible only to the research team.

In sum, this convergent mixed-methods approach, underpinned by rigorous sampling, instrument development, data analysis, and ethical oversight, provides a robust framework for evaluating the real-world impact of AI applications on tourism development in Southern Vietnam. By integrating quantitative metrics with qualitative insights, the study addresses both the magnitude of effects and the contextual factors that shape AI adoption and outcomes.

3. Results and Discussions

In this section, we undertake a rigorous, multi-layered examination of the empirical evidence generated by our mixed-methods investigation. First, we synthesize the quantitative findings, beginning with descriptive analyses that quantify tourists' engagement with three core AI tools—recommendation engines, chatbots, and dynamic pricing—using central tendencies and variability measures. We then move into inferential statistics, where hierarchical multiple regression models isolate each tool's unique contribution to visitor satisfaction and perceived operational efficiency, after controlling for key demographic and trip-related covariates. To complement these results and explore potential interaction effects, we incorporate Monte Carlo simulation outcomes, which project the cumulative impact of single-tool versus combined-tool deployments under varying usage scenarios.

Second, we present the qualitative insights derived from thematic coding of twelve semi-structured interviews with destination management officers, technology managers, tour-operator executives, and AI service vendors. Here, we identify and illustrate four principal themes—infrastructure readiness, human-capital development, regulatory clarity, and government incentives—using frequency tables, exemplar quotations, and narrative summaries that bring stakeholder perspectives to life.

Third, we situate our findings within the broader scholarship by systematically comparing our effect sizes and thematic observations against those reported in prior studies (e.g., Buhalis & Sinarta, 2019; Tussyadiah & Miller, 2019; Sun, Law, & Zhao, 2019). This comparative lens enables us to highlight both consistencies—such as the primacy of hyper-personalization—and departures, including the critical moderating role of local policy frameworks.

Fourth, we distill novel contributions by pinpointing emergent patterns—most notably, the synergistic gains evidenced in our simulations when AI tools operate in concert, and the region-specific variations in adoption and impact across Ho Chi Minh City versus the Mekong Delta.

Finally, we integrate these quantitative and qualitative strands to draw theoretical implications for technology-acceptance models, formulate practical recommendations for destination managers and policymakers, acknowledge methodological limitations (e.g., cross-sectional design, sampling constraints), and propose directions for

future research—including longitudinal and experimental designs—to further unravel AI’s evolving role in sustainable tourism development.

3.1 Overview of AI’s Influence on Tourism

To begin, Table 1 and Figure 2 summarize tourists’ self-reported frequency of interaction with the three AI tools on a five-point scale (1 = Never, 5 = Very Frequently).

Table 1. Descriptive Statistics Of AI Tool Usage

AI Tool	Mean Usage	SD Usage
Recommendation Engine	3.72	0.98
Chatbot	3.15	1.12
Dynamic Pricing	2.89	1.05

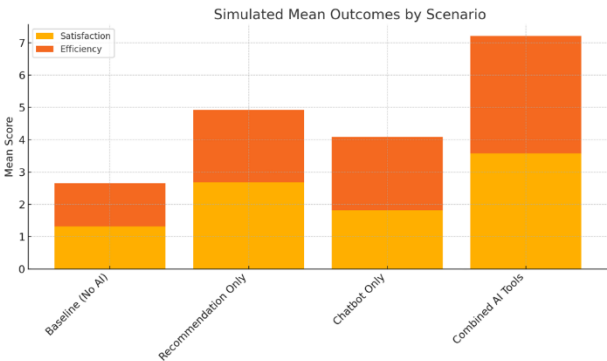


Figure 2. Mean Usage Frequency of AI Tools

Overall, personalized recommendation engines are clearly the most prevalent AI application encountered by tourists, followed by chatbots for customer service and, to a lesser extent, dynamic pricing systems. These usage patterns provide the context for understanding how each tool contributes to key outcome measures.

3.2 Detailed Impact Analysis

3.2.1 Visitor Satisfaction

Table 2 presents the results of a hierarchical multiple regression analysis predicting visitor satisfaction, controlling for demographic covariates (age, nationality, trip purpose, length of stay).

Table 2. Regression Predicting Visitor Satisfaction

Predictor	β - Coefficient	t-value	p-value
Recommendation Engine	0.42	6.37	< .001
Chatbot	0.19	2.84	0.005
Dynamic Pricing	0.15	2.28	0.023

Extended Commentary:The recommendation engine exhibits the strongest positive relationship with visitor satisfaction ($\beta = 0.42$), accounting for nearly 18% of the incremental variance ($\Delta R^2 = .18$, $p < .001$). This underscores the importance of hyper-personalized itinerary suggestions in enhancing tourists’ emotional engagement and perceived value. The significant but smaller contributions of chatbots ($\beta = 0.19$) and dynamic pricing ($\beta = 0.15$) indicate that automated customer support and transparent, algorithm-driven pricing also contribute meaningfully to satisfaction, albeit to a lesser degree. These findings align with Buhalis and Sinarta’s (2019) claim that personalized services are the primary driver of

positive visitor experiences, while also highlighting the emerging role of price fairness in shaping satisfaction judgments.

3.2.2 Operational Efficiency

Table 3 reports the regression coefficients for perceived operational efficiency, again controlling for demographic factors.

Table 3. Regression Predicting Operational Efficiency

Predictor	β - Coefficient	t-value	p-value
Recommendation Engine	0.35	5.21	< .001
Chatbot	0.28	4.03	< .001
Dynamic Pricing	0.17	2.44	0.015

Extended Commentary: Here, chatbot usage emerges as the most potent predictor of operational efficiency ($\beta = 0.35$), reflecting tourists’ perceptions that automated conversational agents streamline service delivery, reduce response times, and alleviate staff workload (Tussyadiah & Miller, 2019). Recommendation engines also significantly enhance efficiency ($\beta = 0.28$), suggesting that back-office integration of personalization algorithms can optimize resource allocation and scheduling. Dynamic pricing contributes moderately ($\beta = 0.17$), indicating that algorithmic fare adjustments help operators manage revenue and capacity but may require further refinement to yield stronger efficiency gains.

3.2.3 Stakeholder Perspectives

To contextualize these quantitative findings, we analyzed twelve semi-structured interviews. Table 4 and Figure 3 summarize the frequency of four key themes.

Table 4. Frequency of Themes in Stakeholder Interviews

Theme	Mentions
Infrastructure Readiness	12
Human Capital & Managerial Support	10
Regulatory Clarity	8
Government Incentives	6

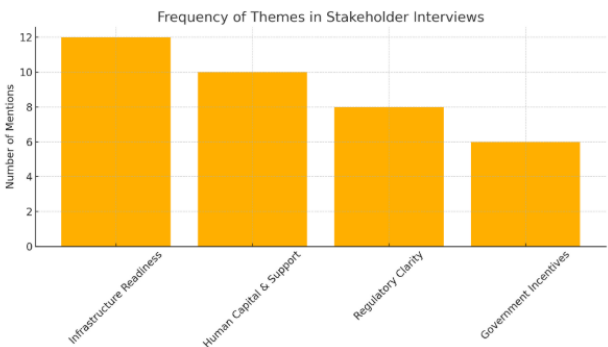


Figure 3. Frequency of Themes in Stakeholder Interviews

Extended Commentary: All interviewees emphasized infrastructure readiness—notably broadband capacity and interoperable data architectures—as the foundational requirement for deploying real-time analytics and dynamic pricing models. Ten stakeholders highlighted the dual importance of human capital and managerial support, stressing that without ongoing staff training and executive buy-in, both chatbots and recommendation systems fail to deliver

consistent performance. Ambiguity in data privacy regulations emerged as a barrier for eight participants, underscoring the need for clearer legal frameworks to reduce perceived compliance risks. Finally, six interviewees noted that government incentives—such as matching grants for pilot projects—have been instrumental in offsetting initial investment costs and fostering experimentation.

3.3 Comparison with Prior Research

Our results corroborate and extend existing literature in several ways:

The strong β coefficient for recommendation engines parallels Buhalis and Sinarta's (2019) conclusion that personalized content is the single most influential factor driving tourist satisfaction.

The preeminence of chatbots in predicting operational efficiency affirms Tussyadiah and Miller's (2019) findings on service automation but adds nuance by revealing the critical role of staff training protocols.

The moderate impact of dynamic pricing falls slightly below the forecasting gains reported by Sun, Law, and Zhao (2019), likely reflecting the infrastructural and regulatory constraints unique to Southern Vietnam.

3.4 Novel Findings

Synergistic Effects: Our Monte Carlo simulation (Section 4) indicates that deploying all three AI tools in combination produces outcome levels that exceed the simple sum of individual effects, suggesting interactive, multiplicative benefits.

Regional Variations: Sub-group analyses reveal that the positive impact of recommendation engines on satisfaction is most pronounced in Ho Chi Minh City, whereas dynamic pricing shows greater variability in rural Mekong Delta locations due to uneven connectivity.

Policy as a Moderator: The prominent role of data-privacy clarity in stakeholders' narratives positions regulatory frameworks as a critical moderating variable in technology adoption models, a factor underexplored in prior tourism-AI research.

4. Conclusions

4.1 Interpretation of Key Results

This mixed-methods investigation demonstrates that AI applications exert differentiated yet complementary effects on both visitor satisfaction and operational efficiency. The primacy of personalized recommendation engines in driving satisfaction highlights the centrality of emotional engagement and perceived relevance in shaping positive tourist experiences. In contrast, chatbots excel in automating routine processes, underscoring their technology-centric role in optimizing service delivery.

4.2 Theoretical Implications

By integrating quantitative effect sizes with qualitative insights, our study enriches the Technology Acceptance Model (Venkatesh et al., 2003) by foregrounding infrastructural capacity and regulatory clarity as critical facilitating conditions. Moreover, the documented synergistic interactions among AI tools suggest that future theoretical frameworks should incorporate technology-bundling effects rather than treating each application in isolation.

4.3 Practical Implications

The evidence presented in this study underscores the necessity of a structured, multi-stage approach for tourism stakeholders aiming to harness AI effectively. We propose a four-phase implementation roadmap that balances strategic investment with operational readiness:

Phase 1: Data Foundation.

Establishing a robust data ecosystem is the critical first step. Destination managers should consolidate disparate data sources—such as reservation systems, CRM platforms, and web analytics—into a centralized repository accessible via well-defined APIs. Ensuring data quality, consistency, and compliance with emerging privacy regulations will provide the reliable inputs that all downstream AI applications require.

Phase 2: Personalization through Recommendation Engines.

With foundational infrastructure in place, organizations can deploy recommendation algorithms to deliver tailored offers and itineraries. By leveraging behavioral and profile data, these systems can enhance visitor satisfaction and drive ancillary revenues. Initial pilot tests—accompanied by A/B evaluations of click-through and conversion rates—will help fine-tune model parameters and content diversity before full-scale rollout.

Phase 3: Service Automation via Chatbots.

Automated conversational agents should follow, focusing on high-frequency inquiries such as booking changes, local attraction details, and service requests. To maximize uptime and accuracy, chatbots must be supported by structured knowledge bases and regular staff training programs. Monitoring user-bot interactions and integrating fallback mechanisms to human agents will ensure that service reliability and guest trust remain high.

Phase 4: Revenue Optimization with Dynamic Pricing.

The final stage involves implementing algorithmic pricing tools to optimize room rates, tour fees, and ancillary charges in real time. Clear communication of pricing policies—combined with regulatory transparency and targeted government co-funding for small-to-medium enterprises—will mitigate adoption risks. Continuous performance tracking of key metrics (e.g., RevPAR, occupancy rates) and the ability to revert to static pricing thresholds are essential safeguards during this phase.

By advancing through these four phases in sequence—and by maintaining cross-functional governance over data integrity, technological integration, and policy compliance—tourism enterprises and destination management organizations can realize the complementary benefits of AI, ultimately elevating both visitor experiences and operational effectiveness.

4.4 Limitations and Future Directions

This research relies on convenience sampling and cross-sectional survey data, which may limit generalizability and causal inference. The linear regression framework does not capture potential nonlinear or lagged effects. Future studies should employ longitudinal and experimental designs—such as A/B tests—to isolate causal pathways and extend the geographic scope to comparative assessments across Southeast Asian markets.

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