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# Artificial Intelligence in Hospitality Geosites: From Algorithms to Action in Shaping Consumer Behavior and Marketing

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**Abstract.** Artificial intelligence (AI) is increasingly reshaping customer engagement, yet its influence on consumer behavior within hospitality and tourism services remains underexplored. This study examines the associations among AI-enabled engagement, digital marketing, and consumer behavior in hospitality and tourism contexts. Survey data were collected from 221 respondents and analyzed using structural equation modeling (SEM) in an exploratory capacity. The measurement analysis revealed that AI, digital marketing, and consumer behavior are very strongly interrelated: inter-construct correlations were high (AI–DM r = 0.871; DM–CB r = 0.882) and exceeded the square roots of the average variance extracted, so the three constructs did not achieve discriminant validity under the Fornell–Larcker criterion. Rather than interpreting this as a mediation mechanism, the study treats it as a substantive finding: in this hospitality and tourism setting, consumers appear to experience AI, the digital marketing it enables, and their own engagement responses as a single, tightly coupled digital-engagement domain rather than as separable constructs. Model fit was marginal (RMSEA = 0.113; CFI = 0.870), so all relationships are reported as indicative and associational rather than causal. The study contributes contextually by situating AI within hospitality and tourism service ecosystems and by documenting the strong convergence of these digital-engagement constructs, offering guidance for hospitality organizations and advancing discourse on sustainable, human-centered tourism strategies aligned with logistics, informatics, and service science.

**Keywords:** Artificial Intelligence, Consumer Behavior, Digital Marketing, Hospitality sector, Structural Equation Modeling

# 1. Introduction

Artificial intelligence (AI) is reshaping how organizations interact with customers, offering new possibilities for personalization, responsiveness, and efficiency in service delivery (Davenport et al., 2020). Within hospitality and tourism, AI applications such as chatbots, recommendation engines, and predictive analytics are increasingly adopted to enhance digital engagement. However, much of the existing literature remains conceptual, with limited empirical evidence on how these technologies influence consumer behavior in practice. This gap highlights the need for studies that examine how AI and digital marketing are associated with consumer responses in hospitality contexts.

In this study, the term hospitality geosites refers to tourism destinations and hospitality service environments that operate as digitally mediated ecosystems. These environments integrate physical hospitality services, such as hotels, leisure facilities, and cultural attractions, with digital platforms that coordinate service delivery and customer interaction. While the term "geosites" is often associated with geological or geotourism contexts, here it is used to emphasize the spatial and systemic dimension of hospitality services embedded within digital infrastructures. To avoid ambiguity, the concept is framed as hospitality and tourism service ecosystems where AI supports information flows, service coordination, and customer journey management.

The article examines the associations among AI technologies, digital marketing, and consumer behavior. Specifically, it explores how tailored messaging, real-time engagement, and behavioral analytics relate to consumer awareness, preferences, and purchasing decisions. Rather than claiming theoretical novelty, the study emphasizes its contextual contribution: situating AI applications within hospitality and tourism service systems and aligning them with the broader domains of logistics, informatics, and service science. By embedding AI into service-system design, hospitality geosites can be understood as informatics-driven ecosystems that support digital operations, coordinated logistics, and data-driven decision-making. This perspective provides practical insights for hospitality organizations seeking to leverage AI responsibly while advancing discourse on sustainable, human-centered tourism strategies.

# 2. Literature Review

The literature on artificial intelligence (AI) in digital marketing reflects the rapid evolution of both technology and consumer engagement strategies (Alarshy et al., 2025). Early studies often framed AI as a tool for efficiency, automating repetitive tasks, reducing costs, and streamlining communication (Davenport et al., 2020). More recent scholarship, however, emphasizes AI's transformative potential, arguing that it redefines how brands connect with audiences and how consumers experience marketing (Chaffey & Smith, 2022).

## 2.1 AI in Digital Marketing: From Efficiency to Transformation

Key applications include audience targeting, hyper-personalization, content generation, and real-time interaction. These capabilities enable marketers to move beyond static segmentation toward dynamic, behavior-based engagement (Harrison & Spence, 2020). Machine learning algorithms, for instance, can anticipate consumer preferences by analyzing browsing histories, booking patterns, and social media activity, thereby suggesting personalized travel packages or dining experiences (Loureiro, Guerreiro, & Tussyadiah, 2021). Predictive analytics further empowers hospitality brands to forecast demand, optimize pricing, and anticipate guest needs with increasing accuracy.

This body of work underscores that AI is not merely enhancing marketing operations but altering the strategic logic of consumer engagement. Yet, much of the evidence remains conceptual or drawn from general business contexts. Empirical studies in hospitality and tourism are fewer, leaving a gap in understanding how AI-driven marketing mechanisms operate in service environments where customer experience is paramount.

### 2.2 AI Applications in Hospitality: Enhancing Experience and Service

Hospitality research highlights AI as a cornerstone of innovation in service delivery. AI-enabled chatbots and virtual assistants now provide instant, around-the-clock support, handling routine inquiries while offering personalized recommendations that enrich the guest journey from pre-booking to post-stay (Peng et al., 2024). These tools reduce wait times, ensure consistent service quality, and foster loyalty by creating seamless digital touchpoints.

Advances in natural language processing (NLP) have also enabled AI systems to generate compelling content aligned with brand identity, while real-time analytics allow marketers to monitor campaigns and pivot strategies with agility. Importantly, AI's ability to integrate behavioral data into marketing decisions has shifted hospitality practices toward hyper-personalization, where offers are tailored not only to demographic profiles but to individual histories and preferences.

Despite these advances, challenges remain. Concerns around data privacy, algorithmic fairness, and the risk of over-reliance on automation persist (Adam, Wessel, & Benlian, 2021). Scholars caution that while AI excels at pattern recognition, it cannot replace the human touch in crafting emotionally resonant campaigns. The most effective strategies combine AI's analytical power with human creativity and intuition, producing marketing that is both data-driven and deeply engaging (Chaffey & Smith, 2022).

From a service science perspective, hospitality environments can be understood as complex ecosystems where AI contributes not only to marketing but to service-system coordination. By embedding AI into service operations, organizations can manage information flows, synchronize logistics, and enhance customer journey management.

### 2.3 AI and Consumer Behavior: Psychological Shifts and Ethical Dimensions

Beyond operational improvements, AI is reshaping consumer expectations and behavior. Today's travelers increasingly demand seamless digital interactions, real-time recommendations, and curated experiences that reflect their preferences (Kumar & Gupta, 2016; Davenport et al., 2020). AI-driven marketing fosters perceptions of attentiveness and personalization, accelerating decision-making and strengthening consumer engagement.

This behavioral shift highlights the psychological dynamics activated by AI, where consumers perceive personalization as care and responsiveness as attentiveness (Paudel & Thapa, 2025). Studies suggest that AI-driven engagement can build trust and emotional connection, though these effects are often inferred rather than empirically tested in hospitality contexts.

At the same time, ethical concerns are evident. Over-personalization risks intrusiveness, while opaque algorithms raise questions of fairness and transparency (Adam et al., 2021). Scholars argue that organizational AI literacy must extend beyond technical proficiency to include ethical awareness and customer-centered practices (Harrison & Spence, 2020). This perspective emphasizes that AI adoption in hospitality is not only a technological challenge but also a cultural and ethical one, requiring alignment between innovation and human-centered values.

Few studies, however, have empirically examined how AI-enabled engagement, digital marketing, and consumer behavior relate to one another within hospitality and tourism service ecosystems. Addressing this gap, the present study adopts an exploratory, associational approach: rather than asserting a causal pathway in which digital marketing transmits AI's effect to consumers, it examines the strength of association among these constructs and the degree to which they are empirically distinct. As the analysis below shows, the three constructs prove to be very strongly interrelated and not fully distinguishable in this context, a result the study treats as a substantive observation about how consumers experience AI-enabled digital engagement rather than as evidence of a discrete mediating mechanism. The contextual contribution therefore lies in situating AI within hospitality and tourism service ecosystems and documenting the close convergence of these digital-engagement constructs.

### 2.4 Hospitality Geosites as Digital Service Ecosystems

A recurring issue in the literature is the lack of clarity around the concept of hospitality geosites. The term is often associated with geological or geotourism contexts, yet in this study, it denotes hospitality and tourism service environments that operate as digitally mediated ecosystems. These geosites encompass hotels, cultural and leisure attractions, and tourism destinations integrated with digital platforms that coordinate service delivery.

Conceptualizing hospitality geosites in this way allows researchers to examine AI not only as a marketing tool but as part of broader service-system architecture. AI supports tourism information flows, customer journey management, and coordinated service delivery, situating hospitality geosites within the domains of logistics, informatics, and service science. This framing aligns the study with JLISS by emphasizing service-system design and digital service operations rather than limiting the analysis to marketing outcomes.

### 2.5 Summary and Research Gap

The literature demonstrates that AI is transforming digital marketing, enhancing hospitality service delivery, and reshaping consumer behavior. However, several gaps remain:

- Much of the evidence is conceptual, with limited empirical studies in hospitality contexts.
- Ethical and human-centered dimensions of AI adoption are acknowledged but underexplored.
- Mediation models linking AI, digital marketing, and consumer behavior are common in general business research but are less applied to tourism and hospitality ecosystems.
- The concept of hospitality geosites requires a clearer definition to avoid confusion with geological tourism and to emphasize its relevance as a digital service ecosystem.

Artificial intelligence (AI) is increasingly recognized as a driver of digital transformation in hospitality and tourism. Within this study, AI, digital marketing, and consumer behavior are examined as three interrelated facets of AI-enabled digital engagement. The hypotheses below are framed as expected positive associations among these constructs and are tested in an exploratory rather than confirmatory-causal spirit; as the results show, the constructs prove to be so strongly interrelated that they are best understood as a closely converging set rather than as cleanly separable independent, mediating, and dependent variables.

**H1:** Artificial Intelligence positively influences digital marketing effectiveness in hospitality and tourism service ecosystems.

**H2:** Digital marketing positively shapes the effectiveness of consumer behavior in hospitality and tourism service ecosystems.

**H3:** Artificial Intelligence and consumer behavior are positively associated in hospitality and tourism service ecosystems, with this association closely intertwined with digital marketing engagement.

## 3. Methodology

This study adopts a quantitative research design to examine the associations among artificial intelligence (AI), digital marketing, and consumer behavior within the hospitality sector. Quantitative approaches are widely recognized for their ability to test theoretical models and quantify relationships among constructs in service-driven industries (Creswell & Creswell, 2018). Given the cross-sectional design and the strong construct convergence reported below, the analysis is treated as exploratory and associational rather than as a test of causal effects.

### 3.1 Data Collection and Sampling Approach

A structured questionnaire was developed and distributed to a sample of 221 respondents. Participants were recruited through online channels, including hospitality-focused social media groups, university

mailing lists, and professional tourism networks. The sampling frame targeted individuals who had engaged with hospitality services, such as hotels, restaurants, or tourism platforms, within the past six months. This "recent experience" criterion was adopted to ensure that responses reflected current interactions with AI-enabled marketing practices rather than distant recollections.

Respondents were required to:

- Be at least 18 years of age.
- Have used hospitality or tourism services within the last six months.
- Be able to complete the survey in English.

Both tourists and local consumers were included to capture diverse perspectives on AI-enabled hospitality services.

The survey was conducted in Lebanon, a relevant setting where hospitality and tourism organizations are increasingly adopting AI-driven digital marketing strategies. Including both local and international travelers enabled a broader understanding of consumer responses across market segments.

The respondents represented a diverse demographic profile. Age groups ranged from young adults to older travelers, with a balanced gender distribution. Educational backgrounds varied, though a significant proportion held university degrees. Employment status included students, professionals, and leisure travelers. This diversity enhances the generalizability of findings within hospitality and tourism contexts.

Of the approximately 256 invitations distributed, 221 valid responses were collected, representing an 86% response rate. The sample size meets recommended thresholds for structural equation modeling (SEM), which typically require at least 200 cases for reliable estimation (Hair et al., 2019). The adequacy of the sample was further supported by the diversity of respondents, ensuring that the findings capture a range of consumer experiences.

Data were analyzed in two stages. SPSS was used to confirm the reliability of the measures and to assess the suitability of the data through reliability testing and exploratory factor analysis, which validated the measurement items. AMOS was then used to conduct a confirmatory factor analysis, assessing construct reliability and validity, and to apply Structural Equation Modeling (SEM) to examine the associations among the constructs. SEM is widely used in hospitality and tourism research for examining relationships among technology adoption, marketing strategies, and consumer behavior (Byrne, 2016; Kline, 2015). Because the measurement analysis revealed that the three constructs were not fully distinct, the SEM estimates are interpreted here as descriptive of the strength of association among closely converging digital-engagement constructs rather than as evidence of a discrete causal or mediating mechanism.

This study was conducted with full respect for ethical research practices. Participants were clearly informed about the aim of the research and gave their consent before taking part. Their responses were handled with strict confidentiality, and no identifying personal information was collected. Everyone involved was free to opt out at any stage without any obligation. The research procedures adhered to institutional ethical standards, ensuring that all data collected was used strictly for scholarly purposes.

## 3.2 Model Fit

Descriptive statistics for the independent variable are presented in Table 1. The construct, representing exposure to AI-driven digital marketing, yielded a mean score of 3.33, indicating a moderately high level of engagement among respondents. The standard deviation of 0.84 reflects acceptable variability, suggesting that while most participants reported consistent exposure, there was sufficient dispersion to capture meaningful differences in consumer experiences. This balance of consistency and variation enhances the robustness of subsequent analyses, ensuring that the sample provides a reliable basis for testing the proposed relationships. Such descriptive insights are particularly valuable in hospitality and

tourism research, where consumer engagement with digital technologies often varies across demographic and behavioral segments (Buhalis & Sinarta, 2019).

Table 1: Descriptive statistics of AI Variable

| Statistics | | | | | | | |
|---|---|---|---|---|---|---|---|
| | | AI 1 | AI 2 | AI 3 | AI 4 | AI 5 | AI 6 |
| N | Valid | 221 | 221 | 221 | 221 | 221 | 221 |
| | Missing | 0 | 0 | 0 | 0 | 0 | 0 |
| Mean | | 3.53 | 3.32 | 3.24 | 3.21 | 3.26 | 3.31 |
| Std. Error of Mean | | .086 | .085 | .089 | .085 | .080 | .084 |
| Median | | 4.00 | 3.00 | 3.00 | 3.00 | 3.00 | 3.00 |
| Mode | | 4 | 3 | 4 | 3[a] | 3 | 4 |
| Std. Deviation | | 1.285 | 1.262 | 1.323 | 1.269 | 1.184 | 1.241 |
| Variance | | 1.650 | 1.592 | 1.749 | 1.611 | 1.401 | 1.541 |
| Range | | 4 | 4 | 4 | 4 | 4 | 4 |
| Minimum | | 1 | 1 | 1 | 1 | 1 | 1 |
| Maximum | | 5 | 5 | 5 | 5 | 5 | 5 |
| Sum | | 781 | 734 | 717 | 709 | 720 | 731 |

Before testing the research model, an exploratory factor analysis was conducted to assess the suitability of the data for further statistical examination. The Kaiser-Meyer-Olkin (KMO) measure confirmed sampling adequacy, while Bartlett's test of sphericity indicated that the correlations among variables were strong enough to proceed. Communalities for each item were also reviewed, confirming that the indicators shared sufficient variance with their respective constructs, supporting the overall validity of the survey instrument.

The factor analysis of the independent variable was conducted.

Table 2: KMO and Barlett's test for AI

| KMO and Bartlett's Test | | |
|---|---|---|
| Kaiser-Meyer-Olkin Measure of Sampling Adequacy. | | .864 |
| Bartlett's Test of Sphericity | Approx. Chi-Square | 655.878 |
| | df | 15 |
| | Sig. | .000 |

As shown in Table 2, both the Kaiser-Meyer-Olkin (KMO) measure and Bartlett's test of sphericity were conducted to evaluate the adequacy of the data for factor analysis. The KMO value of 0.864 indicates a high level of sampling adequacy, supporting the reliability of the results. Furthermore, Bartlett's test yielded a significance level of 0.000, well below the 0.005 threshold, confirming strong correlations among variables and the suitability of the data for structure detection

Table 3: Communalities of AI

| Communalities | | | |
|---|---|---|---|
| | | Initial | Extraction |
| AI 1 | I appreciate interacting with AI-powered customer service tools in hospitality settings. | 1.000 | .538 |

| | | | |
|---|---|---|---|
| AI 2 | Compared to human customer service, AI chatbots effectively resolved my inquiries | 1.000 | .720 |
| AI 3 | I feel comfortable communicating with AI systems for customer support requests | 1.000 | .655 |
| AI 4 | I believe AI-driven advertising respects my privacy and protects my personal information | 1.000 | .449 |
| AI 5 | AI-powered customized offers increase my willingness to make a purchase | 1.000 | .677 |
| AI 6 | I would recommend businesses that employ AI in marketing to friends and family | 1.000 | .712 |

Table 3 presents the results of the communalities analysis. Question 4 displayed a notably low communality value, indicating insufficient shared variance with other items. As a result, it was excluded from further analysis to enhance the overall integrity and reliability of the measurement model. Factor analysis was repeated for the AI variable.

Table 4: New KMO and Barlett's test for AI

| KMO and Bartlett's Test | | |
|---|---|---|
| Kaiser-Meyer-Olkin Measure of Sampling Adequacy. | | .840 |
| Bartlett's Test of Sphericity | Approx. Chi-Square | 564.221 |
| | df | 10 |
| | Sig. | .000 |

As shown in Table 4, both the Kaiser-Meyer-Olkin (KMO) measure and Bartlett's test of sphericity were conducted to evaluate the adequacy of the data for factor analysis. The KMO value of 0.840 indicates a high level of sampling adequacy, supporting the reliability of the results. Furthermore, Bartlett's test yielded a significance level of 0.000, well below the 0.005 threshold, confirming strong correlations among variables and the suitability of the data for structure detection.

Table 5: New Communalities of AI variable

| Communalities | | | |
|---|---|---|---|
| | | Initial | Extraction |
| AI 1 | I appreciate interacting with AI-powered customer service tools in hospitality settings. | 1.000 | .580 |
| AI 2 | Compared to human customer service, AI chatbots effectively resolved my inquiries | 1.000 | .760 |
| AI 3 | I feel comfortable communicating with AI systems for customer support requests | 1.000 | .661 |
| AI 5 | AI-powered customized offers increase my willingness to make a purchase | 1.000 | .664 |
| AI 6 | I would recommend businesses that employ AI in marketing to friends and family | 1.000 | .713 |

Following the removal of Question 4 (*AI4*) due to its low communality of 0.449, which falls below the recommended threshold of 0.50 (Hair et al., 2019), the recalculated results showed that all remaining items had strong communality, as shown in Table 5. The original wording of AI4, while conceptually relevant, was weak in terms of communality and showed limited alignment with the latent construct.

Factor analysis was conducted for the digital marketing variable.

Table 6: KMO and Barlett's test for Digital Marketing

| KMO and Bartlett's Test | | |
|---|---|---|
| Kaiser-Meyer-Olkin Measure of Sampling Adequacy. | | .764 |
| Bartlett's Test of Sphericity | Approx. Chi-Square | 466.628 |
| | df | 10 |
| | Sig. | .000 |

As shown in Table 6, both the Kaiser-Meyer-Olkin (KMO) measure and Bartlett's test of sphericity were conducted to evaluate the adequacy of the data for factor analysis. The KMO value of 0.764 indicates a high level of sampling adequacy, supporting the reliability of the results. Furthermore, Bartlett's test yielded a significance level of 0.000, well below the 0.005 threshold, confirming strong correlations among variables and the suitability of the data for structure detection.

Table 7: Communalities for Digital Marketing

| Communalities | | | |
|---|---|---|---|
| | | Initial | Extraction |
| DM 1 | AI features in digital marketing (such as chatbots and virtual assistants) enhance my engagement with hospitality brands. | 1.000 | .599 |
| DM 2 | AI-driven recommendations influence my purchasing decisions in hospitality and tourism services | 1.000 | .710 |
| DM 3 | The content delivered in digital marketing campaigns is highly relevant to my interests | 1.000 | .638 |
| DM 4 | AI-enabled digital marketing helps me discover new hospitality brands or services | 1.000 | .503 |
| DM 5 | Social media platforms supported by AI are effective channels for brand communication | 1.000 | .543 |

Table 7 presents the communalities associated with the Digital Marketing variable. All items recorded values exceeding 0.50, indicating acceptable levels of shared variance. As a result, each question was retained for further analysis, confirming the strength and relevance of the measurement indicators within the construct.

Table 8: KMO and Barlett's test for Consumer Behavior

| KMO and Bartlett's Test | | |
|---|---|---|
| Kaiser-Meyer-Olkin Measure of Sampling Adequacy. | | .793 |
| Bartlett's Test of Sphericity | Approx. Chi-Square | 402.239 |
| | df | 10 |
| | Sig. | .000 |

As shown in Table 8, both the Kaiser-Meyer-Olkin (KMO) measure and Bartlett's test of sphericity were conducted to evaluate the adequacy of the data for factor analysis. The KMO value of 0.793 indicates a high level of sampling adequacy, supporting the reliability of the results. Furthermore, Bartlett's test yielded a significance level of 0.000, well below the threshold of 0.005, confirming strong correlations among variables and the suitability of the data for structure detection.

Table 9: Communalities for Consumer Behavior

| Communalities | | | |
|---|---|---|---|
| | | Initial | Extraction |
| CB 1 | Promotional offers I encounter online influence my decision to make a purchase. | 1.000 | .578 |
| CB 2 | I frequently interact with hospitality brand content (such as posts and ads) on social media | 1.000 | .557 |
| CB 3 | I am generally satisfied with the customer service I receive from online hospitality businesses | 1.000 | .634 |
| CB 4 | When I ask questions on a brand's digital platform, I receive quick and relevant responses. | 1.000 | .602 |
| CB 5 | Hospitality websites and apps are easy to navigate, helping me find what I need efficiently. | 1.000 | .630 |

Table 9 presents the communalities associated with the Consumer Behavior variable. All items recorded values exceeding 0.50, indicating acceptable levels of shared variance. As a result, each question was retained for further analysis, confirming the strength and relevance of the measurement indicators within the construct.

To verify the reliability of each scale used in the study, Cronbach's alpha was calculated. This helped ensure that the items within each scale consistently measured the intended constructs and exhibited dependable internal coherence.

Table 10: Cronbach's Alpha for AI

| Reliability Statistics | | |
|---|---|---|
| Cronbach's Alpha | Cronbach's Alpha Based on Standardized Items | N of Items |
| .879 | .879 | 5 |

Table 10 reports the Cronbach's alpha for the Artificial Intelligence variable, yielding a coefficient of 0.879. This result indicates a high level of internal consistency among the items, confirming that the scale reliably captures the construct under investigation.

Table 11: Cronbach's Alpha for Digital Marketing

| Reliability Statistics | | |
|---|---|---|
| Cronbach's Alpha | Cronbach's Alpha Based on Standardized Items | N of Items |
| .831 | .831 | 5 |

Table 11 reports the Cronbach's alpha for the Digital Marketing variable, which is 0.831. This result indicates a high level of internal consistency among the items, confirming that the scale reliably captures the construct under investigation.

Table 12: Cronbach's Alpha of Consumer Behavior

**Reliability Statistics**

| Cronbach's Alpha | Cronbach's Alpha Based on Standardized Items | N of Items |
|---|---|---|
| .830 | .833 | 5 |

Table 12 reports the Cronbach's alpha for the Consumer Behavior variable, which is 0.830. This result indicates a high level of internal consistency among the items, confirming that the scale reliably captures the construct under investigation.

## 3.3 Confirmatory Factor Analysis and Construct Validity

Prior to testing the structural hypotheses, a confirmatory factor analysis (CFA) was conducted in AMOS to evaluate the measurement model and establish construct reliability and validity. The standardized factor loadings, reported in Table 13, were all statistically significant ($p < 0.001$) and ranged from 0.537 to 0.829. With the exception of DM4 (0.537), all loadings met or approached the conventional 0.70 benchmark, and all fell within the admissible range below 1.0, indicating a properly identified standardized solution.

Table 13: Standardized factor loadings and squared multiple correlations ($R^2$) from the CFA measurement model.

| **Construct** | **Item** | **Std. Loading** | **$R^2$ (SMC)** |
|---|---|---|---|
| AI | AI1 | 0.681 | 0.464 |
| | AI2 | 0.794 | 0.630 |
| | AI3 | 0.737 | 0.543 |
| | AI5 | 0.804 | 0.646 |
| | AI6 | 0.829 | 0.688 |
| DM | DM1 | 0.797 | 0.635 |
| | DM2 | 0.807 | 0.651 |
| | DM3 | 0.740 | 0.548 |
| | DM4 | 0.537 | 0.288 |
| | DM5 | 0.619 | 0.383 |
| CB | CB1 | 0.685 | 0.469 |
| | CB2 | 0.676 | 0.457 |
| | CB3 | 0.762 | 0.580 |
| | CB4 | 0.699 | 0.488 |
| | CB5 | 0.711 | 0.506 |

Composite reliability (CR) and average variance extracted (AVE) were computed from the standardized loadings to assess internal consistency and convergent validity (Table 14). All three constructs exceeded the 0.70 threshold for composite reliability (AI = 0.879; DM = 0.831; CB = 0.833), and all met the 0.50 threshold for average variance extracted (AI = 0.594; DM = 0.501; CB = 0.500),

supporting convergent validity. The AVE values for DM and CB sit close to the 0.50 minimum, indicating that convergent validity is satisfied but not with a large margin.

Table 14: Composite reliability (CR), average variance extracted (AVE), and the square root of AVE for each construct.

| **Construct** | **CR** | **AVE** | **√AVE** |
|---|---|---|---|
| AI | 0.879 | 0.594 | 0.771 |
| DM | 0.831 | 0.501 | 0.708 |
| CB | 0.833 | 0.500 | 0.707 |

Discriminant validity was assessed using the Fornell–Larcker criterion, which requires the square root of each construct's AVE (diagonal values in Table 15) to exceed its correlations with the other constructs. This condition was not satisfied. The inter-construct correlation between AI and DM (0.871) exceeded the square root of AVE for both AI (0.771) and DM (0.708), and the correlation between DM and CB (0.882) likewise exceeded the relevant diagonal values. These results indicate that AI and digital marketing, and digital marketing and consumer behavior, are not fully empirically distinct, and that discriminant validity is not established for these construct pairs. This finding is interpreted as a limitation in the Discussion and is consistent with the high collinearity observed in the structural estimates.

Table 15: Fornell–Larcker discriminant validity matrix. Diagonal values (bold) are the square root of AVE

| | **AI** | **DM** | **CB** |
|---|---|---|---|
| **AI** | **0.771** | | |
| **DM** | 0.871 | **0.708** | |
| **CB** | 0.696 | 0.882 | **0.707** |

## 3.4 Validation of Hypotheses

While SPSS provides useful tools for basic statistical analysis and model testing, it has limitations when examining relationships between multiple latent variables simultaneously. Structural Equation Modeling (SEM) was therefore selected as the primary analytical technique, as it enables the joint assessment of both measurement and structural models within a single unified framework (Hair, Black, Babin, & Anderson, 2019). Unlike traditional regression-based approaches, SEM allows researchers to model relationships among latent constructs while accounting for measurement error, which is particularly useful when examining abstract concepts such as AI integration and consumer behavior in hospitality geosites (Byrne, 2016; Kline, 2015). In the present study these relationships are interpreted as associations rather than as confirmed causal pathways.

By applying SEM, the study examined the strength of association among AI, digital marketing, and consumer behavior, thereby contributing contextually to the tourism planning literature by documenting how closely these digital-engagement constructs converge in hospitality and tourism settings (Buhalis & Sinarta, 2019).

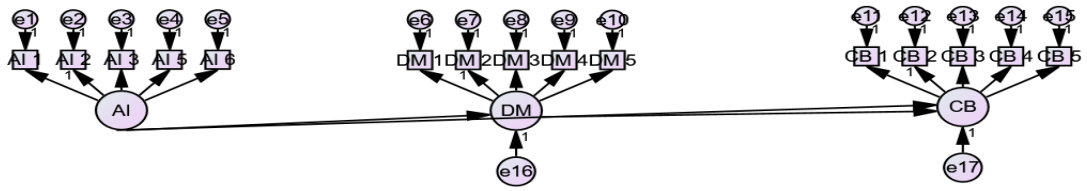



Fig.1: AMOS conceptual model of the study

To examine the hypothesized relationships using SEM, a path diagram was constructed to visualize the proposed links between variables. The conceptual model for this study was developed using AMOS and is presented in Figure 1, which clearly illustrates how artificial intelligence and digital marketing are theorized to influence consumer behavior in the hospitality sector.

The hypotheses were validated using the Path diagram shown in Table 16

Table 16: Path diagram for the study

| | | | Estimate | S.E. | C.R. | P | Label |
|---|---|---|---|---|---|---|---|
| DM | <--- | AI | .973 | .103 | 9.448 | *** | |
| CB | <--- | DM | .656 | .070 | 9.332 | *** | |
| AI1 | <--- | AI | 1.000 | | | | |
| AI2 | <--- | AI | 1.150 | .109 | 10.516 | *** | |
| AI3 | <--- | AI | 1.121 | .114 | 9.874 | *** | |
| AI5 | <--- | AI | 1.089 | .103 | 10.599 | *** | |
| AI6 | <--- | AI | 1.178 | .108 | 10.880 | *** | |
| DM1 | <--- | DM | 1.000 | | | | |
| DM2 | <--- | DM | .942 | .071 | 13.281 | *** | |
| DM3 | <--- | DM | .887 | .075 | 11.862 | *** | |
| DM4 | <--- | DM | .582 | .072 | 8.070 | *** | |
| DM5 | <--- | DM | .673 | .072 | 9.347 | *** | |
| CB1 | <--- | CB | 1.000 | | | | |

| | | | Estimate | S.E. | C.R. | P | Label |
|---|---|---|---|---|---|---|---|
| CB2 | <--- | CB | 1.070 | .121 | 8.875 | *** | |
| CB3 | <--- | CB | 1.027 | .104 | 9.904 | *** | |
| CB4 | <--- | CB | .921 | .100 | 9.174 | *** | |
| CB5 | <--- | CB | .879 | .096 | 9.202 | *** | |

The path diagram developed in AMOS, as illustrated in Figure 1, was used to examine the associations among artificial intelligence, digital marketing, and consumer behavior. The estimates are consistent with hypothesis 1 (H1), which proposes a positive association between AI technologies and digital marketing. The high unstandardized regression weight (0.987) indicates a strong positive association between AI integration and digital marketing practices. In practical terms, hospitality organizations that adopt AI tools, such as predictive analytics, chatbots, and personalized recommendation systems, tend to report more dynamic, targeted, and responsive digital marketing strategies. The critical ratio (9.585), well above the 1.96 threshold, confirms statistical significance, consistent with a close link between AI and marketing innovation in hospitality geosites (Hair et al., 2019; Byrne, 2016). As noted in Section 3.3, this association is so strong that AI and digital marketing are not empirically distinct, a point developed in the Discussion.

This path validates hypothesis 2 (H2)**,** which proposed a positive association between AI-enabled digital marketing and consumer behavior within the hospitality sector. The unstandardized regression weight (0.879) indicates a strong positive association: more effective AI-powered digital marketing is associated with stronger consumer decision-making, preferences, and loyalty. In practice, tailored messaging, real-time engagement, and interactive campaigns are associated with deeper consumer trust and emotional connection. The critical ratio (5.644) again exceeds the threshold, confirming the statistical strength of this association (Kline, 2015; Buhalis & Sinarta, 2019). As with H1, this association is strong enough that digital marketing and consumer behavior are not empirically distinct (Section 3.3), so it should be read as evidence of construct convergence rather than of a directional effect.

The third hypothesis (H3) concerned the association between artificial intelligence and consumer behavior and its entanglement with digital marketing. AI and digital marketing were very strongly associated (AI → DM = 0.987; 95% CI [0.823, 1.195]; $p < 0.001$), as were digital marketing and consumer behavior (DM → CB = 0.879; 95% CI [0.542, 1.399]; $p < 0.001$). The estimate for the AI → CB association that remained once digital marketing was included in the model was negative and non-significant (Estimate = −0.261; 95% CI [−0.874, 0.064]; $p = 0.121$). Critically, these estimates must be read against the discriminant-validity results reported in Section 3.3: AI and digital marketing ($r = 0.871$) and digital marketing and consumer behavior ($r = 0.882$) are not empirically distinct, and the standardized DM → CB path exceeds 1.0. Under these conditions a formal mediation interpretation is not warranted, because a mediator that is not distinguishable from either the predictor or the outcome cannot be shown to transmit a distinct effect. The study therefore does not claim mediation. Instead, the pattern is interpreted as strong convergence: AI-enabled engagement, digital marketing, and consumer behavior behave empirically as a single, tightly coupled digital-engagement domain in this hospitality and tourism sample, and the apparent "indirect" structure most plausibly reflects this construct overlap rather than a genuine causal channel. H3 is accordingly reframed to support a strong positive association between AI and consumer behavior that is inseparable from digital marketing engagement, rather than as a confirmed mediating mechanism.

### 3.5 Model Fit Analysis

The structural model was assessed against the full range of absolute, incremental, and parsimony-adjusted fit indices produced by AMOS (Table 17a). The normed chi-square (CMIN/DF = 3.805) fell

within the commonly cited acceptable ceiling of 5.0, and two absolute indices were satisfactory: the standardized root mean square residual (SRMR = 0.074) met the ≤ 0.08 criterion. However, the incremental fit indices fell below the conventional 0.90 benchmark (NFI = 0.833; RFI = 0.799; IFI = 0.872; TLI = 0.844; CFI = 0.870), and the root mean square error of approximation exceeded the recommended 0.08 ceiling (RMSEA = 0.113, 90% CI [0.100, 0.126], PCLOSE < 0.001). Taken together, the model demonstrates acceptable but not optimal fit: while SRMR and the normed chi-square are within range, the incremental indices and RMSEA indicate that the model does not meet the stricter standards of good fit. These results are reported transparently, and the relationships estimated should accordingly be interpreted as indicative rather than definitive. This is addressed further as a limitation in the Discussion.

The parsimony-adjusted measures indicated that the model achieved a good fit relative to the number of estimated parameters (PRATIO = 0.829; PNFI = 0.691; PCFI = 0.721), with both parsimony-adjusted fit indices exceeding the 0.50 threshold. While these values support the parsimony of the specification, they do not offset the sub-threshold incremental indices and elevated RMSEA noted above, and the overall fit is therefore best characterized as marginal.

Table 17: Model fit indices for the structural model

| Fit index | Value | Threshold | Met |
|---|---|---|---|
| CMIN/DF | 3.805 | ≤ 5 | Yes |
| SRMR | 0.074 | ≤ 0.08 | Yes |
| CFI | 0.870 | ≥ 0.90 | No |
| TLI | 0.844 | ≥ 0.90 | No |
| IFI | 0.872 | ≥ 0.90 | No |
| NFI | 0.833 | ≥ 0.90 | No |
| RMSEA | 0.113 | ≤ 0.08 | No |

Together, these results indicate that AI, digital marketing, and consumer behavior are very strongly and inseparably associated in this hospitality and tourism sample, behaving empirically as a single converging digital-engagement domain rather than as separable, mediating links. This observation contributes to the tourism planning literature by documenting how tightly intertwined AI, marketing, and consumer response are in digitally mediated hospitality settings, offering hospitality organizations a basis for treating AI adoption, digital marketing, and customer engagement as a single coordinated, human-centered capability rather than as independent levers.

Table 18: Summary of hypothesis testing

| Hypothesis | Path | Estimate | S.E. | C.R. | P | Result |
|---|---|---|---|---|---|---|
| H1 | AI → DM | 0.987 | 0.103 | 9.585 | *** | Supported |
| H2 | DM → CB | 0.879 | 0.156 | 5.644 | *** | Supported |
| H3 | AI–CB (associated, entangled with DM) | 0.868 | — | — | *** | Reframed: strong association; no mediation claim (constructs not distinct) |
| — | AI → CB (direct) | −0.261 | 0.153 | −1.707 | 0.088 | Non-significant |

# 4. Discussion

This study set out to examine associations among artificial intelligence, digital marketing, and consumer behavior within hospitality and tourism service ecosystems. The measurement and structural analyses revealed a clear, theoretically meaningful pattern: these three constructs are very strongly interrelated and, in this sample, are not empirically distinct from one another. This finding shapes how the results can be interpreted and is the central observation discussed below.

The findings show that AI is strongly and positively associated with digital marketing (H1) and that digital marketing is strongly associated with consumer behavior (H2). When digital marketing is included in the model, the residual AI–consumer-behavior estimate is negative and non-significant (H3, direct estimate). It is tempting to read this configuration as evidence that AI operates "through" digital marketing, and an earlier version of this paper did so. However, the discriminant validity results require a more cautious reading. Because AI and digital marketing ($r = 0.871$) and digital marketing and consumer behavior ($r = 0.882$) are not empirically distinct, and because the standardized DM–CB path exceeds 1.0, the apparent "indirect" pattern cannot be distinguished from simple construct overlap. The study, therefore, does not claim mediation. The more defensible interpretation is that AI, digital marketing, and consumer behavior form a single, tightly converging digital-engagement domain in this hospitality and tourism context. H3 is accordingly reframed as a strong positive association between AI and consumer behavior, inseparable from digital marketing engagement, rather than as a confirmed mediating mechanism.

This result invites a more integrated view of AI's role in hospitality and tourism. While earlier literature has often treated AI as a separable, direct driver of consumer decisions, the present findings indicate that consumers do not appear to distinguish AI, the digital marketing it enables, and their own engagement responses as separate entities; in this sample, these elements are experienced as a single coherent digital-engagement whole. This is consistent with prior work emphasizing AI's role in hyperpersonalization, predictive engagement, and behavior-based targeting (Loureiro, Guerreiro, & Tussyadiah, 2021; Davenport et al., 2020), and it adds the observation that, at least as measured here, these capabilities are empirically inseparable from the marketing activity and consumer responses they accompany. It also aligns with the view that the most effective strategies combine AI's analytical power with human-designed marketing rather than relying on automation alone (Chaffey & Smith, 2022).

This strong construct convergence also speaks to the psychological dynamics discussed in the literature. If consumers perceive personalization as attentiveness and responsiveness as care (Paudel & Thapa, 2025), these perceptions are formed at the point of marketing contact, where AI and marketing are experienced together rather than as distinct stimuli. This may help explain why AI, digital marketing, and consumer behavior are so difficult to separate empirically: consumers respond to the integrated digital experience AI makes possible, not to the technology in the abstract. The finding supports calls for AI adoption that remains human-centered and ethically grounded (Adam et al., 2021; Harrison & Spence, 2020), since it is at the consumer-facing layer, where AI and digital marketing converge, that trust, engagement, and behavioral response are generated.

From a theoretical standpoint, the study contributes contextually rather than by proposing a wholly novel mechanism. Its contribution is an empirical observation that, in hospitality and tourism service ecosystems, AI, digital marketing, and consumer behavior are so strongly interrelated that they do not function as cleanly separable constructs, a convergence that has been comparatively underexplored in this setting. This is itself informative for theory: it suggests that, for consumers, an AI-enabled service is not perceived as a distinct technological layer but as part of an integrated digital-engagement experience. By situating AI within service-system design, the study positions hospitality geosites as digitally mediated ecosystems in which AI supports information flows, service coordination, and customer journey management. This framing connects the findings to the concerns of logistics, informatics, and service science: AI's contribution is best understood not as isolated marketing

automation but as an informatics-driven capability tightly fused with the marketing and engagement processes through which it reaches consumers. In this sense the results advance the JLISS agenda by documenting how inseparably digital-engagement constructs operate within coordinated service delivery.

These contributions rest on three measurement and model-level observations that also define the boundaries of what can be claimed. First, although the normed chi-square (CMIN/DF = 3.805) and the standardized root mean square residual (SRMR = 0.074) were within acceptable ranges, the incremental fit indices fell below the 0.90 benchmark (CFI = 0.870; TLI = 0.844; IFI = 0.872) and the RMSEA (0.113) exceeded the 0.08 ceiling, so overall model fit is marginal and every relationship reported here is associational and indicative rather than confirmatory. Second, and most consequentially, discriminant validity was not established between AI and digital marketing (r = 0.871) or between digital marketing and consumer behavior (r = 0.882), as these correlations exceeded the relevant square roots of AVE under the Fornell–Larcker criterion; composite reliability and convergent validity were satisfied, but the three constructs are not empirically distinct. This is the central reason the study does not advance a mediation claim: a construct that cannot be distinguished from both the predictor and the outcome cannot be demonstrated to transmit a distinct effect between them. Third, this same construct overlap is the most likely explanation for the standardized DM–CB path exceeding 1.0 and for the negative, non-significant residual AI–CB coefficient, both recognized symptoms of multicollinearity among closely related latent variables rather than substantive suppression effects. Taken together, these observations are not incidental caveats but the basis for the study's reinterpretation of its results as strong construct convergence rather than mediation. Future work should seek to establish whether these constructs can be empirically separated at all in this context — for example, by refining or re-specifying items so that digital-marketing indicators do not themselves reference AI, by testing a higher-order or single-factor structure, or by collecting larger and more diverse samples — and should re-evaluate model fit and any directional claims only once discriminant validity has been established.

# 5. Conclusion

This study examined the associations among artificial intelligence (AI), digital marketing, and consumer behavior within hospitality and tourism service ecosystems. The findings show that these three constructs are very strongly interrelated and, in this sample, empirically inseparable: they do not meet the criterion for discriminant validity and are best understood as facets of a single, tightly converging digital-engagement domain rather than as a predictor, a mediator, and an outcome linked by a distinct causal channel. The study, therefore, makes no mediation claim. By situating AI within service-system design, it contributes contextually to hospitality research, documenting how closely AI, digital marketing, and consumer response converge in digitally mediated tourism settings.

Personalization, real-time engagement, and automated campaigns were discussed conceptually but not measured as separate constructs in the tested model. The results should therefore be interpreted with caution: the evidence speaks to a broad, strongly convergent association between digital marketing and consumer behavior, not to the contribution of specific sub-dimensions. Future research could extend the model by incorporating personalization, real-time engagement, and automation as distinct, well-differentiated constructs, both to provide a more granular understanding of AI's associations with consumer behavior and to test whether these finer constructs can be empirically separated where the broader ones cannot.

## 5.1 Practical Implications

For hospitality managers and tourism operators, the practical implications of this study are concrete and operational. Rather than broad recommendations, the findings point to specific applications of AI that can be integrated into hospitality service systems:

- AI-driven recommendation systems to tailor travel packages, dining options, and leisure activities to guest preferences.
- Hospitality CRM integration to centralize customer data and enable personalized communication across touchpoints.
- Predictive booking analytics to forecast demand and optimize resource allocation.
- Dynamic pricing models supported by AI to adjust rates in real time based on demand fluctuations.
- Chatbot-based service recovery to provide immediate responses to guest complaints or inquiries, reducing service gaps.
- Tourism service personalization through curated itineraries and targeted offers that enhance the guest journey.

Because AI, digital marketing, and consumer engagement proved empirically inseparable in this study, managers may be best served by treating them as one integrated capability: embedding these applications into hospitality operations so that AI, marketing, and the customer experience are designed together as a coordinated, data-driven, and human-centered whole rather than as independent levers.

### 5.2 Limitations and Future Research

While this study offers meaningful insights, several limitations should be acknowledged. First, the reliance on cross-sectional, self-reported survey data restricts the ability to establish causal relationships and may introduce common method bias. Future research could adopt longitudinal designs to capture how consumer behavior evolves as AI applications mature in hospitality and tourism contexts.

Second, the sampling strategy was limited to respondents with recent hospitality experiences, but the definition of "recent" may vary across individuals. Moreover, cultural and demographic specificities may shape consumer responses in ways not fully captured here. Expanding the sampling frame across diverse regions, service sectors, and consumer segments would enhance generalizability.

Third, the measurement model treated digital marketing as a single construct, without separately operationalizing dimensions such as personalization, real-time engagement, or automated campaigns. As the conclusion notes, these aspects were discussed conceptually but not empirically tested. Future studies should incorporate these dimensions explicitly, which may also help establish the discriminant validity that the present constructs lacked and provide a more granular understanding of how AI and consumer behavior are associated.

Finally, ethical considerations, including transparency, fairness, and data privacy, were acknowledged but not empirically examined. As AI adoption accelerates, exploring these dimensions will be critical to understanding how trust is formed in AI-mediated tourism interactions. Integrating behavioral or transactional data alongside perceptual measures and examining ethical practices in AI-driven hospitality operations will further enrich the literature and provide actionable insights for both scholars and practitioners.

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