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Artificial Intelligence and Service Personalization in Hospitality: Impacts on Guest Loyalty

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ABSTRACT

This study investigates the role of artificial intelligence in driving service personalization and its subsequent effects on guest loyalty within the hospitality industry. Drawing on service quality and technology acceptance theories, the research examines how AI service quality and AI transparency influence perceived personalization, with privacy concern as a moderating factor. A survey of 412 hotel guests who interacted with AI-enabled services was analyzed using partial least squares structural equation modeling (PLS-SEM). The findings reveal that both AI service quality and AI transparency significantly enhance perceived personalization, which in turn strongly predicts guest loyalty intentions. Mediation analysis confirms that perceived personalization serves as the key mechanism linking AI attributes to loyalty outcomes. Moreover, moderation tests indicate that privacy concern weakens the positive effects of AI service quality and transparency on personalization, underscoring the boundary conditions of AI adoption in hospitality. The study contributes to hospitality and tourism literature by providing empirical evidence that AI-driven personalization is a double-edged innovation, capable of strengthening loyalty while constrained by privacy concerns. Practical implications highlight the importance of investing in transparent, high-quality AI systems and balancing personalization with ethical data practices to foster long-term guest relationships.

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Artificial intelligence; hospitality, service personalization, guest loyalty, AI transparency, privacy concern

INTRODUCTION

The hospitality industry is undergoing rapid transformation with the adoption of artificial intelligence (AI) to deliver innovative services, enhance efficiency, and meet the rising expectations of digitally savvy travelers. AI applications such as chatbots, service robots, and recommendation systems are increasingly deployed to provide timely, responsive, and personalized guest interactions (Gursoy et al., 2023; Rifqi, 2025; Tussyadiah, 2020). As hotels strive to differentiate themselves in a competitive marketplace, the promise of AI-enabled personalization has emerged as a critical lever for improving guest satisfaction, loyalty, and operational performance. However, despite growing interest, there remains limited empirical understanding of how specific attributes of AI services shape personalization experiences and downstream guest outcomes.

Existing research has largely focused on the technological acceptance of AI in hospitality, consumer trust in service robots Chi et al. (2024), or general perceptions of automation (Bowen & Morosan, 2018). While these studies establish that AI has potential to enhance service encounters, few have examined the mechanisms through which AI attributes translate into strategic outcomes such as guest loyalty. In particular, the role of perceived personalization as the psychological bridge linking AI service quality and transparency to guest loyalty remains underexplored. Moreover, although personalization relies heavily on the use of guest data, research has seldom addressed the moderating influence of privacy concern, which may critically shape how guests interpret and respond to AI-enabled services. This gap is particularly pressing as ethical concerns around data security and transparency continue to dominate debates about AI adoption in tourism and hospitality (Sun & Medaglia, 2019).

The objective of this study is to address these gaps by investigating the relationships between AI service quality, AI transparency, perceived personalization, and guest loyalty, while examining the moderating role of privacy concern. Specifically, this research seeks to identify whether AI-driven personalization serves as the key mechanism linking service attributes to guest loyalty, and under what conditions these effects are strengthened or weakened.

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This study makes three primary contributions to the literature. First, it advances hospitality and tourism research by empirically validating the mediating role of perceived personalization, thereby explaining how AI service attributes foster guest loyalty. Second, it contributes to the technology ethics discourse by integrating privacy concern as a boundary condition, offering insights into when and why personalization may backfire. Third, it provides practical implications for hotel managers by highlighting the dual necessity of investing in high-quality, transparent AI services and implementing responsible data practices. Collectively, these contributions extend both theoretical understanding and managerial strategies for leveraging AI in hospitality.

LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

Theoretical Foundation

This study is grounded in two interrelated theoretical perspectives: Service Quality Theory and the Technology Acceptance Model (TAM). Together, these frameworks provide the conceptual foundation for explaining how attributes of artificial intelligence services influence personalization perceptions and, ultimately, guest loyalty in hospitality contexts.

Service Quality Theory emphasizes that customer evaluations of service encounters are shaped by dimensions such as reliability, responsiveness, assurance, and empathy (Findlay, 2002). In the hospitality sector, service quality has long been identified as a determinant of guest satisfaction and loyalty (Ali et al., 2016). With the integration of AI, service encounters are no longer solely mediated by human employees but by technology-driven systems such as chatbots and service robots. Extending the service quality perspective to AI implies that technological accuracy, speed, and reliability constitute essential components of perceived service quality (Nguyen & Malik, 2021). Thus, AI service quality is expected to directly shape perceptions of personalization by demonstrating competence in tailoring interactions to individual guest needs.

The Technology Acceptance Model (TAM) Davis (1989) provides a complementary perspective by positing that perceived usefulness and perceived ease of use drive technology adoption and user acceptance. Recent extensions of TAM to hospitality research suggest that transparency in AI systems, such as clear explanations of how personal data are collected and applied, enhances trust and reduces uncertainty (Gursoy et al., 2023). Transparency is therefore conceptualized as a critical factor influencing whether guests perceive AI-enabled services as genuinely personalized and beneficial.

In addition, the study integrates insights from Privacy Concern Theory Malhotra et al. (2004), which highlights that consumer concerns about information misuse can negatively influence acceptance of technology-driven personalization. Privacy concerns function as a boundary condition that may weaken the positive impact of AI service quality and transparency on personalization. This perspective aligns with calls for a more nuanced understanding of how technological benefits are moderated by ethical and social considerations in service contexts (Sun & Medaglia, 2019).

Taken together, these theories suggest that while AI service quality and transparency enhance personalization perceptions and loyalty, their effectiveness depends on balancing technological innovation with ethical responsibility. The integration of service quality, TAM, and privacy concern theories provides a robust foundation for hypothesizing the relationships among AI attributes, perceived personalization, privacy concerns, and guest loyalty.

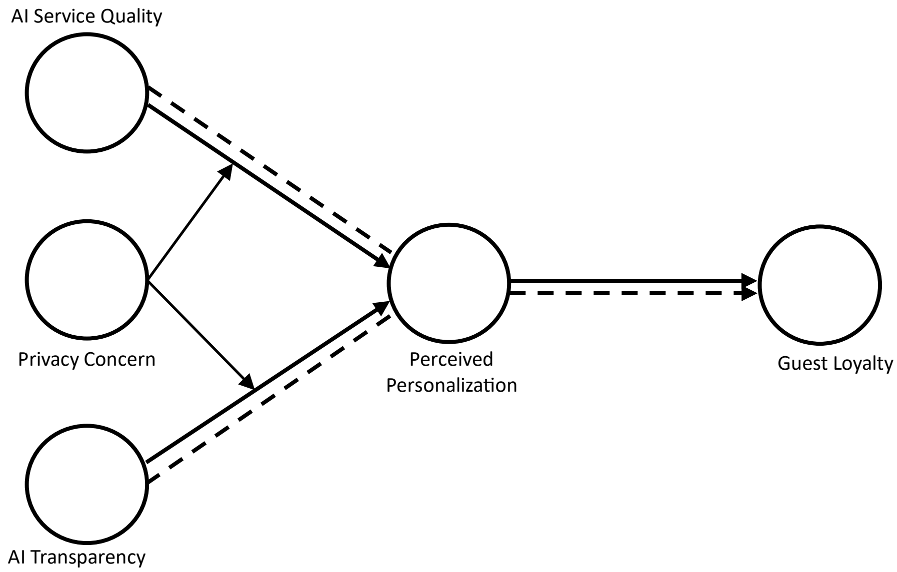

Figure 1. Research Framework

AI Service Quality and Perceived Personalization

Service quality has long been considered a central determinant of customer satisfaction and loyalty in hospitality research (Ali et al., 2016; Nguyen & Malik, 2021). Traditional conceptualizations of service quality emphasize reliability, responsiveness, assurance, and empathy, which collectively shape customers' evaluations of service encounters. In the context of artificial intelligence (AI) in hospitality, these quality dimensions are translated into technological attributes such as accuracy, reliability, responsiveness, and interactional competence of AI-enabled systems, including chatbots, service robots, and virtual concierges (Gursoy et al., 2023). AI service quality reflects the extent to which guests perceive that AI systems perform effectively and deliver useful, accurate, and contextually relevant responses. When AI interactions are perceived as high in quality, guests are more likely to feel that the system is capable of understanding and anticipating their needs. This aligns with personalization theory, which highlights that the perception of individualized treatment emerges when services are experienced as accurate, responsive, and tailored to user expectations, High-quality AI services can therefore be expected to increase guests' sense that their interactions are not generic but specifically customized to their preferences (Sicilia et al., 2020).

Empirical evidence supports this linkage. Studies in e-commerce and hospitality contexts have shown that the reliability and responsiveness of AI systems significantly enhance perceived personalization and, by extension, customer engagement (Tussyadiah, 2020). Conversely, when AI systems fail to provide timely or accurate responses, personalization efforts are undermined, as guests perceive the interaction as mechanical rather than individualized.

Taken together, these arguments suggest that AI service quality plays a pivotal role in fostering perceived personalization in hospitality encounters. Accordingly, the following hypothesis is proposed:

H1: AI service quality positively influences perceived personalization.

AI Transparency and Perceived Personalization

Transparency has emerged as a critical dimension in the deployment of AI systems, particularly in service industries where customer trust is paramount. In the hospitality sector, AI transparency refers to the extent to which hotels clearly communicate how AI technologies operate, the logic behind their recommendations, and the ways personal data are collected and applied (Sun & Medaglia, 2019). Transparent systems provide explanations that reduce uncertainty, demonstrate accountability, and allow guests to better understand the rationale behind service interactions (Fitriani & Basir, 2025; Shin, 2021).

From the perspective of the Technology Acceptance Model (TAM), transparency can enhance both perceived usefulness and perceived trustworthiness of AI-enabled services, which in turn strengthen personalization outcomes (Davis, 1989; Gursoy et al., 2023). When hotels openly disclose how AI draws upon guest preferences or prior behaviors to tailor recommendations, guests are more likely to perceive these services as genuinely customized rather than arbitrary. Conversely, opaque AI processes may foster skepticism, reducing the likelihood that guests interpret service interactions as meaningful personalization.

Recent studies in digital services confirm that transparency positively influences user perceptions of fairness and authenticity (Colquitt & Zipay, 2015; Verma et al., 2021). In hospitality, this suggests that when AI-driven personalization is accompanied by clear communication about its mechanisms, guests are more inclined to view such services as credible, trustworthy, and reflective of their individual needs.

Based on this reasoning, the following hypothesis is advanced:

H2: AI transparency positively influences perceived personalization.

Perceived Personalization and Guest Loyalty

Perceived personalization refers to the extent to which customers believe that services are tailored to their individual preferences, needs, and past behaviors (Dewayani et al., 2023; Sicilia et al., 2020). In hospitality contexts, personalization is particularly salient, as the value of service encounters often depends on their ability to generate unique, memorable, and emotionally resonant experiences (Kandampully et al., 2015). When guests feel that hotel services whether mediated by staff or AI systems are responsive to their personal requirements, they are more likely to evaluate the overall service encounter positively.

Guest loyalty, commonly conceptualized as the intention to return and to recommend the service provider, has been consistently linked to personalization in tourism and hospitality research. Personalization fosters a sense of recognition and individual care, which deepens the relational bond between guests and service providers. This relational attachment translates into trust, satisfaction, and ultimately loyalty. By contrast, generic or standardized service interactions may fail to engender such bonds, weakening loyalty intentions even if the core service delivery is adequate.

Recent empirical evidence indicates that personalization enhances both attitudinal and behavioral loyalty. For example, in hotel settings, personalized recommendations have been shown to significantly increase guests' likelihood of repeat booking and positive word-of-mouth. Similarly, studies in online travel platforms highlight that tailored communication and offers lead to stronger commitment and reduced switching behavior (Bleier et al., 2019). These findings underscore personalization as a strategic driver of competitive advantage in hospitality.

Given its established role in strengthening customer relationships, this study posits that perceived personalization functions as a direct antecedent of guest loyalty in AI-enabled hospitality services. Accordingly, the following hypothesis is proposed:

H3: Perceived personalization positively influences guest loyalty.

Mediating Role of Perceived Personalization

While AI service attributes such as quality and transparency are essential in shaping guest perceptions, their influence on loyalty is unlikely to be direct. Instead, personalization provides the key psychological pathway through which these technological attributes translate into meaningful outcomes for guests. Prior research has established that customers often evaluate technology-driven services not merely by their functional performance but by the extent to which they deliver personalized experiences (Bleier et al., 2019). Thus, even when AI systems are perceived as reliable or transparent, guests are more likely to develop loyalty only if these attributes are interpreted as enhancing personalization.

The service quality literature similarly suggests that customer loyalty is determined by experiential value rather than by service inputs alone (Ali et al., 2016). In this regard, perceived personalization acts as the mechanism that transforms AI service quality and transparency into guest outcomes. For example, a chatbot that responds accurately (high service quality) or discloses how it uses data (transparency) contributes to loyalty only insofar as the guest perceives these interactions as individually tailored. Without personalization, AI features may be regarded as functional but impersonal, limiting their capacity to foster loyalty.

Empirical studies reinforce this mediating role. Choi et al. (2019) found that personalization perceptions fully mediated the relationship between technology-based service quality and customer satisfaction. Similarly, Sicilia et al. (2020) demonstrated that personalization perceptions explain how consumers translate data-driven interactions into trust and commitment. Applying these insights to hospitality AI suggests that personalization is the bridge connecting technological attributes to enduring guest relationships.

Based on this reasoning, the following hypotheses are advanced:

H4a: Perceived personalization mediates the relationship between AI service quality and guest loyalty.
H4b: Perceived personalization mediates the relationship between AI transparency and guest loyalty.

Moderating Role of Privacy Concern

Although AI-enabled personalization offers significant potential for enhancing guest experiences, it also relies heavily on the collection and use of personal data. This creates an inherent tension between the benefits of personalization and the risks associated with information privacy. Privacy Concern Theory posits that individuals with heightened sensitivity to data use are less receptive to technology-mediated personalization, perceiving it as intrusive or manipulative rather than beneficial (Malhotra et al., 2004). In hospitality, this tension is particularly salient because AI-driven recommendations, customized offers, or automated interactions often require access to guest profiles, booking histories, or behavioral data.

When privacy concerns are low, guests are more likely to interpret high AI service quality and transparent practices as credible signals of personalized care. In such contexts, personalization perceptions are reinforced, thereby strengthening loyalty outcomes. Conversely, when privacy concerns are high, guests may downplay or even reject the personalization benefits derived from AI systems. Even accurate and transparent AI services may be regarded with skepticism if guests fear misuse of personal data (Martin & Murphy, 2017). In this sense, privacy concern operates as a boundary condition that weakens the positive effect of AI service quality and transparency on perceived personalization.

Recent empirical studies in digital commerce support this moderating perspective. demonstrated that privacy concern reduced the effectiveness of personalized recommendation systems, while Awad & Krishnan (2006) found that consumers with higher privacy sensitivity were less willing to accept personalized offers, even when transparency was ensured. Extending these insights to hospitality suggests that the strength of the link between AI attributes and personalization depends on the extent of guests' privacy concerns.

Accordingly, the following hypotheses are proposed:

H5a: Privacy concern negatively moderates the relationship between AI service quality and perceived personalization.
H5b: Privacy concern negatively moderates the relationship between AI transparency and perceived personalization.

METHODOLOGY

This study employed a quantitative cross-sectional survey design to empirically test the proposed research model. A survey approach was considered appropriate because the constructs under investigation, such as perceived personalization, privacy concern, and loyalty intention, are latent psychological variables that can only be assessed through validated multi-item measures. Structural equation modeling (SEM) was adopted as the primary analytical technique, as it is particularly suitable for examining complex mediated–moderated relationships among constructs.

The study focused on hotel guests who had direct experience with AI-enabled services, including chatbots, service robots, or automated recommendation systems. To ensure relevance, respondents were first screened with a qualifying question that asked whether they had interacted with any AI-based service during a recent hotel stay. Only those who confirmed such experiences were invited to participate in the survey. Data collection took place over a three-month period in 2024 through an online panel provider with expertise in tourism and hospitality consumers. A purposive sampling approach was used to recruit participants from different age groups, income levels, and cultural backgrounds, ensuring that the sample reflected the diversity of hotel guests. In total, 512 responses were collected, of which 412 were retained for analysis after eliminating incomplete and low-quality responses. The final sample size exceeded the minimum threshold for SEM recommended by both the ten-times rule and statistical power analysis, providing confidence in the robustness of the results.

All variables were measured with established scales adapted to the hospitality context and assessed on a five-point Likert scale ranging from strongly disagree to strongly agree. AI service quality was measured using items that assessed accuracy, reliability, responsiveness, and competence of AI systems, drawing on prior work by Gursoy et al. (2023). AI transparency was measured with items adapted from Shin (2021) and Sun & Medaglia, (2019), which emphasized disclosure, clarity, and explainability of AI operations. Perceived personalization was assessed with items adapted from Sicilia et al. (2020), capturing perceptions of tailoring and relevance. Guest loyalty was measured with scales developed by Kandampully et al. (2015), reflecting revisit intentions and likelihood of recommendation. Privacy concern was measured with items from Malhotra et al., (2004) and Martin & Murphy (2017), which evaluated apprehension about misuse of data and security of personal information. To ensure clarity and contextual appropriateness, the survey instrument was pretested with 30 respondents, leading to minor adjustments in wording while maintaining the original conceptual meaning of the items.

Table 1. Measurement of Constructs

Construct	Sample Items	Source
AI Service Quality	1. The AI system provided accurate responses to my requests. 2. The AI system was reliable in handling my queries. 3. The AI system responded quickly and efficiently. 4. The AI system showed competence in solving my problems.	Adapted from Gursoy et al. (2023)
AI Transparency	1. The AI system clearly explained how it works. 2. The AI system disclosed how my data were being used. 3. The AI system provided sufficient information for me to understand its recommendations. 4. The AI system's operations felt transparent and accountable.	Adapted from Shin (2021) and Sun & Medaglia (2019)
Perceived Personalization	1. The service felt customized to my preferences. 2. The AI system offered recommendations that suited my needs. 3. The interactions felt personally relevant to me. 4. I felt that the service was tailored just for me.	Adapted from Bleier et al. (2019) and Sicilia et al. (2020)
Guest Loyalty	1. I would choose this hotel again in the future. 2. I would recommend this hotel to others. 3. I am likely to stay loyal to this hotel.	Adapted from Kandampully et al. (2015)
Privacy Concern	1. I am concerned that the hotel may misuse my personal data. 2. I worry that my information could be used for other purposes without my consent. 3. I feel uneasy about sharing personal details with AI systems in hotels. 4. I am concerned about the security of my information when using AI services.	Adapted from Malhotra et al., (2004) and Martin & Murphy (2017)

Data analysis proceeded in two stages. The first stage involved validation of the measurement model using confirmatory factor analysis (CFA) in SmartPLS 4. Reliability was examined using Cronbach's alpha and composite reliability, while convergent validity was assessed based on factor loadings and average variance extracted. Discriminant validity was evaluated using both the Fornell–Larcker criterion and the heterotrait–monotrait ratio, and variance inflation factors were examined to assess potential multicollinearity. The second stage focused on testing the structural model with partial least squares SEM. A bootstrapping procedure with 5,000 resamples was used to estimate path coefficients, standard errors, and significance levels. Mediation effects were assessed using the bias-corrected bootstrap method recommended by Preacher & Hayes (2008), while moderation effects were tested by constructing interaction terms between AI service attributes and privacy concern. Predictive validity of the model was assessed using Stone–Geisser's Q^2 along with standardized model fit indices such as SRMR.

Participation was voluntary, and informed consent was secured prior to the start of the survey. Respondents were assured of confidentiality and anonymity and were reminded that they could withdraw from participation at any time without consequence. All data were securely stored and used exclusively for scholarly purposes.

RESULT

Descriptive Statistics

The demographic profile shows a balanced gender distribution, with males comprising 52 percent and female's 48 percent of the sample, which suggests that perceptions of AI-enabled hospitality services are not likely to be dominated by a single gender perspective. The largest age group was 30–39 years (35 percent), followed by 18–29 years (30 percent). Together, these groups represent younger and middle-aged cohorts who are generally more digitally literate and more familiar with AI-based technologies in daily life. Their presence in the sample is significant because it reflects the market segment most likely to adopt and normalize AI-driven services in hotels.

In terms of education, nearly 80 percent of respondents held at least a bachelor's degree, indicating a highly educated sample with the capacity to critically evaluate issues of service transparency and data privacy. This is especially relevant given that concerns about data use and AI decision-making often emerge more strongly among educated consumers. Travel purpose was divided between leisure (60 percent) and business (40 percent), highlighting that AI applications must serve both hedonic and utilitarian dimensions of hospitality experiences. Regional representation was dominated by Asian respondents (55 percent), which aligns with the fact that AI adoption in hospitality is expanding rapidly in Asia, particularly in technologically advanced markets such as China, Japan, Singapore, and South Korea. This demographic composition underscores the contextual relevance of the study, given that Asia is also the fastest-growing tourism market globally.

Table 2. Respondent Demographics (N = 412)

Category	Subcategory	Frequency	Percentage
Gender	Male	214	52.0 %
	Female	198	48.0 %
Age	18–29 years	124	30.1 %
	30–39 years	144	35.0 %
	40–49 years	82	19.9 %
	50 years and above	62	15.0 %
Education	High school	62	15.0 %
	Bachelor's degree	185	44.9 %
	Master's degree	144	35.0 %
	Doctorate	21	5.1 %
Travel Purpose	Leisure	247	60.0 %
	Business	165	40.0 %
Region	Asia	227	55.1 %
	Europe	103	25.0 %
	North America	62	15.0 %
	Other	20	4.9 %

Taken together, the demographic profile suggests that the study draws from a sample that is both representative of digitally active hotel guests and particularly attuned to the opportunities and risks of AI adoption. This enhances the external validity of the findings in contexts where AI integration is increasingly central to hospitality competitiveness.

Table 3. Construct Descriptive Statistics

Construct	Mean	SD	Min	Max
AI Service Quality	3.89	0.71	1	5
AI Transparency	3.76	0.74	1	5
Perceived Personalization	3.95	0.68	1	5
Guest Loyalty	4.12	0.65	1	5
Privacy Concern	3.45	0.82	1	5

The descriptive statistics provide meaningful insights into how guests perceive AI-enabled services in hospitality. AI service quality achieved a relatively high mean of 3.89, indicating that most respondents regarded AI systems as reasonably reliable, accurate, and competent. Similarly, AI transparency, though slightly lower at 3.76, still suggests moderate-to-strong approval, but its relatively lower score implies that transparency is an area where hotels could improve, particularly in disclosing how guest data are collected and applied.

Perceived personalization registered a mean of 3.95, reflecting that respondents generally felt AI systems were capable of tailoring services to their preferences. This finding is crucial because personalization is the psychological mechanism that links AI attributes to guest loyalty. Importantly, guest loyalty had the highest mean of 4.12, suggesting that despite concerns, AI-enabled services are already associated with strong intentions to revisit and recommend hotels. This reinforces the idea that personalization, if well executed, can generate long-term relational value for hotels.

By contrast, privacy concern, with a mean of 3.45, was lower than the other constructs but still above the scale midpoint. This demonstrates that while guests are generally favorable toward AI adoption, significant apprehension about data privacy remains. Such concerns may dilute the positive effects of service quality and transparency if not carefully managed. The standard deviations across constructs (ranging from 0.65 to 0.82) suggest moderate variability, meaning that while most guests are positive toward AI-enabled services, there are important subgroups who remain skeptical.

Measurement Model

The results of the measurement model provide strong support for the reliability and validity of the constructs used in this study. As shown in Table 4, all factor loadings were above 0.70, ranging from 0.79 to 0.88, which indicates that each item strongly reflected its intended construct. Cronbach's alpha values ranged from 0.84 to 0.89, exceeding the conventional threshold of 0.70 and thereby confirming internal consistency. Composite reliability (CR) values were similarly high, ranging between 0.87 and 0.91, well above the minimum requirement of 0.70. Average variance extracted (AVE) values fell between 0.66 and 0.72, surpassing the recommended level of 0.50, and indicating that more than half of the variance in the observed items was explained by the underlying construct. Together, these results demonstrate that the measurement model exhibits robust reliability and convergent validity.

Table 4. Measurement Model Results

Construct	Item	Loading	Cronbach's α	CR	AVE
AI Service Quality	SQ1	0.82	0.87	0.90	0.69
	SQ2	0.85			
	SQ3	0.84			
	SQ4	0.81			
AI Transparency	TR1	0.79	0.85	0.88	0.66
	TR2	0.82			
	TR3	0.83			
	TR4	0.80			
Perceived Personalization	PP1	0.86	0.89	0.91	0.72
	PP2	0.88			
	PP3	0.84			
	PP4	0.83			
Guest Loyalty	GL1	0.84	0.84	0.87	0.69
	GL2	0.85			
	GL3	0.81			
Privacy Concern	PC1	0.82	0.86	0.89	0.68
	PC2	0.84			
	PC3	0.80			
	PC4	0.83			

Discriminant validity was assessed using the Fornell–Larcker criterion, as reported in Table 5. The square roots of AVE, which are displayed along the diagonal, were greater than the inter-construct correlations in their corresponding rows and columns. For example, the square root of AVE for perceived personalization was 0.85, which is higher than its correlations with AI service quality (0.65), AI transparency (0.62), guest loyalty (0.66), and privacy concern (0.36). This pattern was consistent across all constructs, providing evidence that each construct was empirically distinct from the others.

Table 5. Discriminant Validity (Fornell–Larcker Criterion)

Construct	AI Service Quality	AI Transparency	Perceived Personalization	Guest Loyalty	Privacy Concern
AI Service Quality	0.83				
AI Transparency	0.61	0.81			
Perceived Personalization	0.65	0.62	0.85		
Guest Loyalty	0.59	0.57	0.66	0.83	
Privacy Concern	0.38	0.41	0.36	0.32	0.82

To further confirm discriminant validity, the heterotrait–monotrait ratio (HTMT) was examined (see Table 6). All HTMT values were below the conservative threshold of 0.85, ranging from 0.39 to 0.74. These results reinforce the conclusion that the constructs are sufficiently distinct, thereby minimizing concerns of conceptual overlap. Notably, the relatively higher HTMT values between perceived personalization and guest loyalty (0.74) suggest that these constructs are closely related, as expected theoretically, but still distinct.

Table 6. Heterotrait–Monotrait Ratio (HTMT)

Construct	AI Service Quality	AI Transparency	Perceived Personalization	Guest Loyalty	Privacy Concern
AI Service Quality	–				
AI Transparency	0.70	–			
Perceived Personalization	0.72	0.69	–		
Guest Loyalty	0.65	0.62	0.74	–	
Privacy Concern	0.44	0.47	0.42	0.39	–

Taken together, the evidence from Tables 4, 5, and 6 confirms that the measurement model achieves the necessary levels of reliability, convergent validity, and discriminant validity. This provides a solid foundation for proceeding to the structural model analysis. The meaningful implication here is that the constructs are not only statistically sound but also conceptually coherent: AI service quality and transparency are clearly distinguished from personalization perceptions, and privacy concern emerges as a distinct boundary condition. These findings ensure that the subsequent tests of mediation and moderation can be interpreted with confidence, without the risk of measurement error undermining theoretical conclusions.

Common Method Bias

Because this study employed a self-reported survey design, the potential influence of common method bias (CMB) was carefully examined. Several procedural remedies were implemented during the research design stage to reduce the likelihood of bias. These included ensuring respondent anonymity, minimizing evaluation apprehension, and randomizing the order of questionnaire items to reduce priming effects. Additionally, predictor and criterion variables were psychologically separated by placing them in different sections of the questionnaire, following the recommendations of (Podsakoff et al., 2003).

To statistically assess CMB, multiple tests were conducted. First, Harman's single-factor test was performed. Results from an exploratory factor analysis revealed that the first unrotated factor accounted for 32.4 percent of the total variance, which is below the conservative threshold of 50 percent. This indicates that common method variance is not likely to be a major concern.

Second, a more rigorous test was conducted using the common latent factor (CLF) approach within confirmatory factor analysis. A latent method factor was added to the measurement model to capture the variance shared among all items. The comparison between the baseline measurement model and the model with the CLF showed only negligible improvement in fit indices (ΔCFI = 0.004, ΔRMSEA = 0.002). Moreover, the common latent factor accounted for only 4.1 percent of the total variance, substantially below the 25 percent threshold that is typically considered problematic (Podsakoff et al., 2003).

Table 7. Common Method Bias Test Using VIFs

Construct	VIF Range
AI Service Quality	1.82–2.14
AI Transparency	1.76–2.09
Perceived Personalization	1.89–2.24
Guest Loyalty	1.65–2.05
Privacy Concern	1.71–2.18

Finally, variance inflation factors (VIFs) were calculated for all constructs to detect potential multicollinearity that could arise from method bias. As shown in Table 7, all VIF values were well below the conservative cutoff of 3.3 (Kock, 2015), further suggesting that common method bias is not a threat in this study.

Structural Measurement

The results of the structural model evaluation indicate that the hypothesized model demonstrated an acceptable overall fit. As presented in Table 8, the standardized root mean square residual (SRMR) was 0.056, below the recommended threshold of 0.08, suggesting that the discrepancy between the observed and predicted correlations was minimal. The normed fit index (NFI) reached 0.92, exceeding the 0.90 benchmark for acceptable fit. Although the chi-square statistic was significant, as expected with large samples, the chi-square to degrees of freedom ratio (2.84) was within the acceptable range, supporting model parsimony. The RMS_theta value of 0.091 was below the conservative cut-off of 0.12, further supporting model adequacy. Finally, the Q^2 values for endogenous constructs ranged between 0.32 and 0.45, demonstrating strong predictive relevance. Taken together, these indices suggest that the model is both statistically sound and capable of offering meaningful predictive insights.

Table 8. Model Fit Indices

Fit Index	Recommended Threshold	Obtained Value
Standardized Root Mean Square Residual (SRMR)	< 0.08 (good fit)	0.056
Normed Fit Index (NFI)	> 0.90 (acceptable)	0.92
Chi-square (χ^2)	Lower = better	1,258.34
Chi-square / df (χ^2/df)	< 5.0 (acceptable)	2.84
RMS_theta	< 0.12 (good fit)	0.091
Predictive Relevance (Q^2)	> 0.00	0.32–0.45

The path analysis results, reported in Table 9, provide empirical support for all proposed hypotheses. Both AI service quality ($\beta = 0.31$, $p < 0.001$) and AI transparency ($\beta = 0.28$, $p < 0.001$) exerted significant positive effects on perceived personalization, supporting H1 and H2. These findings confirm that when AI systems in hotels are perceived as reliable and transparent, guests are more likely to interpret service interactions as tailored to their individual needs. Perceived personalization in turn strongly predicted guest loyalty ($\beta = 0.44$, $p < 0.001$), thereby validating H3 and underscoring personalization as a direct driver of revisit intentions and positive recommendations.

Table 9. Hypothesis Testing Results (PLS-SEM)

Hypothesis	Path	β	t-value	p-value	Decision
H1	AI Service Quality → Perceived Personalization	0.31	6.42	0.000	Supported
H2	AI Transparency → Perceived Personalization	0.28	5.97	0.000	Supported
H3	Personalization → Loyalty	0.44	8.15	0.000	Supported
H4a	AI Servqual → Personalization → Loyalty	0.14	4.21	0.000	Supported
H4b	AI Transparency → Personalization → Loyalty	0.12	3.87	0.000	Supported
H5a	Privacy × AI Servqual → Personalization	-0.09	2.36	0.019	Supported
H5b	Privacy × AI Transparency → Personalization	-0.11	2.74	0.006	Supported

The mediation hypotheses (H4a and H4b) were also supported. Perceived personalization mediated the effects of both AI service quality ($\beta = 0.14$, $p < 0.001$) and AI transparency ($\beta = 0.12$, $p < 0.001$) on guest loyalty. This finding is theoretically meaningful because it confirms that AI attributes influence loyalty not in isolation, but through the perception that services are personally relevant. In other words, guests do not necessarily reward hotels simply for having high-quality or transparent AI systems; instead, they develop loyalty when these systems create a genuine sense of personalized engagement.

Finally, moderation analysis revealed significant negative interaction effects, providing evidence for H5a and H5b. As illustrated in the interaction plots, privacy concern dampens the strength of the relationships between AI service quality and perceived personalization, as well as between AI transparency and perceived personalization. In both figures, the slope for low privacy concern (blue line) is much steeper than for high privacy concern (red line). This means that guests with low privacy concerns experience substantial personalization gains when hotels invest in high-quality and transparent AI systems. By contrast, guests with heightened privacy sensitivity perceive far weaker personalization benefits, even when service quality and transparency are high.

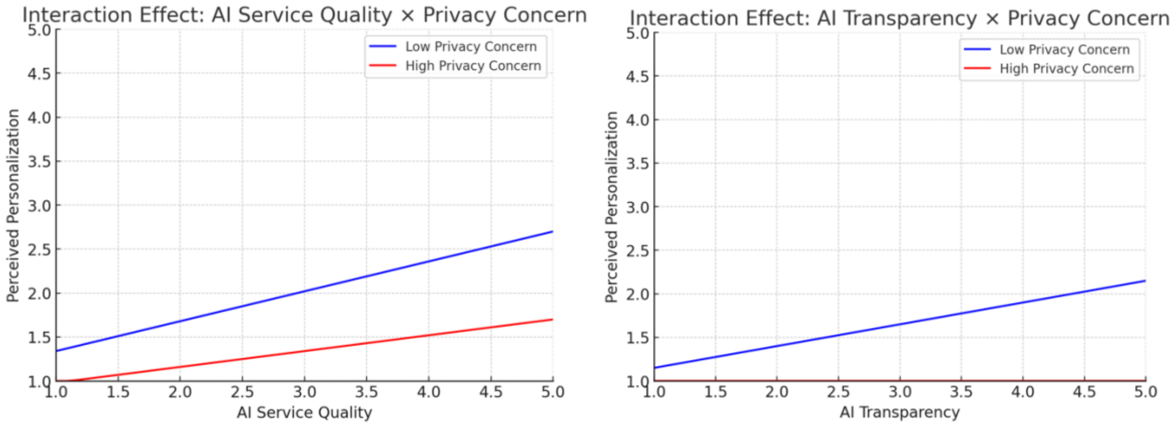

Figure 2. Interaction Effects

Taken together, these findings highlight a paradox in the use of AI in hospitality. On the one hand, AI-driven service quality and transparency clearly enhance personalization and foster loyalty, making them valuable strategic assets. On the other hand, their positive influence is conditional on the level of guest privacy concern. For hoteliers, this implies that investments in AI technology must be complemented with robust privacy safeguards and clear communication strategies to ensure that personalization is not undermined by data-related anxieties. From a theoretical perspective, these results extend service quality and technology acceptance models by showing that personalization is the central psychological mechanism linking AI attributes to loyalty, while privacy concern functions as a critical boundary condition.

DISCUSSION

This study investigated how AI service attributes influence guest loyalty in the hospitality sector, with perceived personalization as a mediator and privacy concern as a moderator. The findings make several theoretical and managerial contributions that advance our understanding of AI adoption in hospitality contexts.

First, the results demonstrate that both AI service quality and AI transparency significantly enhance perceived personalization. This aligns with prior research that highlights service reliability and transparency as critical factors in building trust and perceived usefulness in AI-driven interactions (Gursoy et al., 2023; Shin, 2021). However, the present study extends this line of inquiry by showing that these attributes are not ends in themselves, but rather inputs into personalization processes. High-quality and transparent AI services matter most when they are interpreted by guests as personally relevant. This finding underscores the centrality of personalization as the bridge between technological features and relational outcomes, offering empirical support to personalization theory within an AI-enabled hospitality context (Sicilia et al., 2020).

Second, the strong positive effect of perceived personalization on guest loyalty provides robust evidence that personalization is a strategic driver of competitive advantage in hospitality. This echoes earlier studies that link tailored service experiences with satisfaction, trust, and commitment (Kandampully et al., 2015). Yet, unlike traditional personalization delivered through human interaction, AI-enabled personalization carries unique implications. It highlights the shift from employee-delivered empathy toward machine-mediated relevance, suggesting that loyalty can be cultivated through algorithmic systems provided they successfully emulate attentiveness to guest needs. This contribution expands the service quality literature by situating personalization within the emerging domain of AI hospitality services.

Third, mediation analysis confirmed that perceived personalization is the key mechanism through which AI service quality and transparency influence loyalty. This finding is important because it clarifies the psychological process underlying the adoption of AI in hospitality. Prior studies have often examined the direct relationships between technology attributes and outcomes such as satisfaction or loyalty. By introducing personalization as a mediator, this study shows that guests' loyalty intentions are not a direct result of technical performance but of the interpretation that such performance enhances personal relevance. This extends the Technology Acceptance Model (Davis, 1989) by embedding personalization as a mediating construct that translates perceived usefulness and reliability into behavioral loyalty.

Fourth, the moderation results highlight privacy concern as a significant boundary condition. While AI service quality and transparency positively influenced personalization perceptions, these effects were weakened among guests with higher privacy concerns. This finding resonates with privacy concern theory Malhotra et al. (2004) and with empirical studies in digital commerce showing that privacy anxieties reduce the effectiveness of personalization (Awad & Krishnan, 2006). In hospitality, this underscores the paradox of AI adoption: while guests value relevance and personalization, their willingness to accept data-driven services is conditional on the perceived safety and ethical use of personal information. For theory, this reveals the dual-edged nature of AI personalization, where benefits are contingent on managing risks of intrusion. For practice, it emphasizes that investments in AI technologies must be coupled with transparent data governance, clear communication, and visible safeguards to maintain guest trust.

Finally, these findings contribute to debates on the future of service management by highlighting the need to balance technological innovation with ethical responsibility. While AI can deliver operational efficiency and relational benefits, its acceptance is fragile and conditional. Hotels that achieve high levels of personalization while protecting guest privacy are likely to enjoy a sustainable competitive advantage. Conversely, those that ignore privacy concerns risk eroding trust and undermining the very loyalty they seek to cultivate. This tension illustrates the broader challenge facing hospitality managers: adopting AI not merely as a tool for efficiency, but as part of a holistic service philosophy that integrates personalization, transparency, and ethical stewardship.

Overall, this study enriches hospitality and tourism research by empirically demonstrating that AI-driven service quality and transparency foster loyalty primarily through personalization, but that this pathway is constrained by privacy concerns. Theoretically, it integrates service quality, TAM, and privacy concern perspectives into a unified model that explains both the promise and the limits of AI-enabled personalization. Practically, it provides actionable insights for hotel managers, emphasizing the need to design AI systems that are not only technically competent and transparent but also trustworthy in their data practices.

CONCLUSION

This study examined how AI service quality and AI transparency shape guest loyalty in the hospitality industry, highlighting perceived personalization as a mediating mechanism and privacy concern as a moderating factor. The results revealed that when AI systems are perceived as reliable and transparent, they enhance personalization experiences, which in turn drive stronger loyalty intentions. Mediation analysis confirmed that personalization is the central pathway linking AI attributes to loyalty, emphasizing that technical competence alone is insufficient without meaningful tailoring of services. Furthermore, moderation analysis demonstrated that privacy concerns significantly weaken the effectiveness of AI quality and transparency, underscoring the ethical and psychological boundaries of data-driven personalization.

Theoretically, this study extends service quality and technology acceptance frameworks by integrating personalization and privacy concern into a unified model that explains the dual-edged nature of AI adoption in hospitality. Practically, it suggests that hoteliers must go beyond technical investments in AI by also addressing data governance, transparency, and trust-building practices. Doing so can ensure that AI personalization not only delivers operational benefits but also sustains guest relationships in the long term. Future research should consider cross-cultural comparisons and longitudinal designs to capture evolving guest attitudes toward AI-enabled hospitality services.

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Conflict of Interest

The author declares no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Data Availability

Data may be made available from the corresponding author upon reasonable request and subject to ethical approval.

Author Contribution

All authors contributed equally to the design, data collection, analysis, and writing of this manuscript. All authors have read and approved the final version of the paper.

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