AI-Driven Service Innovation, Customer Satisfaction, and Guest Loyalty: Evidence from Shenyang Airport Hotel, China

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***Abstract*—This study investigated how guests' technological perceptions of Artificial Intelligence (AI) applications perceived usefulness (PU), perceived ease of use (PEOU), enjoyment (ENJ), and privacy concerns (PC) influence customer satisfaction (CS) and customer loyalty (CL) at the Shenyang Airport Hotel, a three-star airport property in a secondary Chinese city. Grounded in an integrated framework combining the Technology Acceptance Model (TAM) with Customer Experience Theory. A quantitative survey of 452 guests who had experienced AI-enabled services during their stay was conducted. Data were analysed using reliability assessment, exploratory factor analysis (to verify the factor structure in a novel context), Pearson correlation, multiple regression, and bootstrap mediation analysis. The results indicated that perceived usefulness ($\beta = 0.314$, $p < 0.001$), enjoyment ($\beta = 0.141$, $p < 0.01$), and perceived ease of use ($\beta = 0.127$, $p < 0.01$) each positively influenced customer satisfaction, whereas privacy concerns exerted a significant negative effect ($\beta = -0.205$, $p < 0.001$). Customer satisfaction, in turn, significantly predicted customer loyalty ($\beta = 0.409$, $p < 0.001$), and partially mediated all four perception-to-loyalty pathways. One-way ANOVA further revealed significant differences in customer loyalty across age groups, educational levels, and income brackets. Theoretically, this study extended TAM by simultaneously incorporating affective and security-related dimensions into AI service acceptance within an underexamined hospitality context. Practically, the findings offer airport hotel managers in secondary cities evidence-based guidance on prioritising utility-enhancing AI features, simplifying service interfaces, enriching hedonic engagement, and communicating data governance policies transparently to mitigate privacy-driven dissatisfaction. The study was limited by its single-site, cross-sectional design; future research should adopt longitudinal or multi-site approaches to strengthen generalisability.**

***Keywords*—Artificial intelligence; airport hotels; technology acceptance model; customer satisfaction; customer loyalty; secondary city; China**

I. Introduction

AI has rapidly become a transformative force in the global hospitality industry. From AI-powered chatbots and facial recognition check-in systems to service robots and predictive analytics platforms, hotels are deploying AI across the full service cycle to enhance operational efficiency, personalize guest experiences, and strengthen competitive positioning [1-2]. In China, this transformation has been further accelerated by strong government policy support and advanced digital infrastructure. Luxury flagship hotels in first-tier cities exemplify the frontier of this trend: Alibaba's FlyZoo Hotel in Hangzhou offers fully AI-integrated experiences spanning autonomous check-in, voice-controlled rooms, and robot concierge services [3], while international chains such as Marriott, Hilton, and Inter Continental have deployed AI-driven dynamic pricing and sentiment analysis platforms across their premier Chinese properties [4]. These innovations have generated a corresponding surge of scholarly interest, with empirical studies consistently reporting that well-implemented AI services improve guest satisfaction and stimulate revisit intention [3, 5].

Despite this growing body of practice and research, the existing literature reflects a pronounced geographical bias. The overwhelming majority of empirical studies on AI in Chinese hotels have concentrated on luxury or upscale establishments in major metropolitan centers such as Shanghai, Beijing, and Guangzhou, where hotels operate with sophisticated technological infrastructure and technologically fluent guest bases [5]. Airport hotels in secondary Chinese cities have received considerably less academic attention. Shenyang, a major industrial and transportation hub in northeastern China, exemplifies such a context. The Shenyang Airport Hotel, located adjacent to Shenyang Taoxian International Airport, operates as a typical three-star airport hotel that serves a mix of business travelers, transit passengers, and increasingly leisure tourists. Despite its strategic location and stable customer flow, the hotel faces persistent operational challenges. According to the hotel's official operational records and a preliminary field survey conducted by the authors in March 2026, which included structured interviews with the hotel manager and three senior front-desk staff members, the hotel's annual repurchase rate stood at only 18% in 2024, substantially below the national average for comparable domestic airport hotels [6-7]. The same sources further reveal the absence of a systematic Customer Relationship Management (CRM) system or loyalty program, and limited technological infrastructure capable of supporting personalized guest retention strategies. These operational realities create both a practical imperative and a research opportunity: to understand how guests perceive AI applications in such a setting and to examine whether these perceptions translate into higher satisfaction and greater loyalty.

There are three research gaps addressed in this study. First, while prior studies have confirmed that AI can improve service efficiency and personalization [2, 5], few have examined how individual technological perceptions, specifically whether an AI system is perceived as useful, easy to use, enjoyable, or privacy-invasive, affect satisfaction and loyalty outcomes in airport hotel contexts. Second, the majority of empirical work has concentrated on first-tier cities or upscale establishments, leaving the dynamics of AI perception formation in secondary-city, mid-scale airport hotels largely unexplored. Third, the mediating role of customer satisfaction in translating technological perceptions into loyalty intentions, although theoretically plausible, has not been rigorously tested in this particular context. Consequently, hotel managers in secondary cities often lack evidence-based guidance on which AI features to prioritize and how to address guests' privacy concerns when deploying AI services.

To fill these gaps, this study empirically investigates how four dimensions of guests' technological perceptions, perceived usefulness, perceived ease of use, enjoyment, and privacy concerns, influence customer satisfaction and, in turn, customer loyalty at Shenyang Airport Hotel. A quantitative survey of 452 guests who had used AI-enabled services during their stay was conducted between March and May 2026. The study addresses six research questions: 1) To what extent does the perceived usefulness of AI applications influence customer satisfaction among hotel guests? 2) To what extent does the perceived ease of use of AI applications influence customer satisfaction among hotel guests? 3) To what extent does the enjoyment derived from AI applications influence customer satisfaction among hotel guests? 4) To what extent do privacy concerns regarding AI applications negatively influence customer satisfaction among hotel guests? 5) Does customer satisfaction positively influence guests' behavioral intentions? 6) Does customer satisfaction mediate the relationships between guests' technological perceptions of AI applications, namely perceived usefulness, perceived ease of use, enjoyment, and privacy concerns, and customer loyalty?

The findings contribute to the literature in three ways. Theoretically, this study extends existing technology acceptance research by incorporating both affective (enjoyment) and security-related (privacy concern) factors into a single model applied to an AI service context that has been largely absent from prior scholarship. Empirically, it provides the first systematic investigation of AI-driven satisfaction and loyalty dynamics in a secondary-city Chinese airport hotel, a context characterized by partial AI infrastructure and low guest retention rates. Practically, it offers hotel managers in analogous settings concrete, evidence-based guidance on AI service design, privacy communication, and demographic differentiated implementation strategies. This study is organized as follows. Section II reviews the relevant literature and develops the study hypotheses. Section III describes the research methodology. Section IV presents the empirical results. Section V discusses the key findings and their theoretical and managerial implications. Section VI presents conclusions. Section VII outlines the research implementation, and Section VIII addresses the limitations of the study and suggests directions for future research.

II. Literature Review

A. AI Adoption in Hospitality and the Airport Hotel Context

AI integration in hotel operations has advanced from rule-based chatbot automation to adaptive systems spanning natural language processing, predictive analytics, and robotics [2, 4]. It falls into three categories: guest interaction systems (chatbots, facial recognition check-in), analytical platforms (revenue management, sentiment analysis), and automated physical operations (service robots, smart room control). Together, these shift service delivery from human-to-human to human-to-machine interaction, introducing efficiency gains alongside new psychological challenges for guests [1]. Airport hotels occupy a structurally distinctive niche, characterized by high turnover, short stays, and guests who prioritize efficiency over experience [8]. This makes them receptive to time-saving AI tools; yet the technological infrastructure of secondary-city airport hotels frequently lags behind first-tier counterparts, creating a context where AI effectiveness is uncertain, and guest perceptions may differ markedly from those documented in luxury urban hotels [5]. Table I contextualizes the AI service profile of the Shenyang Airport Hotel (SAH) against ten landmark hospitality studies. The three features operational at SAH: AI chatbots, facial recognition check-in, and automated check-in/check-out—are among the most frequently documented (frequency 4–5), confirming the study's empirical relevance. The absence of post-stay follow-up systems, recommendation engines, and AI-enabled loyalty programmes delineates the current technological gap and reinforces the study's practical motivation [6-7].

TABLE I. AI Service Features in the Hospitality

No	AI Feature / Application	[4]	[9]	[10]	[11]	[12]	[13]	14]	[15]	[16]	[17]	Authors
1	AI Chatbots	✓	✓		✓	✓	✓					✓
2	Post-stay Follow-up AI		✓			✓			✓	✓		
3	Facial Recognition Check-in	✓		✓		✓		✓				✓
4	Service Robots	✓	✓	✓							✓	
5	AI Recommendation Engines		✓	✓	✓		✓		✓			
6	Automated Check-in/Check-out		✓			✓		✓		✓		✓
7	AI Concierge Systems			✓		✓	✓				✓	
8	Biometric Room Access					✓		✓			✓	
9	Hyper-personalized Services		✓		✓		✓		✓			
10	AI-enabled Loyalty Programme							✓	✓		✓	

B. TAM and Its Extensions

Davis [26] established that PU and PEOU jointly determine technology acceptance. Subsequent extensions accommodate the hedonic and risk dimensions of consumer service contexts [18]. Two extensions are central here. First, perceived enjoyment (ENJ), intrinsic positive affect generated by the AI interaction, independently enhances acceptance in service settings where novelty and interactivity are salient. Second, privacy concern, unease about biometric data collection and use, functions as a consistent negative moderator, particularly acute in airport environments where facial recognition is operationally embedded [19, 21]. Integrating all four perceptions into a single model represents the primary theoretical contribution of this study.

C. Customer Satisfaction and Customer Loyalty

Customer satisfaction is conceptualized as a post-consumption evaluative judgment reflecting whether AI-mediated service encounters have met or exceeded guest expectations [20]. Customer Experience Theory [22] situates this judgment within a multi-dimensional architecture—cognitive, emotional, social, and physical, explaining divergent evaluations of the same AI features across guest segments. In the present study, CET serves as an interpretive scaffold rather than an independently operationalized measurement framework: it motivates the inclusion of both utilitarian (PU, PEOU) and hedonic (ENJ) dimensions alongside a risk-based barrier (PC), and it explains why the same AI features may generate divergent satisfaction evaluations across guest segments defined by age, education, and income. The four TAM-derived constructs are the operationalized variables; CET provides the theoretical rationale for their simultaneous inclusion and for the expectation that satisfaction will mediate their effects on loyalty. Future research could operationalize CET dimensions directly, for example, through validated cognitive and emotional appraisal sub-scales to permit a more complete test of the integrated framework. Customer loyalty is operationalized as revisit intention and word-of-mouth (WOM) recommendation, capturing both the direct economic value and the social amplification of loyalty [23]. Whether technological perceptions shape loyalty primarily through satisfaction or also through direct paths is addressed via bootstrap mediation analysis.

TABLE II. LITERATURE REVIEW AND RESEARCH GAPS

Theme / Construct	Key Finding from Literature	[12]	[8]	[5]	[19]	[21]	Authors
Perceived Usefulness (PU)	Strongest positive predictor of AI-service satisfaction; time-saving and accuracy are most valued.	✓		✓			✓
Perceived Ease of Use (PEOU)	Positively influences satisfaction; interface complexity deters older and less tech-savvy guests.	✓		✓			✓
Enjoyment / Hedonic Motivation	Independently enhances satisfaction beyond utilitarian perceptions; salient in service-intensive encounters.		✓				✓
Privacy Concern	Negatively moderates AI acceptance; biometric data collection intensifies unease without transparent policies.				✓	✓	✓
Satisfaction → Loyalty Mediation	Satisfaction partially mediates the perception-to-loyalty path; direct effects also exist but are weaker.			✓			✓
Context: First-tier / Upscale Hotel	Empirical base dominated by 5-star or chain hotels in major metropolitan centers.	✓	✓	✓	✓	✓	
Context: Airport Hotel, Secondary City	Partial AI infrastructure; high turnover; time-sensitive guests; low CRM maturity — underexamined.						✓
Demographic Moderation (ANOVA)	Age, education, and income moderate technology acceptance and loyalty levels.					✓	✓

Table II maps the thematic coverage of prior literature against the present study, revealing three interrelated gaps: 1) no prior study has examined PU, PEOU, ENJ, and PC simultaneously within an airport hotel model; 2) all comparable studies were conducted in first-tier cities or upscale segments, leaving secondary-city airport hotels unexamined; and 3) the mediating role of satisfaction has not been rigorously tested with bootstrap procedures in this context. Six hypotheses follow directly.

III. RESEARCH METHODOLOGY

This section describes the research design, study context, population, and sampling strategy, instrument development, data collection, and statistical analysis procedures employed in the study.

A. Research Design

A quantitative, cross-sectional survey design was adopted to test the hypothesized relationships among guests' AI service perceptions, customer satisfaction, and customer loyalty. Quantitative methods are well-suited to evaluating predictive relationships among multiple continuous constructs and to drawing population-level inferences from probability-based samples [24]. Primary data were collected through a structured, self-administered questionnaire available in both digital and paper formats.

B. Research Context: Shenyang Airport Hotel

Shenyang Airport Hotel is a three-star property located approximately one kilometer from Terminal 3 of Shenyang Taoxian International Airport, Liaoning Province. The hotel operates 163 rooms, of which 123 are standard, 30 are business, and 10 are family, and all are equipped with smart door locks and smart televisions. The property operates without dedicated IT personnel, a CRM system, or a formal loyalty programme. Its 2024 annual repurchase rate of 18% falls substantially below the national benchmark for comparable airport hotels. A preliminary field survey and management interviews conducted in March 2026 confirmed that three AI services are currently operational: an AI chatbot, a facial recognition self-check-in terminal, and an automated check-in/check-out kiosk—while more advanced retention-oriented AI tools remain absent [6-7].

C. Research Participants: Population and Sample Size

The target population comprised guests who had stayed at the hotel at least once within the two years preceding data collection and had used at least one AI-enabled service during their stay. Because the eligible population is continuous and uncountable, it was treated as theoretically infinite. The minimum sample size of 384 was determined using Cochran's formula [25].

To compensate for anticipated incomplete responses, 500 questionnaires were distributed. After data screening, 452 valid responses were retained (valid response rate = 90.4%), exceeding both the Cochran minimum (384) and the recommended threshold for the planned regression analyses.

D. Sample Size Sampling Procedure

Stratified random sampling was applied to ensure proportionate representation of key guest subgroups. The sampling frame was stratified along three dimensions: travel purpose, age group, and nationality. Within each stratum, respondents were selected randomly. This approach reduces the risk of segment-driven bias and strengthens the external validity of the findings [25].

E. Research Instrument Development and Validation

1) Item generation: All measurement items were adapted from validated scales: PU and PEOU from Davis [26]; ENJ from [18]; PC from [19]; CS from [20]; and CL from Zeithaml et al. [23]. Items were translated into Simplified Chinese and independently back-translated by a second bilingual researcher to ensure semantic equivalence [27].

2) Expert validation: Three subject-matter experts assessed content validity using the Index of Item-Objective Congruence (IOC). The mean IOC across all items was 0.82, exceeding the 0.70 threshold [28]. Two items with IOC values below 0.70 were removed, yielding a final questionnaire of 40 items organized into four sections: 1) sociodemographic and travel characteristics; 2) AI usage history; 3) six Likert-scale constructs rated on a five-point scale (1 = strongly disagree to 5 = strongly agree); and 4) open-ended qualitative questions.

3) Reliability and validity test: Cronbach's alpha coefficients for all multi-item constructs exceeded .85, demonstrating excellent internal consistency. The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was .895, and Bartlett's test of sphericity was statistically significant (χ^2 = 7283.729, df = 253, $p < .001$), confirming factorability of the correlation matrix. Exploratory factor analysis (EFA) using principal component extraction with varimax rotation extracted six factors with eigenvalues greater than 1, collectively accounting for 78.16% of the total variance. All items loaded substantially on their hypothesized factors ($\lambda > .70$), with negligible cross-loadings, supporting both convergent and discriminant validity [29]. EFA was selected over confirmatory factor analysis (CFA) because this study, although guided by theoretically motivated construct definitions, employs items adapted from multiple prior scales and tested together for the first time in the specific context of a secondary-city Chinese airport hotel. EFA was therefore appropriate to verify the empirical factor structure and item behaviour in this new setting before structural relationships were estimated [29]. Future research replicating the model in comparable contexts should employ CFA or structural equation modelling (SEM) to confirm construct dimensionality and provide stronger evidence of model fit.

F. Research Hypothesis

- H1: Perceived usefulness of AI applications has a positive effect on customer satisfaction.
- H2: Perceived ease of use of AI applications has a positive effect on customer satisfaction.
- H3: Enjoyment of AI applications has a positive effect on customer satisfaction.
- H4: Privacy concerns regarding AI applications harm customer satisfaction.
- H5: Customer satisfaction positively affects customer loyalty.
- H6: Customer satisfaction mediates the relationship between guests' technological perceptions of AI applications (perceived usefulness, perceived ease of use, enjoyment, privacy concerns) and customer loyalty.

These hypotheses are illustrated in the conceptual model below (Fig. 1).

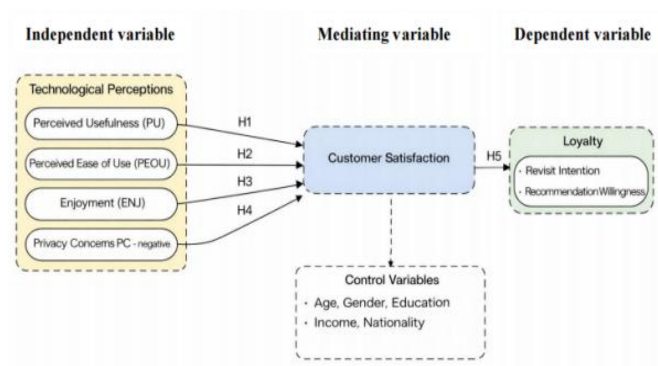

Fig. 1. Research framework of AI perceptions, customer satisfaction, and loyalty.

G. Data Collection

Data were collected between March and May 2026 through four complementary channels: 1) email invitations to opted-in prior guests; 2) QR-code cards displayed at the front desk, lobby, and in each guest room; 3) a pinned post on the hotel's official WeChat account; and 4) paper questionnaires available at the front desk for guests who preferred offline completion. Respondents received a 15% discount voucher for a future stay as an incentive. Ethics approval was obtained from the Research Ethics Committee of Suratthani Rajabhat University (Approval No.: SRU-EC 2026/029). All participation was voluntary and anonymous.

H. Data Analysis

All statistical analyses were performed using Statistics software, following a sequential six-stage procedure:

1) Descriptive statistics: Means, standard deviations, and frequency distributions were computed for all constructs and demographic variables.

2) Reliability and validity: Cronbach's alpha was recomputed for the full sample. Exploratory Factor Analysis (EFA) with principal component extraction and varimax rotation was conducted; the Kaiser-Meyer-Olkin (KMO) measure and Bartlett's test of sphericity verified sampling adequacy [30].

3) Correlation analysis: Pearson's r coefficients were computed for all construct pairs; Variance Inflation Factor (VIF) values confirmed the absence of multicollinearity (threshold VIF < 10) [29].

4) Hypothesis testing (H1–H5): Multiple linear regression examined the effects of PU, PEOU, ENJ, and PC on CS (H1–H4). Simple linear regression examined the effect of CS on CL (H5a–H5b). Standardized beta coefficients (β) and their significance levels were reported.

5) Mediation analysis (H6): Bootstrap mediation with 5,000 resamples was conducted following Preacher and Hayes [31]. Bias-corrected 95% confidence intervals (CIs) were computed; an indirect effect was deemed significant if the CI excluded zero. Partial mediation was inferred when both the direct and indirect effects remained significant.

6) Difference analysis: One-way ANOVA examined whether CL differed significantly across age groups, educational levels, and income brackets. Where F-ratios were significant, Scheffé post-hoc tests identified specific group differences.

All p-values are two-tailed; the significance level was set at $\alpha = 0.05$ throughout the study.

IV. Results

A. Participant Characteristics

This study examined the effects of AI adoption in hotel management on guests' perceptions, satisfaction, and loyalty. Data were collected from guests who had experienced AI-enabled services at Shenyang Airport Hotel. The majority of respondents were male (52.65%), aged between 30 and 49 years (53.10%), and held at least a bachelor's degree (86.94%). Business travel was the predominant purpose of stay (42.48%), and 69.03% of respondents had stayed at the hotel at least once within the preceding two years. Detailed demographic information is presented in Table III.

Table III shows that the majority stayed at the hotel once per year (44.36%), while 48.04% reported using AI services on more than two occasions during their stay. The most commonly encountered AI technology was the facial recognition self-check-in/check-out terminal (68.63%). The primary channels through which respondents became aware of the hotel's AI services were staff recommendations at check-in (68.14%) and prompts displayed on the self-check-in terminal (61.52%). These findings indicate that the sample possessed a sufficient level of familiarity with AI adoption in hotel management to support the validity of subsequent empirical analyses.

TABLE III. DEMOGRAPHIC PROFILE OF RESPONDENTS

Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	238	52.65
	Female	214	47.35
Age	18–29 years	119	26.33
	30–49 years	240	53.10
	50–60 years	93	20.58
Education	High school or below	59	13.06
	Bachelor's degree	220	48.67
	Master's degree or above	173	38.27
Travel purpose	Business	192	42.48
	Leisure	156	34.51
	Transit	71	15.71
	Other	33	7.30
Prior hotel stays (past 2 years)	At least once	312	69.03
	More than a year	140	30.97

B. Descriptive Statistics, Reliability, and Validity

Table IV shows the mean scores of all six constructs. Customer Satisfaction recorded the highest mean ($\bar{x} = 3.95$), followed by Enjoyment ($\bar{x} = 3.88$), Perceived Usefulness ($\bar{x} = 3.87$), Perceived Ease of Use ($\bar{x} = 3.83$), and Customer Loyalty ($\bar{x} = 3.76$), respectively. Privacy Concerns yielded the lowest mean ($\bar{x} = 2.98$), the only construct falling below the scale midpoint of 3.00.

TABLE IV. DESCRIPTIVE STATISTICS AND RELIABILITY COEFFICIENTS

Variable	$\bar{x}$	SD	α	No. of Items
PU	3.87	0.70	0.859	3
PEOU	3.83	0.85	0.906	3
ENJ	3.88	0.83	0.904	3
PC	2.98	1.09	0.900	4
CS	3.95	0.61	0.891	5
CL	3.76	0.77	0.927	5

Table V shows item-level mean scores across all six constructs. Within Perceived Usefulness, time-saving was rated most favourably, affirming speed as the primary utilitarian benefit. For Perceived Ease of Use, unassisted terminal operation recorded the highest item mean, indicating that most guests navigated the interface independently. Novelty dominated the Enjoyment dimension, reflecting the affective appeal of facial recognition technology. All Privacy Concerns items fell around the scale midpoint, confirming a lack of unease over biometric data governance. Terminal accuracy drove Customer Satisfaction most strongly, while willingness to revisit yielded the highest item mean within Customer Loyalty, though preference over competitors remained comparatively low, suggesting limited competitive differentiation.

TABLE V. DESCRIPTIVE STATISTICS OF EACH ASSESSMENT ITEM

Assessment Items	x̄	SD
Perceived Usefulness (PU)	**3.87**	**0.70**
1. The facial recognition self-check-in/check-out terminal saved me time compared to manual front desk service.	3.93	0.79
2. Using the AI terminal improved the efficiency of my check-in/check-out process.	3.88	0.64
3. The AI terminal met my need for quick service (e.g., when I was in a hurry for a flight).	3.81	0.67
Perceived Ease of Use (PEOU)	**3.83**	**0.85**
1. I could operate the facial recognition terminal without staff assistance.	3.86	0.96
2. The terminal's instructions (e.g., interface prompts for ID scanning) were clear and easy to understand.	3.84	0.80
3. Even if I had limited experience with technology, I could still operate the AI terminal easily.	3.79	0.79
Enjoyment (ENJ)	**3.88**	**0.83**
1. Using the facial recognition terminal added a sense of novelty to my stay.	3.98	0.92
2. I felt relaxed using the terminal (e.g., no need to wait in line for the front desk).	3.80	0.80
3. The AI terminal made me perceive the hotel as providing novel services.	3.87	0.77
Privacy Concerns (PC)	**2.98**	**1.09**
1. I worried about the hotel misusing my facial recognition data.	2.93	1.23
2. I did not fully trust that the hotel's AI system would protect my personal data.	2.96	1.01
3. The hotel did not clearly inform me about my facial data storage and deletion policy.	2.94	1.04
4. I am not concerned about how my facial data is stored.	3.07	1.09
Customer Satisfaction (CS)	**3.95**	**0.61**
1. I was satisfied with the accuracy of the facial recognition terminal (e.g., first-try verification).	4.00	0.71
2. I was satisfied with the AI terminal's response speed (e.g., fast room key issuance).	3.93	0.56
3. Using the AI terminal enhanced my overall stay experience.	3.93	0.55
4. Even without using AI services, I was satisfied with the hotel's general services (e.g., airport shuttle).	3.92	0.61
5. Overall, I was highly satisfied with my stay at Shenyang Airport Hotel.	3.96	0.63
Customer Loyalty (CL)	**3.76**	**0.77**
1. I am willing to stay at this hotel again on my next visit.	3.84	0.91
2. I will recommend this hotel to friends/family needing nearby accommodation.	3.73	0.73
3. I will prioritize this hotel for future Shenyang trips (business/transit).	3.74	0.71
4. I am willing to share positive feedback (including AI services) on social media.	3.76	0.74
5. The hotel's services make me more likely to choose it over nearby competitors.	3.72	0.75

C. Correlation Analysis

Table VI shows the Pearson correlation matrix for all key variables. Perceived usefulness, perceived ease of use, and enjoyment were each positively and significantly correlated with customer satisfaction ($r = 0.439$, 0.320, and 0.330, respectively; all $p < 0.01$), whereas privacy concerns exhibited a significant negative correlation with satisfaction ($r = -0.299$, $p < 0.01$). Customer satisfaction and customer loyalty demonstrated a moderate positive association ($r = 0.409$, $p < 0.01$). All inter-variable correlation coefficients fell below 0.80, indicating that multicollinearity was not a concern in the subsequent regression analyses.

TABLE VI. PEARSON CORRELATION MATRIX OF KEY VARIABLES

Variable	PU	PEOU	ENJ	PC	CS
PU	1				
PEOU	.313**	1			
ENJ	.316**	.507**	1		
PC	−.199**	−.112*	−.124**	1	
CS	.439**	.320**	.330**	−.299**	1
CL	.386**	.336**	.301**	−.327**	.409**

[a] Note: **p < 0.01, *p < 0.05.

D. Hypothesis Testing: H1–H4

Multiple regression analysis was conducted with customer satisfaction as the dependent variable and the four technological perception dimensions as predictors. The overall model was statistically significant, $F(4, 447) = 44.836$, $p < 0.001$, accounting for 28.6% of the variance in customer satisfaction ($R^2 = 0.286$). The regression results are summarised in Table VII.

TABLE VII. MULTIPLE REGRESSION RESULTS: AI PERCEPTIONS PREDICTING CUSTOMER SATISFACTION (H1–H4)

Predictor	B	SE	β	t	p
Constant	2.475	0.192	—	12.889	< 0.001
PU (H1)	0.274	0.038	0.314	7.222	< 0.001
PEOU (H2)	0.092	0.034	0.127	2.682	0.008
ENJ (H3)	0.105	0.035	0.141	2.991	0.003
PC (H4)	−0.116	0.023	−0.205	−5.017	< 0.001

Perceived usefulness exerted the strongest positive effect on customer satisfaction ($\beta = 0.314$, $p < 0.001$), followed by enjoyment ($\beta = 0.141$, $p < 0.01$) and perceived ease of use ($\beta = 0.127$, $p < 0.01$). Privacy concerns had a significant negative effect on satisfaction ($\beta = -0.205$, $p < 0.001$). Accordingly, Hypotheses H1, H2, H3, and H4 were all supported.

E. Hypothesis Testing: H5

Simple regression analysis revealed that customer satisfaction exerted a significant positive effect on customer loyalty ($\beta = 0.409$, $t = 9.501$, $p < 0.001$). The model explained 16.7% of the variance in customer loyalty ($R^2 = 0.167$, $F = 90.278$, $p < 0.001$). These findings support Hypothesis H5, confirming that guests who reported higher satisfaction with AI-enabled hotel management services were more likely to express intentions to revisit the hotel and to recommend it to others through word-of-mouth.

F. Hypothesis Testing: H6

To test Hypothesis H6, a bootstrap mediation analysis was performed using 5,000 resamples, following the procedure recommended by Preacher and Hayes. Bias-corrected 95% confidence intervals (CIs) were employed to assess the significance of indirect effects. The results are presented in Table VI. The 95% bootstrap CIs for the indirect effects of all four perception dimensions on customer loyalty, via customer satisfaction, excluded zero, indicating statistically significant partial mediation across all pathways. Thus, Hypothesis H6 was supported. As can be seen in Table VIII.

TABLE VIII. BOOTSTRAP MEDIATION RESULTS: INDIRECT AND DIRECT EFFECTS ON CUSTOMER LOYALTY VIA CUSTOMER SATISFACTION (H6)

Pathway	Effect Type	Effect	Boot SE	LLCI	ULCI
PU → CS →CL	Indirect	0.142	0.029	0.088	0.201
	Direct	0.279	0.051	0.180	0.379
PEOU → CS→ CL	Indirect	0.097	0.023	0.054	0.146
	Direct	0.207	0.040	0.128	0.285
ENJ → CS → CL	Indirect	0.106	0.024	0.063	0.158
	Direct	0.173	0.041	0.091	0.254
PC → CS → CL	Indirect	−0.072	0.017	−0.107	−0.042
	Direct	−0.159	0.031	−0.220	−0.098

b. Note: Bootstrap confidence intervals not containing zero indicate significant mediation.

G. Demographic Differences in Customer Loyalty

One-way analysis of variance (ANOVA) was conducted to examine whether customer loyalty differed significantly across demographic groups. The results indicated statistically significant differences in customer loyalty by age group ($F = 3.782$, $p = 0.024$), educational level ($F = 4.563$, $p = 0.011$), and annual household income ($F = 3.136$, $p = 0.009$). No significant differences were found with respect to gender, occupation, or travel purpose. Detailed results are presented in Table IX.

TABLE IX. ONE-WAY ANOVA RESULTS: DEMOGRAPHIC DIFFERENCES IN CUSTOMER LOYALTY

Variable	Group	x̄	SD	F	p
Age	18–29 years	3.72	0.74	3.782	0.024*
	30–49 years	3.84	0.71		
	50–60 years	3.59	0.91		
Education	High school or below	3.59	0.70	4.563	0.011*
	Bachelor's degree	3.70	0.83		
	Master's degree or above	3.89	0.69		
Annual income (RMB)	Below 30,000	3.42	0.91	3.136	0.009**
	30,000–100,000	3.73	0.83		
	100,000–300,000	3.79	0.76		
	300,000–500,000	3.76	0.70		
	Above 500,000	4.06	0.56		

c. Note: $^{**}p < 0.01$, $^{*}p < 0.05$. The group with the highest mean loyalty score within each variable is shown in bold.

In summary, respondents aged 30–49 years ($\bar{x} = 3.84$), those holding a master's degree or above ($\bar{x} = 3.89$), and those with an annual household income exceeding 500,000 RMB ($\bar{x} = 4.06$) exhibited the highest levels of customer loyalty. These findings suggest that demographic characteristics play a meaningful role in segmenting hotel guests for the purpose of tailoring AI adoption strategies in hotel management to specific target groups.

H. Summary of Hypothesis Testing Results

TABLE X. SUMMARY OF HYPOTHESIS TESTING RESULTS

H	Statement	Key Statistic	Outcome
H1	The perceived usefulness of AI applications positively affects customer satisfaction.	$\beta = 0.314$, $p < 0.001$	Supported
H2	Perceived ease of use of AI applications positively affects customer satisfaction.	$\beta = 0.127$, $p = 0.008$	Supported
H3	Enjoyment of AI applications positively affects customer satisfaction.	$\beta = 0.141$, $p = 0.003$	Supported
H4	Privacy concerns regarding AI applications negatively affect customer satisfaction.	$\beta = -0.205$, $p < 0.001$	Supported
H5	Customer satisfaction positively affects customer loyalty (revisit intention and word-of-mouth).	$\beta = 0.409$, $p < 0.001$	Supported
H6	Customer satisfaction partially mediates the relationship between technological perceptions and customer loyalty.	95% Bootstrap CI excludes zero on all paths	Supported

Table X summarises the hypothesis testing results. All six hypotheses were supported at conventional significance levels. Perceived usefulness exerted the strongest positive effect on customer satisfaction ($\beta = 0.314$), followed by enjoyment ($\beta = 0.141$) and perceived ease of use ($\beta = 0.127$), while privacy concerns had a significant negative effect ($\beta = -0.205$). Customer satisfaction, in turn, positively predicted customer loyalty ($\beta = 0.409$), and bootstrap mediation analysis confirmed that it partially mediated all four perception-to-loyalty pathways, with 95% confidence intervals excluding zero across all paths.

V. DISCUSSION

A. Results Discussion

1) Perceived usefulness and customer satisfaction RQ. 1

Research Question 1: To what extent does the perceived usefulness of AI applications influence customer satisfaction among hotel guests? The regression results confirmed that PU was the strongest positive predictor of customer satisfaction ($\beta = 0.314$, $p < 0.001$), thereby supporting Hypothesis H1. This finding is consistent with Davis's [26] foundational TAM, which postulates that perceived usefulness, the degree to which a technology is believed to enhance task performance, is the primary determinant of user acceptance and satisfaction. In the present context, AI features such as the facial-recognition self-check-in terminal and the automated check-in/check-out kiosk reduce guest wait times and streamline administrative procedures. Functions that guests overwhelmingly value in an airport environment characterised by time pressure and schedule sensitivity [17]. This utilitarian primacy replicates findings reported by [12], who identified time-saving and accuracy as the most valued attributes of AI chatbots in hotel settings, and by [3], who documented that AI-customised experiences improving service efficiency exert the strongest influence on satisfaction in Chinese hotels. Furthermore, the magnitude of the PU effect in the present study ($\beta = 0.314$) is commensurate with that reported by [5] (β = 0.29) in a comparable Chinese hotel context, suggesting that the relationship is robust across hotel tiers and city classifications. Collectively, these results reaffirm that, in functional service environments where performance outcomes are paramount, the instrumental dimension of AI perception takes precedence over hedonic and social considerations.

2) Perceived usefulness and customer satisfaction RQ. 2

Research Question 2: To what extent does the perceived ease of use of AI applications influence customer satisfaction among hotel guests? The results confirmed a significant positive effect of PEOU on customer satisfaction ($\beta = 0.127$, $p = 0.008$), supporting Hypothesis H2, albeit with a smaller effect size than perceived usefulness. This ordering aligns with Davis's [26] original TAM, which posited that PEOU exerts an indirect effect on acceptance primarily through its influence on PU, whereas PU retains a stronger direct path. In the hospitality context, Buhalis and Moldavska [1] demonstrated that interface complexity constitutes a significant barrier to guest adoption of voice assistant technologies, particularly among older and less technologically experienced users. The comparatively modest PEOU coefficient observed in the present study may reflect the relatively straightforward design of the facial recognition terminal, which minimises the cognitive load imposed on guests through intuitive workflow design and minimal required input. Venkatesh et al.'s [18] Unified Theory of Acceptance and Use of Technology (UTAUT) similarly found that ease of use becomes less salient as users gain familiarity with a system; given that 48.04% of respondents reported using the hotel's AI services on more than two occasions, habitual use may have attenuated the perceived difficulty of the interaction. Nonetheless, the significant positive coefficient confirms that interface simplicity remains a meaningful contributor to overall satisfaction and should not be overlooked in the design of AI service encounters.

3) Enjoyment and customer satisfaction

Research Question 3: To what extent does the enjoyment derived from AI applications influence customer satisfaction among hotel guests? Hypothesis H3 was supported, with enjoyment emerging as the second most influential positive predictor of satisfaction ($\beta = 0.141$, $p = 0.003$). This finding extends the hedonic dimension of the TAM framework, as elaborated by [18], into the airport hotel context, confirming that intrinsic positive affect generated by the AI interaction independently enhances satisfaction beyond utilitarian and ease-of-use considerations. The effect magnitude is noteworthy given the functional, time-sensitive nature of airport hotel stays: even in an environment that prioritises efficiency, guests derive a degree of affective value from novel and interactive AI encounters. This pattern is consistent with [3] observation that the novelty and interactivity of AI-customised hotel services engender positive emotional responses that contribute independently to satisfaction, and with [11] systematic review, which identified enjoyment as a consistent predictor of automation acceptance across tourism and hospitality contexts. The present finding is particularly significant insofar as it challenges a purely utilitarian view of AI adoption in secondary-city airport hotels; guests at Shenyang Airport Hotel, like their counterparts in more technologically mature properties, appear to respond effectively as well as cognitively to AI service encounters. This has implications for service design, suggesting that incorporating hedonic elements such as engaging interfaces and personalised recommendations can augment satisfaction even within operationally constrained AI environments.

4) Privacy concerns and customer satisfaction

Research Question 4: To what extent do privacy concerns regarding AI applications negatively influence customer satisfaction among hotel guests? The regression results confirmed that PC exerted a significant negative effect on customer satisfaction ($\beta = -0.205$, $p < 0.001$), thereby supporting Hypothesis H4. The magnitude of this negative coefficient is the second largest among the four predictors, underscoring the substantive role of privacy perceptions in shaping the AI service experience. This finding aligns with the theoretical arguments advanced by [19], who identified privacy unease as a consistent negative moderator of technology acceptance in hospitality settings, particularly when biometric data collection is involved. Wang and Liu [21] further documented that facial recognition-specific privacy concerns significantly depress satisfaction ratings among hotel guests, an effect amplified in transit-oriented environments such as airports, where the involuntary nature of biometric exposure is perceived as especially intrusive. The present finding that the mean privacy concern score ($\bar{x} = 2.98$) was the only construct to fall below the scale midpoint, combined with its negative regression coefficient, indicates that privacy anxiety is a marginal concern. This trade-off dynamic, wherein guests simultaneously appreciate the convenience afforded by facial recognition whilst harbouring reservations about data collection and retention, is consistent with the ambivalence documented by [19] in their analysis of mobile payment acceptance in hotels. Addressing these concerns through transparent data governance communication is therefore not merely a compliance consideration but a direct lever for improving guest satisfaction.

5) Customer satisfaction and customer loyalty

Research Question 5: Does customer satisfaction positively influence guests' behavioural intentions, specifically revisit intention and word-of-mouth recommendation? The simple regression analysis confirmed that customer satisfaction exerted a significant positive effect on customer loyalty ($\beta = 0.409$, $t = 9.501$, $p < 0.001$), supporting Hypothesis H5 in both its revisit intention and word-of-mouth recommendation dimensions. This result is consistent with the foundational satisfaction-loyalty framework advanced by [20] and the service-quality consequences model proposed by [23], both of which posit that positive evaluative judgments of service encounters are the primary antecedent of behavioural loyalty intentions. Liu et al. [3] and Zhang et al. [5] similarly reported significant satisfaction-to-loyalty paths in AI-enabled Chinese hotel studies, reinforcing the cross-contextual stability of this relationship.

However, the model's explained variance for loyalty ($R^2 = 0.167$) is modest, indicating that customer satisfaction, while a necessary condition, is not sufficient to guarantee loyalty in the airport hotel context. This finding is interpretable in light of Liu and Wang's [8] structural characterisation of airport hotels as high-turnover, short-stay properties in which guests' accommodation choices are frequently determined by flight schedules, corporate rates, and proximity to the terminal rather than by service satisfaction alone. As Zeithaml et al. [23] noted, the behavioural consequences of satisfaction vary markedly across service categories; in commodity-like, transaction-oriented settings such as airport hotels, the satisfaction-loyalty linkage is predictably weaker than in experiential or relationship-oriented segments. The present R^2 value nonetheless compares favourably with that reported by Soliman [17] (R^2 = 0.14) in a developing-country hotel context, suggesting that the relationship strength is consistent across settings with partial AI infrastructure. The modest explained variance (16.7%) also signals that important predictors of loyalty remain outside the present model. Three categories of omitted variables warrant attention in future research. First, perceived value guests' overall assessment of the cost-benefit ratio of the hotel stay has been identified as a direct antecedent of loyalty independent of satisfaction in multiple hospitality studies [14]. Second, trust in the hotel brand and in the AI systems themselves may constitute a partially distinct loyalty mechanism, particularly in contexts involving biometric data collection where relational confidence is a precondition for continued patronage [19, 21]. Third, structural switching costs, including corporate rate agreements, proximity to the airport, and frequency-stay benefits, are especially salient in the airport hotel segment, where accommodation choices are often constrained by logistical factors rather than purely evaluative ones [8]. Incorporating these constructs into future models would decompose the residual loyalty variance and produce a more complete and practically actionable framework.

6) Mediating role of customer satisfaction

Research Question 6: Does customer satisfaction mediate the relationships between guests' technological perceptions of AI applications and customer loyalty? Bootstrap mediation analysis (5,000 resamples; Preacher and Hayes [31]) confirmed that customer satisfaction partially mediates all four perception-to-loyalty pathways, with bias-corrected 95% confidence intervals excluding zero on all indirect effect estimates. Hypothesis H6 was therefore supported. The partial mediation pattern wherein direct effects from all four perception dimensions on loyalty remain significant alongside the significant indirect effects through satisfaction has important theoretical implications.

First, the findings indicate that technological perceptions shape loyalty through two complementary mechanisms: an evaluative route, whereby favourable perceptions enhance satisfaction and satisfaction subsequently drives loyalty intentions, and a direct attitudinal route, whereby favourable AI perceptions independently generate loyalty predispositions that bypass the satisfaction evaluation. This dual-pathway structure is consistent with the theoretical extensions to TAM proposed by [18], who argued that technology beliefs influence behavioural intentions both through affective and evaluative intermediaries and through direct cognitive appraisals. Second, the finding that all four perception dimensions, including the negative pathway through privacy concerns, exhibit partial mediation through satisfaction suggests that satisfaction is a robust but not exhaustive transmission mechanism. Zhang et al. [5] similarly documented partial mediation by satisfaction in a Chinese hotel AI study, and Liu et al. [3] observed that the AI-customisation-to-loyalty path retained direct components even after controlling for satisfaction, corroborating the present pattern. Third, the indirect effect of perceived usefulness through satisfaction (0.142) is the largest among the four indirect pathways, consistent with its dominant direct effect, confirming that utility-driven satisfaction has the most substantial indirect impact on loyalty. By contrast, the negative indirect effect of privacy concerns (−0.072) is the smallest in absolute magnitude, suggesting that while privacy anxiety depresses satisfaction, its downstream impact on loyalty is partially buffered by the direct positive effects of usefulness and enjoyment. These mediation results collectively affirm that improving guest satisfaction through AI service optimisation constitutes a strategically effective, if not singular, pathway to enhancing customer loyalty in the airport hotel context.

7) Demographic differences in customer loyalty

One-way ANOVA revealed significant inter-group differences in customer loyalty by age ($F = 3.782$, $p = 0.024$), educational level ($F = 4.563$, $p = 0.011$), and annual household income ($F = 3.136$, $p = 0.009$), while gender, occupation, and travel purpose yielded no significant differences. Guests aged 30–49 years exhibited the highest mean loyalty score ($\bar{x} = 3.84$), followed by those holding postgraduate qualifications ($\bar{x} = 3.89$) and those with annual household incomes exceeding 500,000 RMB ($\bar{x} = 4.06$). These patterns are consistent with [11] finding that actual digital experience and cognitive engagement with technology, rather than chronological age per se, are the more proximate determinants of AI acceptance; the 30–49 cohort's higher loyalty likely reflects greater professional familiarity with AI interfaces rather than generational disposition alone. The absence of elevated loyalty among the youngest respondents (18–29 years) challenges the commonly invoked assumption that digital natives automatically embrace all forms of AI-mediated service, a supposition that [9] cautioned against in their review of age as a technology acceptance moderator. The education and income gradients align with [17] finding that higher socioeconomic status is associated with greater receptiveness to AI in hotel settings, potentially because highly educated and higher-income guests are more accustomed to interacting with digital systems and interpret AI features as quality signals rather than sources of anxiety. For managerial practice, these demographic differentiations imply that a uniform AI strategy is unlikely to optimise loyalty across all guest segments.

VI. Conclusion

Drawing on an integrated TAM and Customer Experience Theory framework, this study examined how guests' technological perceptions of AI applications influence satisfaction and loyalty at Shenyang Airport Hotel. Data from 452 guests confirmed that perceived usefulness, perceived ease of use, and enjoyment positively affect customer satisfaction, while privacy concerns exert a significant negative effect, supporting H1–H4. Customer satisfaction in turn positively predicts customer loyalty (H5) and partially mediates all four perception-to-loyalty pathways (H6). Demographic analysis further revealed significant differences in loyalty across age, educational level, and income groups, but not across gender, occupation, or travel purpose.

These findings collectively demonstrate that, even within a technologically constrained secondary-city airport hotel, guests' multidimensional AI perceptions systematically shape satisfaction and loyalty outcomes. For practitioners, the results highlight the importance of maximising perceived utility, simplifying service interfaces, enriching hedonic engagement, and communicating data governance policies transparently. For researchers, this study extends TAM into an underexamined hospitality context and provides rigorous mediation evidence clarifying the perception satisfaction loyalty mechanism. Ultimately, effective AI adoption in hotel management requires attending simultaneously to utilitarian, affective, and privacy-related perceptions to convert technological investment into sustainable guest retention.

VII. Research Implications

1) Theoretical implications: This study makes three principal theoretical contributions. First, it extends the TAM [26] beyond its original workplace and basic utilitarian boundaries by integrating both an affective facilitator (enjoyment) and a risk-based barrier (privacy concerns) into a single model applied to AI-mediated guest services in a secondary-city airport hotel. Prior research in the hospitality domain had typically addressed these constructs in isolation: [12] examined PU and PEOU without incorporating hedonic or privacy dimensions, while [16] and [23] focused exclusively on privacy concerns. The present simultaneous treatment of all four perception dimensions demonstrates that both affective and security-related factors play statistically significant and conceptually distinct roles in satisfaction formation, confirming that a purely utilitarian view of AI acceptance is insufficient in service contexts where emotional responses and risk perceptions are salient, as argued by [18] and [11].

Second, the bootstrap mediation results provide rigorous empirical evidence of partial mediation through satisfaction, clarifying the perception-to-loyalty transmission mechanism that has remained theoretically postulated but empirically underexamined in prior work [3, 20, 22]. By demonstrating that direct perception-to-loyalty paths coexist with satisfaction-mediated indirect paths across all four constructs, this study contributes a more nuanced causal architecture to the existing satisfaction-loyalty literature [20, 23]. Future research incorporating additional mediators — such as perceived value or trust, as suggested by [14] could further decompose the residual direct effects.

Third, by focusing on an airport hotel in a secondary Chinese city, a context characterised by partial AI infrastructure, low CRM maturity, and an annual repurchase rate of 18%, this study addresses a significant gap in a literature dominated by first-tier urban luxury properties [13, 16]. The finding that TAM-based perceptions are systematically related to satisfaction and loyalty even in technologically constrained settings implies that the framework is transportable across varying levels of AI infrastructure maturity. This aligns with [17] demonstration that TAM relationships hold in developing-country hotel contexts, and with [10] multi-case study findings from Thailand, collectively suggesting that the model's explanatory power is not contingent upon sophisticated technological ecosystems.

2) Practical implications: The findings carry several actionable implications for hotel managers, particularly those operating three-star airport properties with limited technological resources. First, as perceived usefulness emerged as the dominant driver of satisfaction, investment in AI features that deliver clear, measurable time savings should be prioritised. Automated check-in/check-out and facial recognition terminals must be robust, fast, and error-free, as any friction in these high-stakes interactions directly erodes perceived utility [12, 18, 26]. Second, interface simplicity should be treated as a design principle rather than a secondary consideration. Buhalis and Moldavska [9] demonstrated that clear instructions, logical workflow sequences, and multilingual support are low-cost interventions that substantially improve perceived ease of use for older and less technologically experienced guests; such enhancements are within reach even for properties operating without dedicated IT personnel, as is the case at Shenyang Airport Hotel.

Third, the significant enjoyment effect indicates that augmenting AI interactions with hedonic elements — such as gamified loyalty point accrual, personalised welcome messages, or voice-interactive features- can strengthen satisfaction without requiring substantial capital expenditure. Liu et al. [3] and Tussyadiah [11] both emphasised that guests respond to novelty and interactivity, suggesting that incremental enhancements to engagement design can yield disproportionate satisfaction gains. Fourth, the negative effect of privacy concerns represents the most urgent operational priority. Hotels deploying facial recognition should provide concise, comprehensible explanations of what biometric data are collected, the duration of retention, and the parties with access, following the transparency communication model advocated by [19] and [21]. Offering a privacy-preserving opt-out alternative for guests who prefer conventional check-in may reduce anxiety without disrupting service continuity for the majority.

Finally, the ANOVA-derived demographic differences in loyalty suggest that a one-size-fits-all AI deployment strategy is suboptimal. In particular, the higher loyalty reported by postgraduate and high-income guests indicates receptiveness to personalised, data-driven service enhancements such as AI-driven loyalty programmes and recommendation engines — features that Makivic et al. [13] and Chen [16] identified as particularly effective loyalty drivers in technologically sophisticated hotel segments. Conversely, the lower loyalty among the youngest and lowest-income cohorts signals a need for simplified, guided AI interactions supplemented by strong privacy assurances, in line with the segmentation principles advocated by [14].

VIII. Limitations and Future Work

Several limitations of this study merit acknowledgment. First, the cross-sectional survey design permits the examination of associations among constructs at a single point in time but precludes the establishment of temporal causality. Longitudinal designs tracking the same guests across multiple stays would more robustly establish the causal direction and stability of the perception-satisfaction-loyalty relationships documented here.

Second, data were collected from a single three-star airport hotel in Shenyang, a deliberate design choice that enables contextual depth but constrains generalisability. The findings should not be generalised uncritically to other hotel categories (four- or five-star properties, boutique hotels, or resort segments), to first-tier Chinese cities with more mature AI infrastructure, or to international hospitality markets with different regulatory and cultural orientations toward biometric data collection. Future research should replicate the model across multiple airport hotels in both secondary and primary Chinese cities, and potentially in comparable international contexts such as the Thai airport hotel setting examined by [10], to assess whether the TAM-based relationships hold under varying levels of AI infrastructure maturity and cultural orientation.

Third, the study relied exclusively on self-reported Likert-scale measures, which may be subject to common method variance and social desirability bias despite the procedural safeguards implemented [32]. No objective behavioural measures—such as actual repeat bookings, transaction records, or AI usage logs—were included to validate the reported loyalty intentions, which limits the correspondence between stated and enacted behaviour. Integrating objective behavioural data, including verified repurchase records from the hotel's reservation system, actual check-in duration logs from the facial recognition terminal, and transaction-level spending data, with perceptual survey data in future work would substantially strengthen causal inference, mitigate common method bias, and provide a more complete picture of the satisfaction-loyalty conversion process. Furthermore, the study did not control for potentially confounding factors such as room quality, service quality beyond AI interactions, room pricing, or locational convenience (e.g., proximity to the terminal and shuttle availability), all of which may independently influence satisfaction and loyalty and whose omission may have inflated the estimated effects of AI perceptions. Future studies should include these covariates, or employ matched-pair designs that hold non-AI service quality constant, to isolate the incremental contribution of AI perceptions more rigorously.

Fourth, the conceptual model did not include theoretically plausible moderating variables. Venkatesh et al. [18] demonstrated that prior experience, technology anxiety, and cultural orientation moderate TAM relationships; in the present context, guests from different national backgrounds may hold systematically divergent privacy expectations regarding biometric data collection, a moderating pathway unexplored in this study. Morosan and DeFranco [19] similarly called for research examining how cultural and individual difference variables shape the privacy-acceptance dynamic in hospitality AI deployments. Future studies incorporating these moderators would produce a more complete and generalisable model of AI perception formation. In particular, technology readiness [18], prior AI experience, frequency of hotel stays, and individual-level trust dispositions each represent theoretically motivated moderators that may alter the strength or direction of the perception-satisfaction and satisfaction-loyalty relationships identified in this study. Incorporating such variables would clarify boundary conditions and enhance the practical precision of the model.

Finally, this study did not examine the cost-effectiveness of different AI implementations, an omission that limits its managerial utility in the context of resource-constrained properties such as Shenyang Airport Hotel. Integrating economic evaluation frameworks such as return-on-investment analysis for each AI feature with the perceptual satisfaction and loyalty models developed here would provide hotel managers with the complete evidence base needed to prioritise AI investments strategically. This represents a productive and practically significant direction for future inquiry.

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