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EXPLORING CUSTOMER ACCEPTANCE OF ARTIFICIAL INTELLIGENCE IN VIETNAM'S HOTEL INDUSTRY

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ARTICLE INFO	ABSTRACT

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Artificial Intelligence (AI) is rapidly becoming integral to global industries, including hospitality. This study investigates the antecedents and mediating factors influencing hotel customers' intention to adopt AI in Vietnam. A conceptual model was developed, integrating Social Influence, Anthropomorphism, and Hedonic Motivation as predictors, with Performance Expectancy, Effort Expectancy, and Emotion as mediators. Data were collected through a structured online questionnaire distributed to hotel service users, yielding 388 valid responses. Structural equation modeling (SEM) was applied to test the measurement and structural models.

The findings show that Social Influence and Hedonic Motivation significantly affect both Performance Expectancy and Effort Expectancy, while Anthropomorphism influences only Performance Expectancy. Hedonic Motivation also enhances Emotion. In turn, both Emotion and Performance Expectancy directly and significantly predict customers' acceptance of AI. Importantly, the results reveal two novel insights: the negative effect of Anthropomorphism on Performance Expectancy, and the strong direct role of Performance Expectancy in shaping AI adoption. These findings highlight unique cultural and contextual factors within Vietnam's hospitality sector, extending prior research conducted in other countries. Furthermore, a competitive model comparison revealed that Performance Expectancy exerts a strong direct influence on customers' readiness to adopt AI, underscoring its pivotal role in the acceptance process.

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AI device use acceptance; Anthropomorphism and hedonic motivation; Effort expectancy and emotion; Performance expectancy; Social influence.

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The study offers theoretical contributions by advancing the AI acceptance framework in an emerging market context and uncovering new relationships among key constructs. From a managerial perspective, the results emphasize the need for hotel operators to strengthen guests' confidence in AI's performance benefits, create emotionally engaging and user-friendly AI experiences, and leverage social influence and hedonic value to increase customer readiness for AI adoption.

1. Introduction

Artificial intelligence (AI) technology is increasingly emerging as a pivotal component across global industries, and the hospitality sector is no exception. In Vietnam, amid the robust growth of the tourism and service industries, hotel enterprises are actively integrating AI solutions to enhance customer experiences, improve service efficiency, and optimize business operations. AI enables personalized services, ranging from automated booking processes to customer support via chatbots or voice recognition systems.

Empirical studies have demonstrated that AI-driven applications and robots exhibit superior information processing capabilities; their perceptual and task execution abilities are enhanced compared to those facilitated by traditional mechanisms as leading to a rising trend in the adoption of AI-related solutions (Ivanov et al., 2019). In essence, AI pertains to machine-exhibited intelligence that reacts and interacts with the surrounding environment and customer demands through deep learning algorithms, delivering services perceived as relatively superior to those provided by humans (Huang & Rust, 2018). Within the accommodation services domain, AI-controlled devices fundamentally address customer inquiries, furnish relevant information, and offer real-time suggestions, enabling customers to manipulate and control the physical ambiance in their rooms (virtual assistants like Alexa) and provide comprehensive customer services (check-in and check-out procedures, laundry, housekeeping, itinerary planning and execution, dining services, etc.) via robots and robotic technologies (Bellini & Convert, 2016; Osawa et al., 2017; Chen et al., 2025). Globally and in Vietnam, AI technology has been and continues to be applied extensively.

Whether Vietnamese customers accept these advanced technologies depends on various factors, such as their understanding of the technology, attitudes toward innovation, and perceptions of AI's efficacy in enhancing service experiences. The question of what motivates customers to accept AI represents a significant concern for hospitality organizations. Addressing this query will enable hotel service providers to conceptualize, design, and implement AI devices and technologies in a beneficial and efficient manner, potentially eliciting positive customer responses in terms of acceptance and utilization. However, profound insights into the factors driving customer decisions to accept AI in accommodation services remain underexplored.

Regarding consumer behavior, existing literature has substantiated the presence of antecedent-consequent relationships between an individual's behavioral intentions or readiness and their actual exhibited behaviors (Cronan et al., 2018; Fishbein & Ajzen, 1975).

Although prior studies have offered valuable insights into the interplay between readiness and behaviors related to AI and associated tools, these investigations derive conclusions from empirical findings rooted in traditional technology acceptance models such as the Technology Acceptance Model (TAM) or the Unified Theory of Acceptance and Use of Technology (UTAUT). These models primarily identify technology antecedents (ease of use, usefulness, usability, and anxiety); effort expectancy (personal attitudes, self-efficacy beliefs, perceptions, and performance); social influence; and facilitating conditions as key correlates of customer technology acceptance (Taherdoost, 2018). Conceptual critiques suggest that traditional technology acceptance models fall short in fully explaining the phenomenon of AI acceptance and use (Lu et al., 2019; Song, 2017). Specifically, scholars argue that these models lack the capacity to adequately examine the acceptance and utilization of AI devices (Gursoy et al., 2019). Notably, factors such as hedonic motivation and social influence warrant particular consideration in the AI acceptance context (Morgan-Thomas & Veloutsou, 2013; Venkatesh & Davis, 2000; Wang et al., 2018).

In particular, customers in the hospitality sector often exhibit higher expectations for hedonic benefits compared to other service domains (Lin et al., 2019). Moreover, traditional technology acceptance models do not account for the influence that AI anthropomorphism may exert on customers' performance expectancy and effort expectancy (Fan et al., 2020). Finally, customer emotions, grounded in cognitive appraisals of stimuli (Breitsohl & Garrod, 2016), are anticipated to play a crucial role in their acceptance or rejection of AI devices and related technologies (Kuo & Wu, 2012) as elements overlooked in traditional models (Taherdoost, 2018).

Researchers in technology acceptance behavior have integrated cognitive appraisal theory with the UTAUT model, delineating three stages in the AI technology acceptance process (Gursoy et al., 2019; Ribeiro et al., 2021). For instance, Gursoy et al. (2019) conducted their study on Amazon Mechanical Turk, a crowdsourcing platform developed by Amazon, while Ribeiro et al. (2021) examined acceptance behaviors toward autonomous vehicles in tourism and travel in the United States. These authors posit that customers engage in three evaluation stages as primary, secondary, and outcome as during their decision-making process. Initially, customers appraise AI devices based on social influence, hedonic motivation, and anthropomorphism, which contribute to shaping performance expectancy and effort expectancy, thereby forming emotions and ultimately the readiness to accept AI.

In Vietnam's hotel business landscape, customer interactions with AI during service establishment and experiences are not uncommon in 4- and 5-star hotels, through applications such as chatbots, automated bookings, and self-check-in/check-out. Specifically, several Vietnamese hotels have adopted AI in customer services: InterContinental Saigon employs intelligent chatbots for 24/7 customer support, swiftly addressing queries and providing information; Vinpearl has implemented data analytics and AI for real-time booking optimization and pricing adjustments to boost revenue; Fusion Suites utilizes AI applications for automated check-in and check-out, reducing wait times and elevating customer experiences. These technologies enhance operational efficiency, optimize customer experiences, and align with Industry 4.0 trends in tourism and hospitality.

As evident, AI technology is permeating deeply into hotel operations and other service sectors, rendering the investigation of customer acceptance levels toward AI applications essential. Thus, our study is formulated by integrating the UTAUT model with cognitive appraisal theory to test and evaluate customer acceptance of AI applications in Vietnamese hotel services as a topic scarcely researched, particularly in Vietnam's hospitality sector, where AI adoption remains nascent. This research not only elucidates the relationships across cognitive stages of AI technology acceptance in hospitality but also generalizes the technology acceptance theoretical model across diverse research contexts and economies. Concurrently, it offers critical implications for managers in this field to maximize benefits and mitigate unnecessary risks or stresses for customers encountering AI technologies.

2. Theoretical overview and research model

It is apparent that AI technology fundamentally differs from prior technologies, and while traditional acceptance models like TAM have adequately addressed acceptance of earlier innovations, they appear insufficient for AI acceptance. According to Lu et al. (2019), this distinction manifests in two dimensions: First, customers engaging with AI seek to ascertain whether the underlying technology of AI devices delivers customer services comparable or superior to human-provided ones as a particularly vital factor in service provision for determining AI device acceptance levels; Second, AI acceptance hinges on cognitive evaluation processes assessing potential threats to consumers during AI encounters, including whether substantial efforts are required to familiarize oneself with AI. If AI usage poses harm or benefits, customers desire knowledge of actions to avert threats or enhance prospects. The AI acceptance process necessitates coping mechanisms for requisite efforts in acclimating to and experiencing the technology as contrasting with the emphasis on perceived ease and usefulness in models like TAM. From the initial Unified Theory of Acceptance and Use of Technology (UTAUT1; Venkatesh et al., 2003), with core components as performance expectancy, effort expectancy, social influence, and facilitating conditions as proven to positively impact technology acceptance. Venkatesh et al. (2012) augmented this with hedonic motivation, price value, and habit to better suit modern consumer behavior contexts, forming UTAUT2.

Cognitive appraisal theory (Lazarus, 1991) posits that human emotions do not arise directly from external events or stimuli but from individuals' perceptions and evaluations of those events. Lazarus outlines that upon confronting a situation, individuals undergo two primary appraisal steps: first, assessing whether the situation affects them; second, evaluating their coping capabilities, considering available resources like skills, social support, and strategies.

Gursoy et al. (2019) integrated UTAUT with cognitive appraisal theory to explain AI device acceptance processes, comprising three stages: primary appraisal, secondary appraisal, and outcome stage. In primary appraisal, customers' initial perceptions are influenced by factors such as social influence, hedonic motivation, and anthropomorphism. Transitioning to secondary appraisal, customers form attitudes toward AI, manifested through performance expectancy, effort expectancy, and personal emotions during AI service usage. Finally, the outcome stage reflects customers' intentions and readiness to adopt AI, governed by multiple factors indicating AI integration into service experiences and openness to new technologies. This model has been corroborated by Lin et al. (2019) in U.S. hospitality contexts and Roy et al. (2020) in Indian hospitality services.

Relationship between social influence and performance expectancy/effort expectancy

Social influence refers to the degree of impact from an individual's social network as including family, friends, and colleagues as on decisions to use AI technology in service experiences. This factor mirrors social norms, where perceptions of approval and behaviors from surroundings significantly affect readiness to accept and apply AI. When individuals perceive societal support for AI usage, they tend to develop positive attitudes and proactive engagement with these technologies. Meanwhile, performance expectancy encapsulates anticipated benefits and efficiency improvements from AI applications, encompassing beliefs that AI enhances service quality, optimizes processes, and yields superior customer experiences. Performance expectancy is pivotal in shaping behavioral intentions, as high expectations foster acceptance and active interaction with AI, especially in hospitality.

Studies by Gursoy et al. (2019), Ribeiro et al. (2021), and Roy et al. (2020) have evidenced that social influence positively impacts users' performance expectancy perceptions when utilizing automated and AI-supported services in tourism (China) and accommodation (India). Our investigation into AI acceptance in Vietnam's hotel industry anticipates analogous correlations, thus proposing the following hypothesis:

Hypothesis H1. Social influence regarding AI technology use in hotel service experiences positively affects customers' performance expectancy.

Another critical element in customer attitudes toward AI is effort expectancy, defined as users' perceptions of ease or difficulty in employing AI devices. This concept reflects subjective evaluations of interaction complexity, where high effort expectancy implies perceived difficulty, time consumption, and substantial acclimation. Conversely, perceived ease lowers expected effort. Lazarus (1991) and subsequent empirical works, social norms can substantially influence effort expectancy. Gursoy et al. (2019) indicate that social influence inversely relates to effort expectancy, meaning supportive social cues conveying AI ease reduce perceived difficulty. Hence, the following hypothesis:

Hypothesis H2. Social influence regarding AI technology use in hotel service experiences negatively affects customers' effort expectancy.

Relationship between hedonic motivation and performance expectancy, effort expectancy, and emotions

Hedonic motivation denotes the intrinsic enjoyment and pleasure users derive from AI technology. When usage is deemed entertaining or gratifying, users are more inclined to accept and engage with AI devices. Fryer et al. (2017), this motivation satisfies personal preferences or exploratory needs. Thus, high hedonic motivation often cultivates positive attitudes, elevating performance achievement potential. Accordingly, we propose:

Hypothesis H3. Hedonic motivation in using AI technology during hotel service experiences positively affects customers' performance expectancy.

Prior psychological research illustrates motivation's interaction with task difficulty (Humphreys & Revelle, 1984). Studies by Capa et al. (2008) and Gendolla and Wright (2005) confirm relationships between motivation and perceived difficulty/effort expectancy for tasks. Gursoy et al. (2019) further demonstrate that in services, high hedonic motivation toward AI devices diminishes perceived usage difficulty, reducing effort expectancy. Based on these discussions, we specify that hotel service consumers with high hedonic motivation are less likely to perceive AI-related tasks as challenging. Therefore:

Hypothesis H4. Hedonic motivation in using AI technology during hotel service experiences negatively affects customers' perceived effort expectancy.

The emotion construct pertains to emotional responses consumers experience when interacting with AI technologies, encompassing excitement, happiness, or satisfaction in service settings. Positive emotions can bolster user willingness to adopt AI, whereas negative ones may impede acceptance. This construct underscores emotional engagement's role in shaping overall consumer experiences with AI devices.

Hedonic motivation can amplify user satisfaction and adoption intent, highlighting emotional involvement's importance in technology acceptance. This is affirmed in Roy et al. (2020). Prior studies suggest hedonic benefits from new technologies can evoke positive emotions in AI device users (Lin et al., 2019). Thus, hedonic motivation is expected to trigger positive emotions in hotel customers experiencing AI.

Hypothesis H5. Hedonic motivation in using AI technology during hotel service experiences positively affects customers' emotions.

Relationship between anthropomorphism and performance expectancy/effort expectancy

Anthropomorphism refers to the extent consumers perceive AI devices as possessing human-like traits, such as emotions, behaviors, or appearances. This similarity activates initial user evaluations of alignment with personal beliefs about service technologies. However, human-like features may threaten human identity (Ackerman, 2016; Gursoy, 2019), fostering resistance. Consumers may rationalize resistance by doubting AI's operational capabilities. Research by Gursoy (2019) and Roy et al. (2020) shows anthropomorphism negatively influences performance expectancy in AI usage.

Hypothesis H6. Perceived anthropomorphism of AI technology in hotel service experiences negatively affects customers' performance expectancy.

Consumers may resist AI devices in services by deeming interactions more effortful than with humans, requiring them to treat AI as intelligent entities fitting personal norms (Kim & McGill, 2018). The "robotic" identity engenders dual efforts: human-like communication and technology learning. Hence, AI's human-like traits may heighten perceived complexity and difficulty, increasing effort expectancy.

Hypothesis H7. Perceived anthropomorphism of AI technology in hotel service experiences positively affects customers' effort expectancy.

Relationship between performance expectancy and emotions

Advancing to secondary appraisal, customers forming positive attitudes toward AI devices in primary evaluation tend to concur in subsequent stages, and vice versa. During secondary appraisal, as customers weigh AI usage costs and benefits, service-related emotions emerge. If they believe AI delivers swift, accurate, reliable, and consistent services (Lu et al., 2019; West et al., 2018), thereby improving quality (high performance expectancy), positive emotions arise. Thus:

Hypothesis H8. Performance expectancy positively affects customers' emotions toward experiencing AI in hotels.

However, AI device usage in services may pose communication barriers (Lu et al., 2019) or demand heightened cognition to comprehend complex designs (Thompson et al., 1991), escalating required effort. Consequently, if customers perceive excessive effort for AI usage, negative emotions ensue, Lazarus (1991). Hence:

Hypothesis H9. Effort expectancy negatively affects customers' emotions toward experiencing AI in hotels.

Relationship between emotions and ai acceptance

Following primary and secondary appraisals, emotions toward AI usage crystallize, determining customers' readiness or reluctance to accept AI devices in future service encounters as the outcome stage. Positive emotions like anticipation, satisfaction, joy, delight, and surprise influence consumption-related intentions (Watson & Spence, 2007). Per cognitive appraisal theory, customers with such positive emotions toward AI exhibit higher readiness to accept AI in service provision. Accordingly:

Hypothesis H10. Emotions positively affect customers' acceptance of AI usage in hotel service experiences

Based on the elucidated hypotheses, the study's theoretical model is formulated in Figure 1.

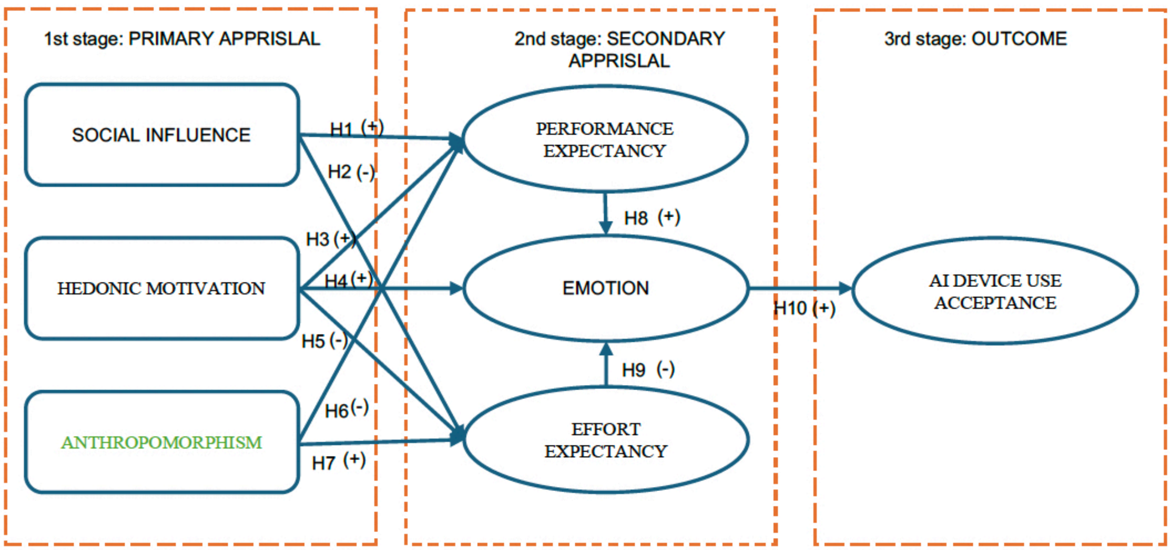

Figure 1. Theoretical model of factors influencing AI device use acceptance in hotel services, integrating UTAUT and Cognitive Appraisal Theory

3. Research Methodology

3.1. Sampling method

The study adopted a quantitative design and employed an online survey distributed through a convenience (non-probability) sampling method. The target population comprised hotel guests who had stayed at properties in Vietnam that employ artificial intelligence (AI) technologies in customer service, such as chatbots and virtual assistants, facial recognition systems for check-in/check-out, and service robots.

To ensure that respondents had relevant exposure to AI-enabled services, the questionnaire was disseminated via Google Forms to guests of leading AI-adopting four-star and five-star hotels in Ho Chi Minh City and Hanoi. The Survey questionnaire consisted of two sections: (1) demographic information of the respondents, and (2) items measuring constructs related to factors influencing customer acceptance of AI.

Following the guidelines of Hair et al. (2014), covariance-based structural equation modeling (CB-SEM) typically requires a minimum of 200 observations, with more complex models requiring 300-500 observations. To meet this requirement, a total of 500 survey invitations were distributed. Of these, 412 responses were received, of which 388 were deemed valid after data screening, yielding a valid response rate of 77.6%. These data were used for subsequent statistical analysis.

3.2. Measurement scale

To measure and test the theoretical model, the study inherits scales from Gursoy et al. (2019), Chi et al. (2020), and Venkatesh et al. (2012). A qualitative study was conducted to refine the scales. This involved focus group discussions with 15 loyal customers who had utilized 5-star hotel services in Ho Chi Minh City incorporating AI in customer provision. Results adjusted measurement variables for hospitality context suitability, proposing scales with observed items as follows: Social Influence – 5; Hedonic Motivation – 5; Anthropomorphism – 4; Performance Expectancy – 5; Effort Expectancy – 4; Emotions – 4; Readiness to Use – 3 (Appendix). A seven-point Likert scale (ranging from 1 to 7) was employed in this study (*see Appendix 1 online).*

3.3. Data analysis method

The study employed AMOS 24.0 software to test both the measurement model and the structural research model. For the measurement model, statistical techniques including Cronbach's alpha reliability test and confirmatory factor analysis (CFA) were applied. The theoretical model was subsequently examined using structural equation modeling (SEM).

4. Research results and evaluation

4.1. Research results

Following the survey implementation by distributing questionnaire links to hotel customers (as described in Section 3). The descriptive statistics of the research sample are presented in *(see Appendix 2 online)*.

Measurement Model Validation

The reliability of the measurement scales was assessed using Cronbach's alpha, with the results summarized in Table 1.

Table 1. Results of scale reliability testing

Factor	Code	Cronbach's Alpha (First Iteration)	Cronbach's Alpha (Second Iteration)	Number of Observed Variables for CFA
Social Influence	AHXH	0.904		5
Hedonic Motivation	DLKL	0.832	0.899	5
Anthropomorphism	NHCH	0.899		4
Performance Expectancy	KVHS	0.914		5
Effort Expectancy	KVNL	0.903		3
Emotions	TICA	0.829		4
Readiness to Use	SSSD	0.933		3

These findings indicate that all scales corresponding to the constructs in the research model achieved Cronbach's alpha coefficients greater than 0.7 following the initial assessment. However, for the Hedonic Motivation factor, the observed variable DLKL4 exhibited a corrected item-total correlation of 0.189, which falls below the threshold of 0.3, suggesting inadequate correlation with the overarching construct. Consequently, this variable was eliminated. Post-removal, the scale's Cronbach's alpha improved to 0.899, with the number of retained observed variables reduced to four.

Confirmatory Factor Analysis (CFA)

The subsequent step in validating the measurement model involved conducting confirmatory factor analysis on the saturated measurement model. The CFA results are as follows: (1) The model possessed 327 degrees of freedom; Chi-square = 743.94 (p = 0.000); CMIN/df = 2.275, which is less than 3; TLI and CFI values were 0.939 and 0.947, respectively, both exceeding 0.9; and RMSEA = 0.057, below 0.08 as these metrics collectively affirm a strong fit between the measurement model and the market data. (2) Examination of the standardized regression coefficients revealed that all observed variables were statistically significant (p-values < 0.05), with coefficients ranging from 0.547 to 0.981, all surpassing 0.5 as this underscores the robust explanatory power of the observed variables for their respective latent factors. (3) The assessment of convergent validity and discriminant validity for the saturated measurement model is presented in Appendix 3 *(see Appdendix 3 online)*. It is evident that the composite reliability (CR) values for all factors exceed 0.7, thereby confirming the reliability of the scales. Similarly, the average variance extracted (AVE) values surpass 0.5, indicating satisfactory convergent validity. The maximum shared variance (MSV) for each factor is consistently lower than its corresponding AVE, and the square roots of the AVE for each construct are greater than the inter-construct correlations with other latent factors as thus ensuring discriminant validity. Collectively, these results affirm that the constructs in the research model achieve adequate reliability, convergence, and discrimination.

Structural Equation Modeling (SEM) for theoretical model testing

The outcomes of the SEM analysis for the theoretical model are depicted in Appendix 4 *(see Appendix 4 online)*. The model exhibits 338 degrees of freedom, with a Chi-square value of 931.3 (p = 0.000) and CMIN/df = 2.76, which is below the threshold of 3. The fit indices include TLI = 0.916 and CFI = 0.925, both exceeding 0.9, alongside RMSEA = 0.067, which is less than 0.08. These metrics collectively demonstrate a robust fit between the model and the empirical data.

Table 2. Standardized regression weights for the theoretical model

Relationship			Estimate	S.E.	C.R.	P
AHXH	→	KVHS	0,191	0,05	3,854	***
DLKL	→	KVHS	0,392	0,07	7,221	***
NHCH	→	KVHS	-0,214	0,046	-4,298	***
NHCH	→	KVNL	-0,048	0,039	-0,959	0,338
AHXH	→	KVNL	-0,313	0,044	-5,991	***
DLKL	→	KVNL	-0,352	0,059	-6,421	***
DLKL	→	TICA	0,137	0,053	2,467	0,014
KVNL	→	TICA	-0,514	0,049	-9,205	***
KVHS	→	TICA	0,191	0,038	3,754	***
TICA	→	SSSD	0,285	0,103	5,197	***

The SEM results as mentioned in Table 4 substantiate that all hypothesized relationships attain statistical significance at the 95% confidence level ($p < 0.05$), with the exception of the linkage between anthropomorphism and effort expectancy (Hypothesis H7), where $p = 0.332 > 0.05$, leading to its rejection.

Competitive model testing

Competitive models play a pivotal role in theory building, particularly within the social sciences. Evaluating a research model against competing alternatives within the same study enhances comparative reliability (Nguyen Dinh Tho & Nguyen Thi Mai Trang, 2008). In this investigation, the proposed model draws from the theoretical framework advanced by Gursoy et al. (2019), which has been empirically validated in hospitality customer contexts, as detailed earlier. To this end, we tested competitive models by introducing additional paths: performance expectancy and effort expectancy directly influencing readiness to use AI devices. Subsequent re-estimation of the model with each added path yielded the following insights (1) Incorporating the path from effort expectancy to AI acceptance revealed a standardized beta coefficient of 0.014 for KVNL → SSSD, with a p-value of $0.282 > 0.05$ as indicating no statistical significance and no enhancement in model efficacy. Thus, this supplementary relationship is not supported; (2) Adding the path from performance expectancy to AI acceptance produced the SEM results illustrated in Appendix 5 *(see Appendix 5 online).*

This model features 337 degrees of freedom, with Chi-square = 882.6 ($p = 0.000$) and CMIN/df = 2.619 < 3. The fit indices are TLI = 0.922 and CFI = 0.931, both above 0.9, and RMSEA = 0.065 < 0.08, confirming a strong alignment with market data.

To assess the competitive model's (CPTM) efficacy relative to the original proposed model (PRPM), we adhered to Byrne (2016) for comparative analysis:

Step 1: The Chi-square difference test yields a difference of 48.7 (931.3 - 882.6) and a degrees-of-freedom difference of 1 (338 - 337). Consulting the Chi-square table, the p-value < 0.001 indicates a statistically significant difference in market efficacy between the models.

Step 2: Comparative fit indices are presented in Table 3.

Table 3. Comparison of model fit indices

Index	Proposed Model (PRPM)	Competitive Model (CPTM)
Chi-square/df	2.755	2.619
TLI	0.916	0.922
CFI	0.925	0.931
RMSEA	0.067	0.065

The results in Table 3 reveal that all indices for the competitive model surpass those of the theoretical model, signifying superior market efficacy. Consequently, the competitive model is accepted. The standardized regression coefficients for the relationships in the competitive model are detailed in Table 4.

Table 4. Standardized regression weights for the competitive model

Relationship	Estimate	S.E.	C.R.	P
AHXH → KVHS	0.192	0.050	3.890	***
DLKL → KVHS	0.403	0.070	7.400	***
NHCH → KVHS	-0.219	0.046	-4.414	***
NHCH → KVNL	-0.049	0.039	-0.970	0.332
AHXH → KVNL	-0.313	0.044	-5.991	***
DLKL → KVNL	-0.352	0.059	-6.427	***
DLKL → TICA	0.124	0.054	2.208	0.027
KVNL → TICA	-0.520	0.050	-9.277	***
KVHS → TICA	0.177	0.039	3.433	***
TICA → SSSD	0.113	0.099	2.116	0.034
KVHS → SSSD	0.376	0.075	6.903	***

Table 6 confirms that all hypothesized relationships are statistically significant, except for the influence of NHCH on KVNL ($p > 0.05$). Moreover, the competitive model introduces Hypothesis H10 as "performance expectancy exerts a direct positive impact on readiness to use AI in hotel service experiences" as which is supported with statistical significance.

Higher-order structural models typically encompass direct and indirect effects of antecedent factors on outcome variables. To furnish a comprehensive view of the influences on readiness to accept AI technology in hotel services, we computed the direct, indirect, and total effects of AHXH, DLKL, and NHCH on SSSD, as summarized in Table 5.

Table 5. Direct, indirect, and total effects

Effect on	Type	NHCH	AHXH	DLKL	KVNL	KVHS	TICA
KVNL	Direct		-0.313	-0.352			
	Indirect						
	Total		-0.313	-0.352			
KVHS	Direct	-0.219	0.192	0.403			
	Indirect						
	Total	-0.219	0.192	0.403			
TICA	Direct			0.124	-0.520	0.177	
	Indirect		0.197	0.255			
	Total		0.197	0.378	-0.520	0.177	
SSSD	Direct					0.376	0.113
	Indirect	-0.084	0.094	0.194	-0.059	0.020	
	Total	-0.084	0.094	0.194	-0.059	0.396	0.113

4.2. Discussion

Since the outset, this study employed the theoretical framework of AI acceptance proposed by Gursoy et al. (2019) to examine the influence of key factors on customers' willingness to adopt AI. While Gursoy et al. conducted their empirical study in the broader service sector, our investigation focuses specifically on the hospitality and lodging industry in Vietnam. Similarly, Roy et al. (2020) applied the same framework in the hotel industry in India, providing empirical evidence that fully supported the proposed relationships. In contrast, our findings not only generally align with prior studies conducted in other contexts (e.g., the United States, India, and China) but also reveal several notable differences and novel insights.

First, whereas both Gursoy et al. (2019) and Roy et al. (2020) reported a non-significant relationship between Anthropomorphism and Performance Expectancy, our results indicate a significant negative relationship (standardized $\beta = -0.29$). This supports the reasoning underlying Hypothesis H6, which suggests that human-like features of AI devices may pose a perceived threat to customers' human identity, leading them to resist adoption by questioning the devices' promised capabilities. This effect appears particularly salient among hotel customers in Vietnam.

Second, unlike the positive relationship between Anthropomorphism and Effort Expectancy observed in previous studies, our results did not confirm this association. A plausible explanation is that recent advances in AI have reduced the complexity and hesitation traditionally associated with using human-like AI technologies. As a result, anthropomorphic features may no longer shape customers' perceptions of effort when interacting with AI in hospitality services.

Finally, a unique and novel contribution of our study lies in the examination of a competing model, where we discovered that not only affective factors directly influence customers' willingness to adopt AI but also performance expectancy exerts a strong and positive direct effect ($\beta = 0.396$). This finding underscores the critical role of performance-related considerations in shaping AI adoption in the hospitality sector, offering valuable implications for both theoretical refinement and managerial practice.

4.3. Generational differences

Although not explicitly tested in this study, the descriptive statistics suggest potential variations in AI acceptance across age groups. Younger respondents (under 35) constituted 70% of the sample and may exhibit higher technological readiness, curiosity, and hedonic motivation toward AI services compared to older groups. In contrast, older customers (35 and above) may value performance reliability and emotional assurance more strongly. These generational contrasts highlight the need for future research to explore cohort-based behavioral patterns and for hotel managers to tailor AI interfaces and communication strategies to varying age-based preferences.

5. Conclusion and Implications

Conclusion

Drawing from the measurement and model testing results, we synthesize the scale means for the research constructs in Table 6.

Table 6. Mean scale values for research constructs

Factor	SSSD	AHXH	NHCH	DLKL	KVHS	KVNL	TICA
Mean	4.921	4.068	4.295	5.376	4.539	3.845	3.929

Table 8 indicates that the mean score for AI adoption readiness is 4.92 on a seven-point Likert scale, which reflects a moderate level of willingness. This finding suggests that hotel customers in Vietnam are not yet fully ready to embrace AI in their service experiences. Consequently, the results highlight an important managerial implication: hotel operators must make greater efforts to encourage customers to engage more confidently with AI technologies in hospitality settings.

Managerial implications

Based on the results of the structural model analysis, several managerial recommendations can be drawn for hotel practitioners seeking to enhance customers' readiness to adopt AI in lodging and hospitality services.

First, both Performance Expectancy (β = 0.376) and Affect (β = 0.113) were found to exert significant direct effects on customers' willingness to adopt AI (see Table 7). Despite their importance, the mean scores indicate that customers' perceptions of performance expectancy (M = 4.539) are only moderate. This suggests that hotel managers must strengthen guests' confidence in the effectiveness of AI-enabled services. Specifically, customers need to be convinced that AI technologies genuinely improve service quality and facilitate superior outcomes during their hotel stay. Similarly, since affective responses were also moderate (M = 3.929), hoteliers should focus on ensuring that AI-driven experiences are engaging, enjoyable, and emotionally positive. For example, AI-assisted self-check-in processes should be designed to be seamless, user-friendly, and personalized, with friendly greetings that elicit excitement and positive emotions from guests.

Second, Effort Expectancy was shown to have a strong negative impact on Affect (β = –0.52), indicating that perceived effort in using AI-based services can substantially reduce customers' positive emotions. Encouragingly, the mean score for Effort Expectancy (M = 3.845) suggests that customers generally perceive AI-related services as moderately easy to use. This reflects the increasing familiarity and accessibility of AI in hospitality. As customers become more accustomed to these technologies, feelings of hesitation or intimidation decrease, thereby creating opportunities for hotels to enhance the affective value of AI-based experiences.

Third, Social Influence, Anthropomorphism, and Hedonic Motivation emerged as key antecedents in the early stage of AI acceptance. The findings provide the following managerial insights:

- *Social Influence* positively affected Performance Expectancy (β = 0.192) and negatively affected Effort Expectancy (β = –0.313). This suggests that favorable evaluations from customers' social circles increase perceptions of AI usefulness and reduce perceptions of complexity. However, the mean score for Social Influence (M = 4.068) indicates only a moderate level. Hotel managers should therefore leverage opinion leaders, industry experts, influencers, and loyal customers to spread positive messages about the efficiency and ease of AI adoption, thereby reinforcing customers' confidence at subsequent stages of acceptance.
- *Anthropomorphism* demonstrated a negative effect on Performance Expectancy (β = –0.219), consistent with concerns that human-like AI features may threaten consumers' sense of human identity (Ackerman, 2016; Gursoy et al., 2019). To mitigate this perception, managers should emphasize that anthropomorphic features are intended to enhance service interactions rather than replace human identity. Given that the mean score for Anthropomorphism

(M = 4.295) is only moderate, this factor may not pose a major threat but requires careful communication strategies to maintain trust.

- *Hedonic Motivation* showed strong positive effects on Performance Expectancy (β=0.430) and Affect (β=0.124), and a negative effect on Effort Expectancy (β = −0.352). With the highest mean score among all constructs (M = 5.376), hedonic motivation is clearly a central driver of AI acceptance. Customers derive joy and excitement from personalized services, customized experiences, and entertaining interactions with AI-driven robots in reception and in-room service. These enjoyable encounters not only enhance emotional satisfaction but also reduce perceived effort. Thus, hotel managers should prioritize designing service processes that maximize hedonic experiences through playful, personalized, and engaging AI applications.

In sum, the results highlight the importance of enhancing performance-related perceptions, fostering positive emotions, and strategically managing social influence, anthropomorphic features, and hedonic value. Together, these managerial actions can significantly increase customers' readiness to adopt AI in the hospitality sector.

Limitations

This study on hotel customers' acceptance of AI was conducted using convenience sampling and restricted to hotels located in Hanoi and Ho Chi Minh City, which may limit the generalizability of the findings. Furthermore, the study did not account for generational differences in consumer demographics, representing another limitation, as prior research suggests that technology acceptance may vary significantly across age cohorts. Future research could therefore usefully examine AI adoption readiness by comparing different generational groups, offering deeper insights into heterogeneous acceptance patterns.

Future Research Directions

Future studies should explore longitudinal analyses to understand how customer perceptions of AI evolve as exposure increases. Examining the interplay between technological anxiety, trust, and cultural factors would provide deeper insights into AI acceptance. Comparative studies across service sectors or countries could further validate the proposed model. Additionally, investigating generational or gender-based differences in AI readiness, as well as the moderating role of prior digital experience, could enrich future theoretical and managerial implications.

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