Buket Yasar / Emrah Ozkul

Predicting Customer Intentions to Use Hotel Chatbots: The Role of Perceived Competence and Usefulness

Abstract

This research examines the adoption of AI-powered chatbots in the hospitality industry by extending the conventional Technology Acceptance Model (TAM) to include perceived competence and perceived understandability. Using data from 266 hotel guests, the study applies Partial Least Squares Structural Equation Modeling (PLS-SEM) to test the hypothesized relationships. The results indicate that perceived competence and perceived understandability significantly shape customers' perceptions of ease of use and usefulness. Among these, perceived ease of use emerged as the dominant factor influencing customers' attitudes toward hotel chatbots, which in turn strongly affected their behavioral intentions. In contrast, perceived usefulness showed no meaningful association with attitude development in this context. The study contributes to the hospitality chatbot literature by extending TAM in the hotel context by including perceived understandability and perceived competence, and it offers practical guidance for improving chatbot adoption in hotel settings.

Keywords: hotel chatbots, perceived competence, perceived understandability, AI in hospitality, PLS-SEM

1. Introduction

Recent advances in artificial intelligence (AI) and machine learning have driven significant innovations across many industries, with the hospitality sector among the earliest adopters (Sam & Jasim, 2025). As of 2025, global chatbot usage has exceeded 987 million users and is projected to surpass 2 billion by 2029 (Kumar, 2026). AI-enabled chatbots are increasingly used to improve customer interactions and deliver tailored services. For example, KLM Royal Dutch Airlines uses a chatbot integrated with Facebook Messenger to assist customers by delivering booking confirmations, real-time flight updates, check-in notifications, and responses to common queries. Similarly, leading hotel chains such as Marriott and Hyatt have adopted chatbot technologies to streamline reservations, answer guest questions, and provide immediate support for hotel facilities and policies (Dua, 2015; Buhalis & Cheng, 2020). These implementations aim to shorten response times, provide consistent service quality, and meet the expectations of modern, tech-savvy travelers. As digital technologies become more embedded in hotel operations, understanding how guests perceive chatbots and their intention to use them is increasingly important (Loureiro et al., 2024).

Chatbot effectiveness in hospitality largely depends on foundational constructs such as Perceived Ease of Use (PEOU) and Perceived Usefulness (PU), central to Davis's (1989) Technology Acceptance Model (Wu et al., 2025). According to this framework, individuals are more likely to adopt new technology if they believe it is both easy to navigate and beneficial in enhancing performance. For hotel chatbots, these constructs significantly influence users' evaluations and future usage intentions (Liu et al., 2024; Xu & Chen, 2026). When hotel guests perceive chatbot interactions to be seamless and responsive to their needs, their overall attitude toward the technology becomes more favorable, increasing the likelihood of continued usage (Majid et al., 2025; Park et al., 2025). Prior research across service-oriented industries supports the predictive validity of PEOU and PU

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in explaining technology adoption (Ali, 2016; Liu et al., 2024; Venkatesh et al., 2003). In this study, we expand the TAM framework to include perceived understandability and perceived competence. These variables assess how accurately users believe the chatbot can interpret their requests and respond effectively (Lei et al., 2021; Song et al., 2024). Existing evidence suggests that when chatbots demonstrate high competence by providing timely, context-specific information, users are more likely to trust and rely on the technology during hotel interactions (Loureiro et al., 2024). Integrating these external constructs into TAM allows for a more holistic understanding of the factors influencing chatbot adoption in hospitality environments (Ma et al., 2025).

Although chatbot use has expanded significantly in hospitality contexts (Liu et al., 2024; Loureiro et al., 2024; Majid et al., 2025), scholarly research on the specific variables that shape guest adoption remains limited. Much of the existing literature on chatbot applications has focused on sectors such as online retail, finance, and healthcare, leaving the hospitality field comparatively underexplored (Loureiro et al., 2024). In particular, the influence of external variables such as perceived understandability and competence on user satisfaction and adoption behavior in hotel settings remains underexplored (Song et al., 2024). Prior studies have tended to examine broad themes in technology-driven service delivery without focusing on how distinct variables beyond the TAM model affect guest decision-making (Luger & Sellen, 2016). Additionally, while TAM and the Theory of Planned Behavior (TPB) are frequently used to explain technology adoption more generally, few studies apply these models directly to hotel chatbot usage (Ma et al., 2025). Similarly, researchers have not thoroughly explored perceived competence, the system's ability to execute tasks and respond effectively to user needs, in this context (Zhang et al., 2023). These gaps point to the need for research that systematically evaluates how such constructs interact to influence hotel guests' behavioral intentions toward chatbot adoption.

This study examines the key factors that influence hotel guests' intention to adopt AI-driven chatbots. It focuses on how perceived understandability, competence, ease of use, and usefulness shape attitudes and, ultimately, behavioral intentions to use chatbot technology in hotel settings. Beyond examining the direct relationships among these variables, the study aims to enrich the hospitality literature on technology adoption and offer concrete recommendations for practitioners, including hotel operators and technology developers. Specifically, the study pursues three objectives: (1) to evaluate how perceived understandability and competence influence guests' perceptions of ease of use and usefulness; (2) to examine how ease of use and usefulness affect guests' attitudes toward hotel chatbots; and (3) to determine how these attitudes drive intentions to adopt chatbot services within hotel environments.

The remainder of this paper is structured as follows. First, the literature review outlines prior research on chatbot adoption in hospitality and elaborates on the theoretical framework used. It then presents a detailed explanation of the methodology, including data collection and analysis techniques. The next section presents the study's findings, followed by a discussion of the results. The final section outlines the theoretical and practical implications, acknowledges limitations, and proposes avenues for future research.

2. Literature review

2.1. Chatbots in the hospitality industry

The adoption of chatbots in the hospitality sector has steadily increased as organizations seek to improve service quality and streamline operations. These AI-enabled systems replicate human dialogue through written or spoken communication, allowing hospitality businesses to automate guest interactions while still providing personalized support. Their applications include front-desk assistance, booking management, information delivery, and customer service. Buhalis and Cheng (2020) highlight that hotel chatbots facilitate guest engagement by providing instant responses, managing reservations, and delivering timely information about hotel amenities and policies (Almeida & Herter, 2025).

One of the core advantages of chatbot implementation in hospitality is the improvement of operational workflows and guest satisfaction. According to Nandaniya (n.d.), these systems offer around-the-clock support, reducing reliance on human staff and ensuring immediate assistance for guests without delays. This transition toward automation not only boosts service consistency but also contributes to the overall efficiency of hotel operations. Additionally, as Ukpabi et al. (2019) note, chatbots are effective at handling repetitive or straightforward queries, allowing human employees to focus on more complex, high-touch service requests.

Despite these operational and experiential benefits, integrating chatbot technology is not without challenges. One notable limitation is the lack of human warmth and emotional sensitivity, often considered essential to guest satisfaction in hospitality contexts (Loureiro et al., 2024). While chatbots excel at delivering factual and transactional responses, they typically lack the emotional intelligence needed to build rapport with guests. Moreover, a chatbot's effectiveness hinges on the quality of its design and training. Inadequate programming or poor language recognition can lead to misunderstandings and user dissatisfaction, as noted by Duan et al. (2025). Another challenge is user resistance, particularly among those who prefer direct human interaction over AI-mediated communication (Brandtzaeg & Følstad, 2017). Addressing these limitations requires ongoing refinement of chatbot capabilities and proactive efforts to educate users about the benefits and limitations of technology.

Table 1 summarizes key academic studies examining the application of chatbot technology in the hospitality and tourism industries.

Table 1
Summary of studies on chatbots in hospitality and tourism industry

Study	Key ifndings	Application in hospitality and tourism
Buhalis and Cheng (2020)	Hotel chatbots help manage guest services, reduce staff workload, and enhance engagement.	Used for booking, guest inquiries, and enhancing guest interaction in hotels.
Calvaresi et al. (2021)	Chatbots provide personalized experiences, automate customer service, and gather valuable data.	In tourism, chatbots assist with tasks like answering questions, providing recommendations, and booking reservations.
Ukpabi et al. (2019)	Chatbots enhance guest satisfaction by automating customer service and offering real-time support.	Chatbots are used for providing customer service, booking management, and making personalized recommendations in hotels.
Nandaniya (n.d.)	Chatbots help hotels improve operational efficiency and offer 24/7 support.	Chatbots are used in hotels for guest interactions, bookings, and customer support.
Rafiq et al. (2022)	Chatbots increase customer engagement by providing tailored, real-time experiences.	Chatbots used to answer guest queries, provide assistance, and create personalized experiences for hotel guests.
Lei et al. (2021)	Factors such as perceived ease of use and perceived usefulness influence chatbot acceptance.	Chatbots are assessed for ease of use, usefulness, and their impact on guests' intention to use them in the hospitality sector.

Source: Author's own creation.

2.2. Technology acceptance model (TAM)

The Technology Acceptance Model (TAM), introduced by Davis, has long served as a foundational framework for explaining how individuals adopt and interact with emerging technologies. TAM identifies two primary constructs—perceived usefulness (PU) and perceived ease of use (PEOU)—as the critical determinants of a user's intention to engage with a specific technology. Per Davis (1989), perceived usefulness refers to the belief that using technology will enhance task performance, whereas perceived ease of use concerns the degree to which the system is considered user-friendly and requires minimal effort to operate.

TAM has been widely applied across domains to examine technology adoption, including chatbot use. Research consistently shows that individuals are more likely to adopt a system they find both helpful and easy to use (Venkatesh & Davis, 2000). Within the hospitality sector, TAM offers a useful lens for understanding guest receptivity toward hotel chatbots. When guests perceive that a chatbot improves service (usefulness)

and is easy to use (ease of use), they are more likely to develop a favorable attitude, which can increase usage (Guo et al., 2023).

Despite its widespread utility, TAM has been criticized for not capturing other relevant factors, such as trust, emotional engagement, and anxiety about technology—elements that are particularly important in human-AI interactions, such as chatbots (Pillai & Sivathanu, 2020). To address these limitations, recent studies have extended TAM by integrating variables such as perceived competence and perceived understandability to provide a more nuanced understanding of chatbot adoption in the hospitality field (Lei et al., 2021).

In this study, TAM provides the conceptual foundation for examining guests' attitudes and behavioral intentions toward hotel chatbot use. The model is extended by incorporating perceived competence, which reflects the extent to which users consider the chatbot capable of delivering relevant and accurate responses, and perceived understandability, which captures how well users interpret and follow the chatbot's responses. These additions help explain the broader context in which guests evaluate chatbot interactions, especially in hospitality settings where communication clarity and task fulfillment are essential.

Within this study's extended framework, perceived competence and perceived understandability are expected to influence users' perceptions of both ease of use and usefulness. These perceptions, in turn, shape overall attitudes toward the chatbot and ultimately affect the intention to use it. For instance, when guests find a chatbot easy to understand and believe it can handle their inquiries effectively, they are more likely to view it as both easy to use and helpful. This combination fosters a more favorable attitude and increases the likelihood of future engagement. Including these constructs enhances TAM's explanatory power and offers practical insights for designing and implementing chatbots that align with user expectations (Pillai & Sivathanu, 2020; Lei et al., 2021).

2.3. Hypotheses development

Perceived understandability is the extent to which users can grasp and interpret a chatbot's responses. Human-computer interaction research suggests that when system responses are easy to comprehend, users experience less cognitive strain, improving their overall interaction with the technology (Kosch et al., 2023). Clear communication minimizes the mental effort required by users, which in turn contributes to the perception that the system is simple to use (Porcheron et al., 2018). As Venkatesh and Davis (2000) noted, perceived ease of use significantly shapes user acceptance of technology, influencing both attitudes and behavioral intentions. Thus, when chatbot outputs are easy to understand, users are more likely to view the system as user-friendly, enhancing the overall experience. Moreover, research on customer service technologies has emphasized that effective communication is vital to smooth, efficient interactions with automated tools (Følstad & Brandtzaeg, 2020).

H1: The perceived understandability of a hotel chatbot positively influences its perceived ease of use.

Perceived competence is the extent to which individuals believe a technological system can perform tasks effectively. Heerink et al. (2010) report that users tend to interact more readily with systems they perceive as knowledgeable and proficient. This view aligns with cognitive fluency theory, which holds that systems deemed competent are perceived as easier to interact with because users are more likely to trust the accuracy and reliability of the information they provide (Zhang et al., 2023). This concept aligns with the Technology Acceptance Model (TAM), which identifies perceived ease of use as a key predictor of technology adoption (Venkatesh & Davis, 2000). When users view a chatbot as competent, it simplifies interactions and strengthens their perception that the system is easy to use (Dinç et al., 2026).

H2: Perceived competence of a hotel chatbot positively influences its perceived ease of use.

Perceived understandability shapes how users assess a system's value. According to Cognitive Fit Theory (Venkatesh & Davis, 2000), users are more likely to find a system useful when its communication style aligns with their cognitive processes. When users can easily understand a chatbot's responses, they can make more informed decisions and perceive the system as more useful for their tasks. Studies in human-computer interaction, such as van der Goot and Pilgrim (2020), show that clear, understandable communication directly enhances perceived usefulness, making this relationship essential to understanding technology acceptance.

H3: The perceived understandability of a hotel chatbot positively influences its perceived usefulness.

Competence shapes users' perceptions of a system's utility. According to the Technology Acceptance Model, users' beliefs about a system's ability to help them accomplish tasks effectively strongly influence perceived usefulness (Davis, 1989). When users perceive a chatbot as competent, they trust its ability to provide accurate, relevant, and timely responses, thereby increasing its perceived usefulness (Lee & Turban, 2001). Previous human-computer interaction studies show that users' trust in a system's competence directly shapes their perception of its value (Zhang et al., 2023).

H4: The perceived competence of a hotel chatbot has a positive influence on its perceived usefulness.

Perceived ease of use is widely recognized as an important factor in shaping users' attitudes toward technology (Venkatesh & Davis, 2000). When users find a technology easy to use, they develop positive attitudes toward it because it minimizes the cognitive effort required to interact with it (Lin & Bhattacherjee, 2010). In the hospitality context, users are more likely to form favorable opinions about chatbots when they perceive them as user-friendly and simple to operate. The relationship between ease of use and attitude is well-documented in technology acceptance literature, supporting the idea that a positive user experience leads to more favorable attitudes toward technology (Venkatesh & Davis, 2000).

H5: Perceived ease of use of a hotel chatbot positively influences guests' attitudes toward the hotel chatbot.

Perceived usefulness is a key factor in shaping users' attitudes toward a technological system. As outlined in the Technology Acceptance Model (TAM), individuals are more inclined to adopt technology when they believe it will help them accomplish their tasks or objectives (Davis, 1989). In the context of hotel chatbots, guests tend to form favorable attitudes when they perceive the chatbot as effective in meeting their service-related needs, such as handling bookings, answering questions, or offering tailored suggestions. Previous research on technology acceptance has repeatedly demonstrated that the more useful users find a technology, the more likely they are to develop positive perceptions of it (Venkatesh et al., 2003).

H6: The perceived usefulness of a hotel chatbot has a positive influence on guests' attitudes toward the hotel chatbot.

A positive attitude toward technology strongly predicts users' intentions to adopt and use it. The Theory of Planned Behavior (Ajzen & Fishbein, 1977) holds that attitudes significantly shape behavioral intentions. When guests have favorable views of hotel chatbots, they are more likely to intend to use them in the future. Extensive research on technology adoption supports this relationship, showing that favorable attitudes toward technology are associated with stronger intentions to use it (Moon & Kim, 2001). Moreover, positive attitudes typically precede technology adoption and lead to actual use (Ajzen & Fishbein, 1977).

H7: Guests' attitude toward the hotel chatbot positively influences guests' intentions to use the hotel chatbot.

3. Methodology

3.1. Research instrument

This study used a structured questionnaire as the primary data collection tool to assess the core constructs associated with hotel chatbot usage. Each variable was measured on a five-point Likert scale, with responses ranging from 1 (strongly disagree) to 5 (strongly agree). Perceived competence was evaluated with three items adapted from Cheng et al. (2022). Perceived ease of use was captured with four statements, and perceived usefulness with three, both adopted from Pillai and Sivathanu (2020). Attitudinal responses toward hotel chatbots were measured with four items developed by Dabholkar and Bagozzi (2002), while the intention to use hotel chatbots was assessed with three items adapted from Li et al. (2021). These instruments were selected for their strong validation in prior studies and their relevance to the hospitality technology context.

Before initiating the main phase of data collection, a pilot study was conducted with a small group of hotel guests. This preliminary test evaluated the clarity and contextual suitability of the questionnaire items for chatbot use. Based on participants' feedback, the researchers made slight adjustments to refine wording and improve the questions' interpretability. These modifications improved overall reliability and ensured the final instrument was well suited to the study's objectives in the hospitality industry.

3.2. Sampling and data collection

The study focused on individuals residing in the United States who had used a hotel chatbot within the past three months. Participants were recruited through self-selection, a widely accepted method in online research in which individuals voluntarily choose to take part in a survey (Saunders et al., 2009). The researchers distributed the survey via Amazon Mechanical Turk (MTurk), a popular crowdsourcing platform frequently used in hospitality and tourism research to reach qualified participants (Cobanoglu et al., 2021). Using MTurk enabled the researchers to target respondents with direct experience of hotel chatbots, thereby enhancing the relevance of the data. To strengthen sample credibility, the researchers invited only MTurk workers with a HIT approval rate of 99% or higher to participate. A screening question confirmed recent chatbot usage (within the past three months), and two attention-check items were included to identify inattentive respondents. Only those who passed all checks were retained for analysis.

Data were collected in two waves, separated by one week, to introduce temporal separation as a procedural remedy for common method bias. Responses from both waves were compared using non-response bias tests, which showed no significant differences across key constructs. Consequently, the datasets were combined for analysis. To ensure sufficient statistical power, a G*Power analysis was conducted prior to data collection. The analysis was based on a small, expected effect size (d = 0.15), with a significance threshold of 0.05 and a desired power level of 0.95. This analysis recommended a minimum of 138 respondents to detect meaningful effects. Ultimately, the study collected 266 valid responses, which surpassed the minimum threshold and conformed to the commonly used rule of thumb of securing at least 10 observations per measurement item for Structural Equation Modeling (Ali, 2026).

The sample represented a broad cross-section of hotel guests. Most participants were 25 to 34 (55%), followed by 34 to 44 (19%) and 45 to 54 (17%). Fewer were in the 18 to 24 and 55 to 64 age groups, each accounting for 5% of the total. Regarding gender, the sample was 64% male and 36% female. Ethnic representation was primarily European/American (68%), followed by Asian participants (26%), with smaller segments identifying as Middle Eastern (2%) or from other backgrounds (4%). In terms of employment, the overwhelming majority (99%) reported full-time work, with just 1% employed part-time. Marital status was also diverse, with 80% identifying as married, 18% as never married, and 2% as living with a partner. This demographic diversity provided a well-rounded view of guest characteristics that may affect their acceptance and use of hotel chatbot services.

3.3. Data normality and common method bias

To assess multivariate normality, we reviewed skewness and kurtosis values for each construct. While most values remained within the generally accepted range of -2 to +2, a few exceeded this threshold, suggesting a non-normal distribution. This non-normality is acceptable and even preferable when using PLS-SEM, which does not require a normal data distribution (Hair et al., 2016). To assess potential common method bias (CMB), we conducted a full collinearity assessment by examining variance inflation factors (VIFs), following Kock's (2015) recommended procedure. All VIF values were below the conservative threshold of 3.3, suggesting that severe collinearity and common method variance are not dominant concerns in the data. However, given the survey's single-source, self-reported design, residual common method bias cannot be entirely ruled out. Accordingly, interpret the results with appropriate caution, and future research should employ multi-source or longitudinal designs to further mitigate common method concerns.

3.4. Analytical methods

To analyze the collected data, the study used Partial Least Squares Structural Equation Modeling (PLS-SEM) in SmartPLS 3.0. This technique was chosen for its effectiveness in modeling complex relationships among variables, particularly when sample sizes are modest and data distributions deviate from normality (Hair et al., 2021). PLS-SEM is also widely recognized in hospitality research for its ability to test conceptual models with multiple latent constructs in a flexible and robust manner (Ali et al., 2018).

4. Findings and analysis

The structural model was estimated using the PLS algorithm, yielding standardized item loadings, path coefficients, and their statistical significance. The evaluation of the measurement model focused on two key aspects: convergent and discriminant validity. Convergent validity was assessed using the Average Variance Extracted (AVE) for each latent construct, while discriminant validity was tested to confirm that the constructs measured distinct concepts. A bootstrapping procedure with 5,000 resamples was used to estimate the precision and significance of path coefficients, ensuring robust hypothesis testing and supporting the credibility of the structural relationships found in the model.

4.1. Measurement model

To evaluate the reliability and validity of the measurement model, several statistical metrics were used. The PLS algorithm was run for up to 300 iterations to ensure convergence. Composite Reliability (CR) was used to assess construct reliability, with 0.70 set as the minimum acceptable value. All constructs exceeded this threshold, confirming the measurement model's internal consistency and reliability. (See Table 2; the full list of measurement items is available in Appendix)

Table 2
Measurement model assessment

Construct	Item	Loading	Cronbach's α	CR	AVE
Attitude toward hotel chatbots (ATHC)	ATHC1	0.861	0.884	0.920	0.742
	ATHC2	0.855			
	ATHC3	0.885			
	ATHC4	0.844			
Intention to use hotel chatbots (IUHT)	IUHT1	0.844	0.786	0.872	0.694
	IUHT2	0.825			
	IUHT3	0.830			
Perceived competence (PC)	PC1	0.859	0.812	0.889	0.727
	PC2	0.840			
	PC3	0.859			

Table 2 ***(continued)***

Perceived ease of use (PEOU)	PEOU1	0.803	0.870	0.911	0.719
	PEOU2	0.851			
	PEOU3	0.865			
	PEOU4	0.873			
Perceived usefulness (PU)	PU1	0.924	0.863	0.907	0.708
	PU2	0.886			
	PU3	0.904			
Perceived understandability (PUS)	PUS1	0.816	0.889	0.931	0.819
	PUS2	0.836			
	PUS3	0.860			
	PUS4	0.854			

4.2. Discriminant validity

Discriminant validity was first checked using the Fornell and Larcker criterion (Fornell & Larcker, 1981). As shown in Table 3, the square roots of the AVEs (on the diagonal) exceeded the correlations between constructs, indicating good discriminant validity. To further confirm this, we calculated the Heterotrait-Monotrait (HTMT) ratio. All HTMT values remained below the 0.90 threshold (Kline, 2011), further supporting that the constructs are conceptually and statistically distinct.

Table 3
Discriminant validity

Constructs	1	2	3	4	5	6
Attitude toward hotel chatbots	0.861					
Intentions to use hotel chatbots	0.742	0.833				
Perceived competence	0.846	0.731	0.853			
Perceived usefulness	0.819	0.791	0.788	0.842		
Perceived ease of use	0.784	0.749	0.788	0.785	0.848	
Perceived understandability	0.786	0.721	0.742	0.731	0.787	0.905
HTMT						
Attitude toward hotel chatbots	-					
Intentions to use hotel chatbots	0.845	-				
Perceived competence	0.847	0.847	-			
Perceived usefulness	0.819	0.823	0.798	-		
Perceived ease of use	0.799	0.814	0.791	0.825	-	
Perceived understandability	0.798	0.833	0.742	0.831	0.817	-

4.3. Structural model

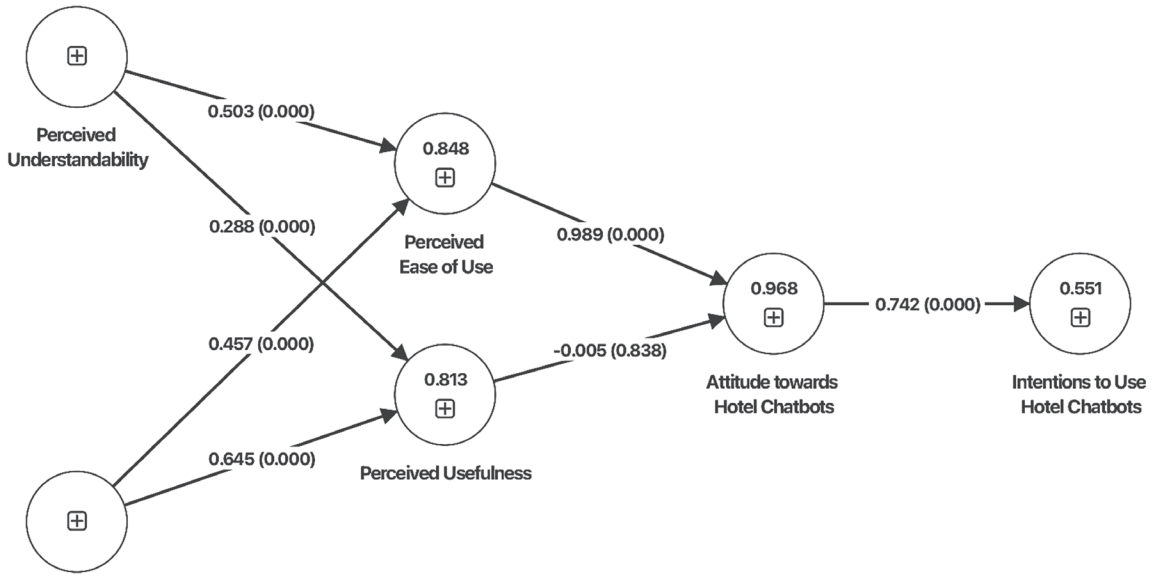
The structural model was evaluated using bootstrapping with 5,000 resamples to assess the significance of the hypothesized paths. Table 4 presents the t-values and p-values for each relationship in the model. Most hypothesized paths were statistically significant, providing empirical support for the proposed relationships among the constructs.

Table 4
Hypotheses testing

	Path	Beta	T-Value	P-Value	Decision
H1	Perceived understandability → Perceived ease of use	0.503	7.512	0.000	Supported
H2	Perceived competence → Perceived ease of use	0.457	6.908	0.000	Supported
H3	Perceived understandability → Perceived usefulness	0.288	4.453	0.000	Supported
H4	Perceived competence → Perceived usefulness	0.645	10.175	0.000	Supported
H5	Perceived ease of use → Attitude	0.989	42.402	0.000	Supported
H6	Perceived usefulness → Attitude	-0.005	0.204	0.838	Not supported
H7	Attitude → Intentions to use hotel chatbots	0.742	23.651	0.000	Supported

The structural results offer meaningful insights into how the constructs interact within the proposed model. As shown in Figure 1, standardized path coefficients (β), t-statistics, and p-values are reported for each hypothesis. Hypothesis H1 was supported, showing that perceived understandability (PUS) positively affects perceived ease of use (PEOU) (β = 0.503, t = 7.512, p < 0.001). This implies that when chatbot responses are easier to understand, users are more likely to perceive the system as intuitive. H2 revealed that perceived competence (PC) significantly influences perceived ease of use (β = 0.457, t = 6.908, p < 0.001), suggesting that chatbots regarded as capable are seen as easier to interact with. H3 was also confirmed, with results showing that perceived understandability positively affects perceived usefulness (PU) (β = 0.288, t = 4.453, p < 0.001). Similarly, H4 was validated, indicating a robust positive link between perceived competence and perceived usefulness (β = 0.645, t = 10.175, p < 0.001), reinforcing the importance of chatbot proficiency in shaping users' perceptions of value. Hypothesis H5 also received strong empirical backing, with perceived ease of use significantly predicting attitudes toward hotel chatbots (ATHC) (β = 0.989, t = 42.402, p < 0.001). This emphasizes that an intuitive and effortless user experience plays a vital role in fostering favorable attitudes. In contrast, H6 was not supported, as perceived usefulness showed no significant impact on attitude formation (β = -0.005, t = 0.204, p = 0.838). This result suggests that ease of interaction may carry more weight than perceived functionality in shaping users' attitudes in this context. Lastly, H7 was confirmed, indicating that positive attitudes toward hotel chatbots significantly influence the intention to use them (β = 0.742, t = 23.651, p < 0.001). This finding highlights the central role of attitude as a determinant of behavioral intention.

Figure 1
Structural model



Unlike covariance-based structural equation modeling (CB-SEM), which provides a comprehensive model fit index, partial least squares structural equation modeling (PLS-SEM) evaluates model adequacy based on predictive performance rather than overall goodness-of-fit (Henseler & Sarstedt, 2013). In this study, the model's predictive strength was assessed using three main indicators: the coefficient of determination (R^2), standardized path coefficients (β), and Stone-Geisser's Q^2 statistic obtained through a blindfolding technique. As suggested by Hair et al. (2016), R^2 values of 0.75 or higher reflect strong explanatory capacity, values between 0.50 and 0.75 denote moderate explanatory power, and those between 0.25 and 0.50 indicate weak explanatory power. Additionally, Falk and Miller (1992) recommend that, for a model to be considered adequate, each endogenous variable should have at least 10% of its variance explained.

In the present model, the R^2 value for intention to use hotel chatbots (IUHT) reached 0.551, which is classified as moderate. The construct measuring attitudes toward hotel chatbots (ATHC) yielded an exceptionally high R^2 of 0.968, indicating excellent explanatory power. Furthermore, perceived usefulness (PU) and perceived ease of use (PEOU) recorded R^2 values of 0.813 and 0.848, respectively, both within the range of strong explanatory strength. The magnitude of the relationship between perceived ease of use and attitudes toward hotel chatbots ($\beta = 0.989$), together with the high R^2 for attitudes (0.968), warrants careful interpretation. To assess potential inflation, collinearity diagnostics were evaluated. The variance inflation factor (VIF) associated with perceived ease of use was elevated (VIF = 6.669), indicating substantial shared variance with other predictors. Given the conceptual proximity between perceived ease of use and attitudinal evaluations, as well as the single-source, self-reported design, the strength of this relationship may partially reflect shared variance rather than purely distinct effects. Accordingly, this result should be interpreted with caution. The predictive relevance of the model was further evaluated using Q^2 values calculated via cross-validated redundancy. As per Sarstedt et al. (2014), Q^2 values above zero signify meaningful predictive capability. All latent constructs in this study recorded Q^2 values exceeding this threshold, affirming their predictive relevance.

Although global goodness-of-fit indices are not central to model evaluation in PLS-SEM, additional diagnostic information was obtained by examining the standardized root mean square residual (SRMR) and the squared Euclidean distance (d_ULS). The SRMR values for both the saturated and estimated models were below the commonly cited threshold of 0.08. These indices are reported as complementary diagnostics only and should be interpreted cautiously, with primary emphasis on measurement quality, explanatory power, and predictive relevance rather than overall model fit.

5. Discussion

This study examined the factors shaping hotel guests' acceptance and intended use of chatbots, building on the Technology Acceptance Model (TAM) framework. To strengthen TAM's explanatory power, two additional constructs were introduced: perceived competence and perceived understandability. The findings contribute to the growing scholarship on chatbot deployment in hospitality by clarifying how perceptions of usability, utility, and system quality affect user attitudes and behavioral intentions.

A central insight from the research is that perceived understandability strongly influences perceived ease of use. This aligns with prior work in human-computer interaction, which emphasizes that when a system communicates clearly and comprehensibly, users experience less cognitive strain during interactions (Sweller, 1999; Porcheron et al., 2018). In the context of hotel chatbots, clear communication enhances usability, enabling users to interpret responses more readily and complete tasks with minimal effort. This result also reinforces earlier TAM findings by Venkatesh and Davis (2000), underscoring ease of use as a key driver of acceptance. In hospitality environments where user experience is paramount, a chatbot that is easy to navigate and interact with plays a pivotal role in influencing guest adoption.

The study also found a significant positive relationship between perceived competence and perceived ease of use. Drawing on cognitive fluency theory (Zhang et al., 2023), the results suggest that systems perceived as capable and efficient facilitate smoother interactions. When hotel guests view a chatbot as skilled at handling requests, they encounter fewer usability barriers, which contributes to a more fluid experience. This supports the central TAM argument that ease of use directly affects user adoption decisions (Venkatesh & Davis, 2000). In the hotel setting, perceptions of chatbot competence help build user confidence, making the technology feel more accessible and trustworthy (Babu & Philip, 2025). This has important implications for system developers, who must ensure that chatbots can handle a range of guest queries accurately and efficiently.

Additionally, perceived understandability was found to positively affect perceived usefulness. According to Cognitive Fit Theory (Venkatesh & Davis, 2000), systems that align with a user's cognitive processing style

are considered more valuable. When a chatbot communicates clearly, users can process the information more effectively, leading to greater perceived utility. This is especially important in hospitality settings, where users rely on chatbots for immediate, accurate service. When a system provides relevant information in an understandable format, whether for booking assistance or service recommendations, users are more likely to view it as a helpful tool worth engaging with.

The study also found that perceived competence significantly enhances perceptions of usefulness. This aligns with findings from Lee and Turban (2001), who emphasized that confidence in a system's ability increases perceptions of its value. If guests believe that a chatbot can consistently provide reliable, contextually appropriate answers, they are more likely to view it as a worthwhile part of the hotel's service offering. This suggests that perceived system performance is central to shaping user evaluations, which in turn influence acceptance.

Perceived ease of use was also found to be a strong predictor of positive user attitudes. This aligns with Venkatesh and Davis (2000), who argued that systems requiring less cognitive effort tend to foster favorable perceptions. In hospitality, where users may face time constraints or unfamiliar systems, ease of use is especially critical. Chatbots with a seamless, intuitive interface are more likely to be viewed positively, which can increase satisfaction and the likelihood of future use. This reinforces the need for hotel managers and developers to prioritize simple, efficient design when implementing chatbot solutions. However, the magnitude of this relationship should be interpreted cautiously, as the conceptual proximity between ease of use and attitudinal evaluations, combined with the single-source design, may inflate estimates.

Interestingly, the hypothesized relationship between perceived usefulness and attitudes toward hotel chatbots was not supported. While perceived usefulness is a core determinant of attitudes in the original Technology Acceptance Model (Davis, 1989), its effect was not statistically significant in the present context. This result should be interpreted cautiously and does not imply that usefulness is unimportant. Rather, it suggests that within hotel chatbot interactions, perceived usefulness may operate more indirectly through other constructs in the model. One plausible explanation is that, for service-oriented conversational technologies, guests may form attitudes primarily based on how easy and intuitive interaction feels rather than on an explicit evaluation of functional outcomes. When chatbot services are relatively standardized, such as providing basic information or handling routine requests, usefulness may be taken for granted and thus exert less influence on attitudinal judgments. In contrast, perceived ease of use and competence may be more salient cues during initial and ongoing interactions, thereby playing a stronger role in shaping attitudes.

Lastly, the analysis confirmed that user attitudes significantly shape behavioral intentions, consistent with the assumptions of the Theory of Planned Behavior (Ajzen & Fishbein, 1977). Guests who view chatbots positively are more likely to intend to use them in future hotel interactions. This association has also been observed in prior technology adoption studies (Moon & Kim, 2001). In the hospitality domain, the implication is clear: improving user sentiment through thoughtful design, responsive service, and perceived benefits can drive sustained use. Hotel operators and technology vendors should therefore focus on enhancing the overall guest experience with chatbots to support long-term engagement and successful technological integration.

5.1. Theoretical implications

This study makes several important contributions to the academic understanding of technology acceptance, particularly regarding the hospitality sector's use of chatbots. By extending the traditional Technology Acceptance Model (TAM) to include perceived competence and perceived understandability, the study deepens existing frameworks and addresses a gap in the literature on user interaction with AI-enabled systems in service contexts.

A key theoretical contribution of this research is establishing perceived understandability as a significant antecedent of both perceived ease of use and perceived usefulness. This finding broadens the TAM framework by showing that when chatbot interactions are communicated clearly, users not only find the technology

easier to use but also recognize its functional benefits. This result supports theories such as Cognitive Fit and Cognitive Load, which suggest that technologies aligned with users' mental processing are more likely to be accepted. The study thus strengthens the argument that reducing the mental effort required to interact with technology enhances both its perceived usability and value.

In addition, this study underscores the role of perceived competence in shaping user trust and system evaluation. By showing that competence positively affects both ease of use and usefulness, the research highlights its foundational role in technology acceptance. This insight builds on the human-computer interaction literature and supports the idea that trust in a system's ability to perform tasks efficiently is a key determinant of user adoption. By integrating competence into TAM, the study offers a more holistic understanding of how users form intentions to engage with intelligent systems, particularly in high-contact service industries such as hospitality.

5.2. Practical implications

The findings of this research offer numerous practical strategies for hotel operators and chatbot developers seeking to improve both the implementation and guest adoption of chatbot technologies in service environments.

One immediate takeaway is the critical role of clear communication in shaping perceptions of ease of use. Hotels should design chatbots that communicate in a straightforward, guest-friendly way. Investing in advanced natural language processing tools can help ensure that chatbot responses are not only accurate but also easy to understand. Reducing technical jargon, offering context-aware replies, and simplifying response structure will minimize guest confusion and create a more intuitive experience. This, in turn, will make technology more appealing and reduce guest resistance.

System competence is equally essential to successful chatbot adoption. To be perceived as capable, chatbots must be equipped with extensive, real-time knowledge bases that enable them to answer a wide range of guest inquiries. From booking-related questions to local recommendations, the chatbot should deliver relevant, precise, and actionable responses. Developers can further improve performance by incorporating adaptive learning algorithms that allow the chatbot to learn from guest interactions over time. This will not only boost the chatbot's perceived value but also increase user trust and reliance on the system.

Interface design also plays a crucial role in shaping user perceptions. Chatbots should feature interfaces that are easy to navigate, with intuitive commands and clearly presented options. These interfaces must function smoothly across devices and platforms—including websites, mobile apps, and messaging services—so guests can engage with the chatbot wherever they are. A consistent, responsive user experience will foster stronger attitudes toward the technology and encourage repeat use.

Another important element is personalization. When chatbots offer tailored recommendations and responses based on a guest's past stays, preferences, or location, they deliver greater relevance and convenience. Personalization strengthens the perception that the chatbot understands the user's needs, making it more useful. Hotels should leverage guest data to deliver these personalized experiences, which can drive loyalty and satisfaction.

Despite the advantages of automation, some guests may still seek the reassurance of human assistance, particularly for nuanced or emotionally sensitive issues. To accommodate these preferences, hotels should adopt a hybrid service model in which chatbots serve as the first point of contact and seamlessly transfer queries to human staff when necessary. This ensures that guests receive appropriate support regardless of the complexity of their request, thereby enhancing overall service quality.

It is also important that hotel employees are well-versed in the capabilities and limitations of the chatbot systems in use. Training staff to work alongside these technologies will help them better assist guests who may be unfamiliar with or uncomfortable with chatbot interactions. This knowledge will enable employees

to resolve issues more effectively and guide guests through digital processes, strengthening the integration of technology and human service.

Lastly, hotels should continuously evaluate and improve their chatbot systems. They can do this by collecting user feedback, regularly monitoring performance, and analyzing conversation logs to pinpoint areas for improvement. Periodic updates to the chatbot's knowledge base, functionality, and interaction style will help keep it relevant, helpful, and aligned with guest expectations. This ongoing refinement will support long-term adoption and demonstrate the hotel's commitment to innovation and guest satisfaction.

6. Limitations and future research suggestions

Although this study offers valuable insights into the factors that influence the adoption of hotel chatbots, it has certain limitations. A primary concern is the limited diversity of the sample, which is drawn from a relatively narrow demographic profile. This homogeneity may constrain the generalizability of the results to other guest populations or hospitality contexts. To address this, future research should recruit participants from a wider range of backgrounds, including differences in age, culture, region, and digital familiarity. Doing so would provide a more nuanced understanding of how demographic and contextual variations influence users' attitudes and behavioral intentions toward chatbot technology, thereby strengthening the external validity of the findings.

Another limitation is the reliance on self-reported data, which can introduce biases such as social desirability and memory inaccuracies. Future studies could benefit from incorporating more objective measures, such as system-generated interaction logs or observational data, to validate and complement self-reported responses. Additionally, the current study offers only a cross-sectional perspective. Longitudinal studies could provide further insight into how guest attitudes, trust, and usage patterns evolve over time through repeated interactions with chatbot systems.

This research primarily draws on the Technology Acceptance Model (TAM), which, while robust, does not capture all potential influences on technology adoption. Constructs such as emotional connection, trust, and user anxiety—particularly relevant in high-contact service industries like hospitality—were not explicitly examined. Future research could enhance TAM's explanatory power by integrating these factors, given the importance of emotional engagement in shaping guest experiences.

Furthermore, this research was limited to the hotel segment of the hospitality industry. Subsequent investigations could broaden the scope to other sectors, such as restaurants, cruise lines, or travel agencies, to examine whether chatbot adoption determinants vary across service environments. A comparative approach could yield broader insights into the distinct roles chatbots play in enhancing service delivery across different tourism and hospitality contexts.

In addition, the high explanatory power observed for attitudes may partly reflect shared method variance and conceptual overlap among constructs, which should be considered when interpreting the strength of the relationships.

Finally, as chatbot technologies continue to evolve with advances in artificial intelligence and natural language processing, future studies should examine how these innovations affect user perceptions and technology adoption. Investigating how next-generation conversational agents affect user satisfaction and engagement could reveal how technological enhancements shape service experiences and reshape customer expectations in the hospitality industry.

Declaration of Competing Interests

The authors declare that they have no known competing interests that could have appeared to influence the work reported in this paper.

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Appendix

Measurement items

Constructs	Items	Statements
Attitude towards Hotel chatbots	ATHC1	I feel that the hotel chatbot is helpful
	ATHC2	The chatbot makes my experience better
	ATHC3	The chatbot is easy to use
	ATHC4	The chatbot improves my service experience
Intentions to use Hotel chatbots	IUHT1	I would use the hotel chatbot again
	IUHT2	I prefer using the chatbot over other service channels
	IUHT3	I trust the chatbot to provide the needed information
Perceived competence	PC1	The chatbot is competent in answering my questions
	PC2	The chatbot performs well in customer service tasks
	PC3	The chatbot provides accurate and relevant answers
Perceived usefulness	PU1	Using the chatbot improves my overall experience
	PU2	The chatbot saves me time
	PU3	The chatbot provides useful information
Perceived ease of use	PEOU1	The chatbot is easy to interact with
	PEOU2	I feel comfortable using the chatbot
	PEOU3	The chatbot is easy to learn to use
	PEOU4	The chatbot is intuitive to use
Perceived understandability	PUS1	The chatbot's responses are easy to understand
	PUS2	The chatbot communicates in a way that is clear and simple
	PUS3	I understand the responses from the chatbot easily
	PUS4	The chatbot uses language that is easy to follow