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Smart Service Interactions in Hospitality: Factors Influencing Customer Switching Intention to Chatbots

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ABSTRACT

The rapid development of conversational artificial intelligence (AI) has transformed customer interaction patterns in the hospitality sector, with chatbots increasingly deployed as frontline support tools across multiple service touchpoints. However, while chatbot usage continues to grow, customer reactions to automated assistance remain mixed, prompting an examination of the technological factors that shape customers' willingness to shift from human agents to chatbots. This study investigates how four key chatbot-related variables: comprehension, perceived humanness, synchronicity, and problem-solving ability, influence customer switching intentions in hospitality contexts. Using a quantitative method, data were collected from 149 Indonesian consumers with prior experience using both chatbots and human service agents during online hospitality-related transactions. Structural Equation Modeling (SEM) via SmartPLS was employed to test the proposed hypotheses. The results show that all four variables have a significant positive influence on switching intention, with problem-solving ability being the strongest predictor, followed by synchronicity, perceived humanness, and comprehension. These findings suggest that customers are more inclined to adopt chatbot-based support when the technology demonstrates efficient problem resolution, real-time responsiveness, and a degree of human-like interaction. The study contributes to chatbot adoption literature by focusing on technological interaction attributes rather than solely psychological acceptance factors and highlights the growing relevance of AI-mediated service encounters in hospitality. Limitations include the cross-sectional design, self-reported data, and sector-specific sampling. Future research is encouraged to investigate sectoral differences, adopt longitudinal or experimental approaches, and examine moderating influences such as digital literacy, trust propensity, or cultural background.

***Keywords* :**
Chatbots; Conversational AI; Hospitality Technology; Human–AI Interaction; Problem-Solving; Synchronicity; Perceived Humanness; Comprehension

A. INTRODUCTION

Rapid changes in conversational interfaces have reshaped the way hospitality companies provide customer support online. Currently, the adoption of artificial intelligence (AI) has altered service experience in various sectors, allowing the businesses to provide faster effective and efficient customer service. Among these technological innovations**,** chatbots have become widely adopted as companies use them more frequently to provide support and interact with customers across various service touchpoints. Narrowing down to the hospitality sectors, the adoption of chatbots are increasingly integrated to various service point such as, pre-arrival information arrangements, booking assistance, concierge services, and post-stay support.

Although chatbots are becoming more common, people respond to them very differently. Some users value the speed and convenience of chatbots. However, there are some customers feel dissatisfied or decide they would rather talk to a real person. These diverging reactions highlight an important need to understand the specific elements of chatbot service quality that shape customers' intentions to continue using chatbots, or to switch back to human support. This pressure is true especially in businesses from hospitality sectors, where service interactions are normally interpersonal and significantly influence overall service experience (Wüst & Bremser, 2025).

The increase of chatbot adoptions have attracted scholars to examine the issues and challenges in implementing this smart technology. Particularly, researchers have focused on various elements that potentially influence consumer's perceptions, attitude and behaviours. Using several theory such as, Technology Acceptance Model (TAM) (Awal & Haque, 2025; Hidayat-ur-Rehman, 2025; C. Wang et al., 2023), Unified Theory of Acceptance and Use of Technology (UTAUT) (Dhanya & Ramya, 2025). Also, there are several studies that have examined the customers' switching intention. These studies scrutinized what factor that may influence customer intention to switch from human agent to chatbots (Awal & Haque, 2025; S. Chen et al., 2025; Huang, 2026). However, these studies are predominantly situated in sectors such as banking, e-commerce, and retail, where service interactions are largely transactional and efficiency-driven, offering limited insight into high-contact service contexts such as hospitality.

Furthermore, there are some scholars that also investigate the relationship between customer's intention to use chatbot and service quality. Nevertheless, according to Chen et al., (2025) there some gaps that still need to be addressed, that is, there are a few research conducted in hospitality area, most research mainly focused on customer's emotion or cognitive responses, and lastly, very few research have examine the chatbot service quality. In

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hospitality services, where customer experiences are collectively built through social connection, emotional participation (Kandampully & Solnet, 2024), elements of service quality such as perceived humanness and interaction synchronisation are especially crucial. Perceived humanness refers to how much chatbots may show warmth, empathy, and social presence (Weckström et al., 2026). Synchronicity, on the other hand, refers to how quickly and smoothly conversations should flow in real-time service encounters (Marconi et al., 2026). Unlike banking or retail services, hospitality customers often want trust, personalised treatment, and emotional understanding. If these areas are lacking, customers are more likely to be unhappy and more prefer to speak with a human.

Evaluating chatbot service quality through dimensions like responsiveness, reliability, empathy, personalization, and communication effectiveness is critical for understanding customer switching intentions. Even though these service quality characteristics are important, they have not been studied much in research on hospitality chatbots. Most of the research has focused on how people accept technology instead of how they experience and interact with it (S. Chen et al., 2025). This study explores how the distinct service quality attributes of chatbots—such as responsiveness, reliability, empathy, personalization, and communication effectiveness—influence customers' decisions to continue using automated chatbots or switch to human service agents, addressing an important gap in the existing literature. Therefore, the study looks at three main questions to understand how different aspects of chatbot service quality affect whether customers are willing to switch from human agents to chatbots.

By focusing on service quality dimensions rather than just technological acceptance, the study sheds light on nuanced chatbot–customer interactions. It uncovers how elements like promptness, trustworthiness, and emotional intelligence affect customer satisfaction, perceived value, and ultimately, retention versus switching intentions. For example, high responsiveness and personalization can reduce the urge to seek human support, while lack of empathy or ineffective communication may prompt a switch. Optimizing these service quality attributes leads to customer journeys that are smoother and more engaging, increasing overall satisfaction and reducing the perceived need for escalation to human agents. This research provides a framework for organizations to identify which chatbot features are most influential and where investments will yield the greatest improvements in customer experience.

B. REVIEW OF LITERATURE

Research on chatbots in service industry has grown rapidly as hospitality companies increasingly adopt automated conversational systems to handle customer–business interactions (Aslam et al., 2022). While early studies predominantly used technology acceptance theories such as TAM and UTAUT to explain chatbot adoption by highlighting perceived usefulness, ease of use, and performance expectancy as primary motivators (Dhanya & Ramya, 2025), recent studies acknowledge that chatbots now also act as frontline service employees, requiring a shift toward service-quality frameworks for a deeper understanding of customer responses (Sfar et al., 2025).

In the tourism industries for instance, chatbots provide smart service interactions that go beyond just being efficient. They help customers have a more complete service experience, which can change how they think about the professionalism, responsiveness, and image of the place in a tourism destination (Orden-Mejía et al., 2025). Chatbot interactions are the first digital touchpoints that customers have, and they can affect how they rate not only the service they received but also the overall quality and credibility of the place (Magano et al., 2025). Likewise, in the hospitality sector, where guests expect high levels of warmth and personalized attention, customers evaluate chatbots not simply as technological innovations but also as service providers who must meet similar quality standards as human agents (Shah, 2023). This shift has led to increased recognition of multiple service quality dimensions, including responsiveness, reliability, personalization, communication clarity, and privacy assurance, all of which are critical in shaping customer satisfaction and behavioural intentions toward ongoing use or switching between automated and human assistance (Truong & Chen, 2025). Service-quality frameworks allow researchers and practitioners to identify which aspects of the chatbot experience most influence customer judgments, thereby guiding efforts to design and implement chatbots that foster trust, satisfaction, and loyalty in sectors characterized by elevated expectations for service excellence. To further ground these service-quality considerations within a comprehensive behavioral framework, the Stimulus–Organism–Response (SOR) model offers a useful lens for explaining how customers interpret and react to chatbot interactions (Elayat & Elalfy, 2025; Fadhly et al., 2024).

The Stimulus–Organism–Response (SOR) framework, originally developed by Mehrabian and Russell and refined by Jacoby, posits that environmental cues or stimuli influence a person's internal state, either cognitive or emotional, which subsequently drives specific behavioural responses (Asyraff et al., 2023). This model is particularly well suited for examining the ways external factors shape customer decisions and has found wide application in contemporary research on chatbot interactions (Fadhly et al., 2024). Prior studies leveraging the SOR model in chatbot contexts have demonstrated its effectiveness for unpacking the pathways through which chatbot features impact customer behaviour (Elayat & Elalfy, 2025). For example, Shahzad et al., (2024) applied the SOR approach to investigate how chatbot service quality dimensions act as stimuli, impacting outcomes like e-brand loyalty and electronic word of mouth (responses) through users' trust and their holistic experience with the chatbot (organism). Building on these foundations, the present study uses the SOR model to analyse how various service quality dimensions of chatbots act as stimuli that shape consumers' willingness to switch from human service agents to automated chatbot services, the behavioural response, with perceived shopping or purchase enjoyment serving as the organism, or the internal evaluative process guiding this switch. This approach enables a nuanced understanding of how environmental features of chatbot interaction can activate positive or negative internal states, ultimately determining customers' adoption and continued use of chatbot-based services in settings such as hospitality.

Stimulus Factors: Chatbot Service Quality Dimensions

Through a comprehensive review of prior studies examining chatbot services across different sectors, we identified a wide range of service quality dimensions and then refined them by selecting the most representative ones from dimensions that overlapped in meaning. Consistent with earlier research (Elayat & Elalfy, 2025), these dimensions were organized into four categories: functional process quality, emotional process quality, outcome quality, and environment quality. Within this classification, *ability to understand* and *synchronicity* were assigned to functional process quality, *perceived humanness* was categorized as emotional process quality, and *problem resolution* was identified as an outcome quality dimension (Li et al., 2021). The ability to understand captures users' belief that a chatbot can interpret human dialogue, conversation context, and subtle linguistic cues (Li et al., 2021). Synchronicity reflects how closely the timing of a user's input aligns with the chatbot's response (Liu & Shrum, 2002). Perceived humanness relates to the extent to which a chatbot exhibits human-like attributes, such as emotions, intentions, or motivations (Q. Chen et al., 2022). Problem resolution refers to how effectively and efficiently chatbots help customers address issues they encounter during the online purchase process (Hsiao & Chen, 2022).

Customers' Trust as the Organism Variable

Trust is a crucial element in shaping how users perceive and adopt chatbot-based services (Nguyen et al., 2023). In interactions with AI-driven service agents, customers often rely on the quality of the chatbot's performance to determine whether the system is dependable and worth relying on. When chatbots provide clear communication, accurate information, and effective problem resolution, users are more likely to trust the chatbot and view it as a competent service provider (Guerrero Diaz, 2026). In contrast, poor service quality, such as slow replies, misunderstandings, or unresolved issues, can quickly weaken trust and reduce users' willingness to use chatbot assistance (Shahzad et al., 2024). Because many customers approach automated service technologies with uncertainty, the quality of service delivered during early interactions becomes a key factor influencing whether users feel confident in the chatbot (Shahzad et al., 2024). This study support the previous research stating that in high-contact service environments, trust influences the connection between the quality of chatbot interactions and customers' behavioural responses, such as their readiness to transition from human agents to automated services (Shahzad et al., 2024). Understanding how different dimensions of chatbot service quality shape trust is therefore essential for explaining user acceptance and continued use of chatbot-based service agents.

Response: Customers' Intention to Shift from Human Support to Chatbot Assistance

Prior studies on chatbot services have predominantly investigated the determinants affecting customers' adoption or their intention to reutilize chatbots (Kumar, 2025; Pillai & Sivathanu, 2020; Tran et al., 2021). This kind of research frequently neglects a significant reality: patrons typically have the option to engage with human agents or utilize chatbot services. The propensity to transition from human to chatbot services denotes a scenario where customer initially favour human support but subsequently choose for chatbot services under specific circumstances (S. Chen et al., 2025). This study used "willingness to switch" as the dependent variable, as it more precisely reflects the change in customer choice. Historically, customer support contacts were primarily managed by human personnel.

Chatbot services are becoming more popular, yet they still have some evident problems, such as not being able to adapt and not being very empathetic. On the other hand, human service agents offer several benefits that chatbots can't yet match, like tailored encounters, a stronger sense of similarity, and the capacity to make social relationships. Because of this, many people still prefer human services to help from chatbots. For this reason, it's crucial to look into what makes clients more likely to switch from human services to chatbot services.

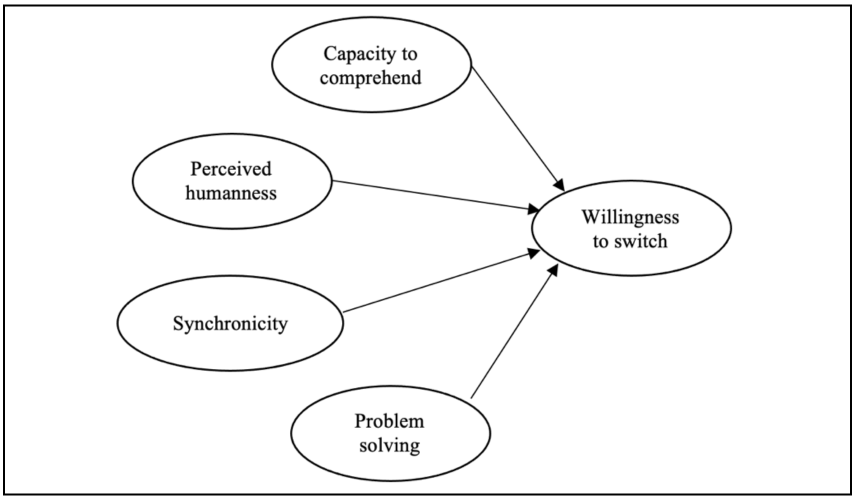
Hypothesis Development

A chatbot's ability to answer customers' questions correctly is what makes for a seamless service experience (Upadhyay & Kamble, 2024). To do this, the chatbot needs to be able to grasp what

customers are asking for. This skill is necessary for making meaningful connections and meeting client needs. People usually think that chatbots that can understand a lot are better at giving helpful and satisfactory answers (Pillai & Sivathanu, 2020). But for now, chatbots are still limited by the fact that they rely on pattern matching and pre-set responses. This makes it hard for them to completely understand requests that are sophisticated, personalized, or relevant to a certain situation. Because of this, chatbots could give stiff or unhelpful answers, which could lead to service failures that make customers less likely to use chatbot services. We suggest the following hypothesis based on this reasoning:
H1: The capacity of chatbots to comprehend consumer inquiries is positively correlated with customers' readiness to transition from human services to chatbot services.

Recently, more chatbots are being made to talk in ways that feel more human, with traits like warmth, empathy, friendliness, and a sense of connection (Xygkou et al., 2024). Customers are more inclined to trust chatbots and feel comfortable talking to them when they seem more human (Folk, 2025). This is mostly because people think that chatbots that look and act like people are better at doing the job of a service worker, which has a big impact on how customers rate the service (Janson, 2023). Because of this, clients might be more willing to use chatbot services instead of getting help from a person (Sfar et al., 2025). Based on this line of thought, we suggest the following hypothesis:
H2: The perceived humanness of chatbots positively correlates with customers' propensity to transition from human services to chatbot services.

Chatbots give clients real-time, automated answers to their questions, which helps them get information or fix problems faster when they make reservations for tourism services. Chatbot services are also available 24/7, which is great for consumers who require help outside of usual office hours. Because chatbots respond quickly and are easy to reach, clients may prefer them to human service workers, who often take longer to respond (Huang, 2026). Previous studies indicate that when confronted with a 15-minute delay for a response, most customers prefer chatbot services over human assistance (Wang & Lo, 2025). So, we suggest the following hypothesis:
H3: The synchronicity of chatbot services positively correlates with customers' propensity to transition from human services to chatbot services.



Gambar 1. Conceptual Framework

Chatbots are an alternative to human support workers (Pillai & Sivathanu, 2020). They use machine learning and natural language processing to help consumers solve problems through text or voice conversations (Tran et al., 2021). Most of the time, customers are focused on getting results. They want their problems answered fast and easily, and they are more likely to use chatbots when these tools can provide quick fixes. But even if people anticipate more from chatbots, they still mostly rely on pattern matching and pre-set answers. This works well for simple and normal requests, but it doesn't always work when consumers have complicated or unstructured difficulties (Greilich et al., 2025). In certain situations, chatbots may give answers that don't make sense or aren't helpful, which might make customers feel more annoyed than supported. Previous studies have shown how important it is to solve problems well in order to get customers to accept something (Adam et al., 2021). Online customers found that the most important factor in getting people to use a chatbot again was its capacity to substantially move a customer's issue forward. Based on this line of thought, we put forward the following hypothesis:
H4: The degree of problem resolution provided by chatbots is positively correlated with customers' propensity to transition from human services to chatbot services.

C. METHODS

This study utilized quantitative approaches using a non-probabilistic purposive sampling strategy, concentrating on Indonesian individuals with past experience in utilizing chatbot services for online purchasing. The research focused on chatbot interactions within hospitality and travel platforms, encompassing hotels, online travel agencies, and destination service providers, where chatbot utilization has become increasingly prevalent. To ensure the sample's relevance, the poll included a screening question to pinpoint respondents with prior experience in chatbot interaction. The screening question asked people to confirm that they have used both chatbot services and human service agents in a hospitality or travel service setting. Only those who met both requirements were allowed to move on to the next part of the survey. From August to December 2025, data were collected from 160 adults using Google form. 149 valid surveys were kept for the final analysis after deleting invalid responses. All of the persons who answered had used both human service agents and chatbots before, which is important. The participants were from three of Greater Jakarta's five administrative cities. The selection of these cities is based on Greater Jakarta's position as a primary center for hospitality consumption, business travel, and tourism services in Indonesia, characterized by high digital literacy, widespread use of online booking platforms, and common use of chatbot-based customer support. This area is a good place to look at how chatbots are used in the hotel business. Finally, We analysed the data using Structural Equation Modelling (SEM) method utilizing SmartPLS (Sarstedt et al., 2014).

In terms of questionnaire development, one author wrote the online survey in English, and then another author, who is also a native Indonesian speaker, looked it over. Before the big poll, a pilot test was done to make sure the questionnaire was as clear as possible and to eliminate any possible misunderstandings. The measurement used in the questionairre were adopted from a previous study. Chatbot service quality—comprehensibility, perceived humanness, synchronicity, and problem-solving ability—along with switching intention, were sourced from established scales developed by Chen et al., (2025), thereby ensuring content validity through prior empirical validation. People were asked to choose one of four options to show which service they liked best: chatbot service, human service, either, or neither. The second section of the poll questioned about essential things like how well individuals understood, how well they could talk to each other, how human they thought they were, how well they could solve problems, and how willing they were to move from chatbot services to human services. The last part asked participants about their age, gender, education level, income level, and where they live, as well as other things about themselves.

D. RESULTS

The final sample consisted of 149 respondents who had previous experience using chatbot services during online purchasing activities. Of these respondents, 55.7% were female and 44.3% were male. The largest age group was 21–30 years (61.1%), followed by 31–40 years (24.2%), and above 40 years (14.8%). In terms of educational background, 52.3% held a bachelor’s degree, 29.5% had completed postgraduate studies, and 18.1% held a high school diploma. Regarding monthly income, 39.6% reported earnings between IDR 5–10 million, 34.2% between IDR 10–15 million, and 26.2% above IDR 15 million. All respondents confirmed prior interaction with both chatbot and human customer service agents, ensuring appropriateness for the study context.

Measurement model

The measurement model was evaluated to assess the reliability and validity of the latent constructs prior to testing the structural model (Hair Jr et al., 2021). Following established guidelines for partial least squares structural equation modeling (PLS-SEM), the assessment focused on indicator reliability, internal consistency reliability, convergent validity, and discriminant validity (Hair Jr et al., 2021).

Indicator reliability was examined by evaluating the outer loadings of each measurement item on its corresponding construct. Items with standardized loadings exceeding the recommended threshold of 0.70 were considered acceptable, indicating that the indicators shared a substantial proportion of variance with their underlying constructs (Hair et al., 2025). Items with loadings slightly below this threshold were retained if their inclusion did not adversely affect composite reliability or convergent validity, ensuring adequate content validity of the constructs (Hair Jr et al., 2021). Furthermore, internal consistency reliability was assessed using Cronbach’s alpha and composite reliability (CR). While Cronbach’s alpha provides a conservative estimate of reliability, composite reliability is considered more appropriate for PLS-SEM as it does not assume equal indicator loadings (Hair Jr et al., 2014).

Table 1. Measurement model

	Loadings	AVE	CR	Cronbach
CO1	0,801	0,806	0,878	0,792
CO2	0,858			
CO3	0,861			
HUM1	0,968	0,89	0,961	0,935
HUM2	0,97			
PS1	0,789	0,842	0,87	0,815

PS2	0,786			
PS3	0,839			
PS4	0,789			
SWITCH1	0,845	0,824	0,83	0,82
SWITCH2	0,858			
SYNC1	0,874	0,812	0,861	0,898
SYNC2	0,812			

All constructs demonstrated reliability values exceeding the recommended cut-off of 0.70, indicating satisfactory internal consistency and suggesting that the measurement items consistently represent their respective latent variables (Sarstedt et al., 2014). Lastly, discriminant validity was assessed using both the Fornell–Larcker criterion and the heterotrait–monotrait ratio of correlations (HTMT). According to the Fornell–Larcker criterion, the square root of each construct’s AVE exceeded its correlations with other constructs, supporting discriminant validity. In addition, HTMT values were below the conservative threshold of 0.85, indicating that the constructs were empirically distinct from one another. Together, these results provide strong evidence of discriminant validity.

Table 1. above presents the results of the measurement model assessment, including indicator loadings, Average Variance Extracted (AVE), Composite Reliability (CR), and Cronbach’s alpha for each construct. All item loadings exceed the recommended threshold of 0.70, indicating sufficient indicator reliability. In terms of convergent validity, all constructs demonstrate AVE values above 0.50 (CO = 0.806, HUM = 0.890, PS = 0.842, SWITCH = 0.824, SYNC = 0.812), showing that the constructs explain more than half of the variance of their indicators. Furthermore, the CR values for all constructs range from 0.830 to 0.961, surpassing the 0.70 criterion and confirming internal consistency reliability. Cronbach’s alpha values, which range between 0.792 and 0.935, also exceed the acceptable 0.70 benchmark, reinforcing the reliability of the constructs. Overall, these results confirm that the measurement model demonstrates strong reliability and convergent validity.

Table 2. Fornell-Larcker Criterion

	Comprehend	Humanness	Prob-Solve	Switch intention	Synchronicity
Comprehend	0,856				
Humanness	0,728	0,969			
Prob-Solve	0,802	0,788	0,876		
Switch intention	0,817	0,776	0,802	0,851	
Synchronicity	0,813	0,615	0,761	0,789	0,844

Table 2 above presents the discriminant validity assessment using the Fornell–Larcker criterion. The square roots of the AVE values, shown on the diagonal, are consistently higher than the corresponding inter-construct correlations in the rows and columns. Specifically, Ability to Comprehend (0.856), Perceived Humanness (0.969), Problem Solving (0.876), Switch intention (0.851), and Synchronicity (0.844) all exceed their shared correlations with other constructs, indicating that each construct shares more variance with its own indicators than with other latent variables. These results confirm that discriminant validity is achieved and that the measurement model adequately distinguishes between the five constructs.

Table 3. Path analysis results

Relationship	Hypothesis	Sample Mean	Standard Deviation	T Statistics	P Values	Result
Comprehend -> Switch intention	H1	0,202	0,066	3,096	0,002	**Supported**
Humanness -> Switch intention	H2	0,222	0,043	5,14	0	**Supported**
Synchronicity -> Switch intention	H3	0,234	0,043	5,419	0	**Supported**
Prob-Solve -> Switch intention	H4	0,351	0,061	5,72	0	**Supported**

Table 4 summarizes the structural path analysis results for the proposed hypotheses. All four hypothesized relationships were found to be statistically significant. Chatbots ability to comprehend demonstrated a positive effect on Switch intention ($\beta = 0.202$, $t = 3.096$, $p = 0.002$), supporting H1. This finding highlights the imperative for hotel management and destination operators to invest in chatbots with advanced natural language comprehension capabilities. If chatbots do not comprehend what visitors want, they may make people more angry and make them rely more on human staff. Improving a chatbot's ability to understand can help avoid service delays, especially during busy times, while still meeting service quality standards in hospitality settings. Next, perceived humanness also showed a significant positive influence on Switch intention ($\beta = 0.222$, $t = 5.140$, $p < 0.001$), supporting H2. This finding indicates that hospitality chatbots should be designed to convey empathy, politeness, and conversational authenticity, rather than functioning merely as transactional tools.

For destination managers, chatbots that act like humans can make customers feel more comfortable and trust them more, making chatbots a good option for giving out information and fixing problems instead of having people on the front lines. Meanwhile, Chatbots Synchronicity exhibited a positive and significant impact on Switch intention ($\beta = 0.234$, $t = 5.419$, $p < 0.001$), in support of H3. This shows how important it is for hotel and tourism managers to build chatbots that can respond in real time. Guests often ask for quick information about reservations, amenities, or neighbouring activities in a tourism destination. Delays or inadequately timed responses can erode trust in chatbot services, whereas optimal synchrony fosters seamless service experiences and diminishes the apparent necessity for human involvement. Finally, Chatbots problem solving indicated the strongest positive effect among all predictors ($\beta = 0.351$, $t = 5.720$, $p < 0.001$), confirming H4. This finding suggests that the design of chatbots should prioritise problem-solving capabilities over basic informative functions. In the fields of hospitality and destination management, chatbots that can help with booking problems, handle complaints, or give useful replies can make things much easier for human staff while still keeping customers happy. Chatbots are better service agents than just extra tools when they can solve problems well. Since all p-values were below the 0.05 threshold and t-statistics exceeded the critical value of 1.96, the results collectively demonstrate that each variables in this research contributes significantly to customers' willingness to switch to chatbot-based services. Among the service quality dimensions, problem-solving ability exhibited the strongest effect on switching intention ($\beta = 0.351$, $p < 0.001$), indicating that customers are more likely to adopt chatbots when the system can resolve their inquiries efficiently. This result aligns with service quality literature emphasizing that customers prioritize outcome-related performance during online interactions, particularly when their goal is to obtain solutions or complete transactions quickly (Chen et al., 2023). In the context of hospitality services, where timely responses are critical, effective problem resolution reduces customers' perceived risk and increases their confidence in automated service tools. Perceived humanness also demonstrated a strong positive effect on switching intention ($\beta = 0.222$, $p < 0.001$). This suggests that users evaluate chatbots not only as technological tools but also as social actors capable of simulating human-like communication cues such as empathy, friendliness, or warmth. This finding supports recent work showing that anthropomorphic design features enhance trust, comfort, and perceived interaction quality, which in turn promote adoption of AI-driven service platforms (Janson, 2023; Sfar et al., 2025). Within hospitality settings, where emotional engagement and social presence are highly valued, humanness appears to compensate for the absence of a live human agent, making chatbot interactions feel more natural and less transactional. Additionally, in the hospitality sector, the perception of humanness is essential because this sector is predominantly about providing experiences that are pleasant, caring, and connected to other people, not just utilitarian efficiency. Unlike regular businesses, hospitality often includes emotional comfort, personalized care, and social interaction, all of which affect how happy and satisfied clients are overall. Guests are more likely to think that the encounter is in conformity with hospitality service standards when chatbots show human-like traits including empathy, conversational flow, and appropriate emotional responses. The fact that people think chatbots are human allows them to work not only as sources of information but also as service agents who make hospitality and travel experiences warmer and more meaningful.

Chatbots synchronicity was also found to be significant ($\beta = 0.234$, $p < 0.001$), reinforcing the idea that timely and responsive communication plays a crucial role in shaping customer preferences. Customers often turn to automated service channels to avoid delays associated with human-based support, especially during peak demand periods. The responsiveness advantage of chatbots (e.g., instant replies, 24/7 accessibility) creates a perceived efficiency gain that encourages switching behavior. This result supports stimulus–organism–response (SOR) research showing that environmental cues like promptness trigger positive internal responses related to satisfaction and perceived convenience, ultimately influencing behavioral outcomes (Elayat & Elalfy, 2025).

Lastly, chatbots comprehension ability had a weaker but still significant effect on switching intention ($\beta = 0.202$, $p = 0.002$). This suggests that while users expect chatbots to understand inputs accurately, comprehension alone may not be sufficient to encourage switching unless paired with other qualities such as effective problem resolution and natural communication. When chatbots fail to grasp context or intent, customers experience breakdowns that lead to escalation to human support. Therefore, although comprehension contributes to adoption, it appears to act more as a foundational functional requirement rather than a primary driver of switching behaviour. This results support previous studies in chatbots switching intention (Huang, 2026).

D. CONCLUSION, LIMITATIONS, FUTURE RESEARCH

This study shows that chatbot service quality significantly influences customers' willingness to switch from human agents to chatbots in the hospitality sector. Among the dimensions tested, problem-solving ability had the strongest effect, followed by synchronicity, humanness, and comprehension. These results indicate that customers value efficient resolution, quick responses, and human-like interaction when engaging with chatbot services.The study is limited by its cross-sectional design, self-reported data, and focus on experienced users within the hospitality context, which may restrict generalizability. Future research could examine other industries, use longitudinal or experimental designs, and explore moderating factors (e.g., user characteristics, cultural context) to deepen understanding of switching behaviour toward chatbot services.

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