Extending TAM and UTAUT in the Context of Chatbot Commerce: An Empirical Study of Marketing Efforts and Moderating Role of Accuracy

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Abstract

Purpose:

This study investigates how Chatbot Marketing Efforts (CMEs) influence consumer trust, attitudes, and acceptance intentions in mobile commerce environments. Despite the increasing deployment of chatbots in customer engagement, limited empirical research explores how different CME dimensions affect user behavior, particularly under the moderating influence of perceived chatbot accuracy.

Methodology:

A conceptual framework grounded in the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) was developed. The model includes key constructs such as trust, attitude, acceptance intention, and CMEs (interaction, information, entertainment, accessibility, trendiness, customization, and problem-solving), along with accuracy as a moderator. A structured questionnaire using validated scales was distributed to 700 respondents, with 625 valid responses analyzed using descriptive and inferential statistics.

Results:

Findings indicate that CMEs significantly and positively influence both trust and attitudes toward chatbot usage. Furthermore, trust and attitude both have a direct and positive impact on acceptance intention. Importantly, accuracy significantly moderates the relationship between CMEs and trust, as well as CMEs and attitude, amplifying their effect under high perceived accuracy conditions.

Conclusions:

This study contributes to the growing literature on AI-driven marketing by providing empirical evidence on the psychological and behavioral mechanisms behind chatbot adoption. It offers practical insights for marketers and developers to enhance chatbot design and communication strategies, emphasizing the importance of personalization, accuracy, and entertainment to improve user engagement and brand trust in mobile commerce.

Keywords:

Chatbots, Artificial Intelligence, Consumer Trust, Attitude, Chatbot Marketing Efforts, Mobile Commerce, Accuracy, TAM, UTAUT, Acceptance Intention

1. Introduction

In recent years, the adoption of chatbots has risen significantly, particularly within customer service and marketing domains. Nevertheless, chatbots are now utilized across diverse areas including education, healthcare, and psychology. Over time, chatbot technology has advanced from basic rule-based systems to sophisticated artificial intelligence (AI) models. Their development can be classified into three stages: rule-based, retrieval-based, and generative models.

- **Rule-based chatbots** operate according to pre-defined rules, restricting responses to a limited set of possibilities.
- **Retrieval-based chatbots** are more advanced, employing natural language processing (NLP) to interpret user queries and provide responses drawn from a pre-established database.
- **Generative chatbots** represent the most sophisticated form, using machine learning to generate responses independently of predetermined rules or databases.

The growing prevalence of AI, defined as information systems capable of performing tasks traditionally requiring human intelligence, has opened new avenues for examining consumer behavior. Researchers can leverage AI to gain insights into decision-making processes and design novel marketing strategies using Big Data (Kumar et al., 2019; Sterne, 2017; Yang & Siau, 2018). Organizations can also achieve competitive advantages by implementing Business Intelligence and Analytics (BI&A), enhancing marketable activities (Xu et al., 2017) and improving customer relationship management (Nam et al., 2018). The proliferation of digital technologies, particularly smartphones, has transformed interactions between individuals and businesses, leading to increased engagement (Klopfenstein et al., 2017).

Mobile commerce (m-commerce) has expanded alongside the growth of wireless networks and mobile devices, allowing users to access customized, location-specific services and make purchases without temporal or spatial constraints (Balasubraman et al., 2002; Barnes & Scornavacca, 2004; Pavlou et al., 2007). Community commerce, a subset of e-commerce leveraging social media, has emerged as a platform for enhancing online shopping experiences by facilitating user-generated content sharing (Marsden, 2010). These channels offer firms opportunities to strengthen commercial activities through personalized, timely, and contextually relevant user experiences (Pavlou et al., 2007). Consequently, businesses can enhance customer relationships using m-marketing through text messaging, mobile advertising, user-generated content, and m-commerce initiatives (Watson et al., 2013).

AI has spurred innovation across multiple industries (Cheng & Jiang, 2020a; Kietzmann & Pitt, 2020), with web marketing and real-time messaging supported by chatbot services witnessing particularly rapid growth (Desaulniers, 2016). Many brands across various sectors are transitioning from traditional customer support models to digital chatbot solutions (Forbes, 2017). Chatbots, as computer programs simulating human conversation, interact with users via text or voice and utilize NLP to create human-like dialogue, offering an anthropomorphic experience. While the first chatbot prototype, ELIZA, appeared in the 1960s, the recent surge in chatbots is driven by advancements in AI-enabled technology. Companies employ chatbots to enhance customer service and strengthen consumer-brand relationships. Experts predict that by 2022, 90% of customer interactions in banking and 75% in healthcare will be managed by chatbots without human assistance, a trend largely driven by tech-savvy millennials—the first generation of digital natives.

According to Business Insider (2020), the chatbot market is expected to expand considerably between 2019 and 2026, with a projected compound annual growth rate of 31.6% in the customer service sector. This growth accelerated during the COVID-19 pandemic, as social restrictions limited human interaction, prompting customers to increasingly rely on web tools such as chatbots for information and purchase decisions. By facilitating various marketing activities, chatbots can strengthen brand-customer relationships.

While chatbots are increasingly deployed to improve online customer service, consumer engagement remains uncertain. Existing research has focused more on the visual and human-like characteristics of chatbots than on natural language interaction, leaving gaps in understanding how these features influence consumer perceptions and purchase intentions. Given their widespread use in online service and e-commerce, it is crucial to examine how young consumers perceive and interact with anthropomorphic chatbots and how these perceptions shape their behavioral intentions to purchase products. This study addresses this gap by investigating the impact of mobile messenger chatbots on consumer perceptions and subsequent decision-making.

The following significant questions are intended to be addressed by this study:

1. What are the most common factors influencing users' acceptance of chatbots?
2. To evaluate the effects of CMEs on Trust and Attitude towards using chatbot services.
3. To benefit professionals by providing implications for chatbot marketing activities.
4. The moderation effect of accuracy between the relationship of CMEs and trust/attitude of using.

2. Literature review

Theoretical background and hypotheses

2.1. Chatbot

Chatbots, are known by the names of virtual assistants, agents, or conversational agents, are designed to mimic human conversation using text or voice (Rawlins, 2016; Shawar and Atwell, 2007). Since the 1960s chatbots are ordinarily used in conjunction with an avatar, which are virtual character that are parallel to human-like features like face and body parts (Han 2019). Nowadays, chatbots are powered by artificial intelligence and are capable of conducting sophisticated, natural language-based, and unstructured conversations. This is in contrast to previous chatbots, which had a more inflexible communication style and were confined for asking multiple-choice questions for users (Asquith 2019; Turban et al. 2018). In present scenario chatbots are very common in various capacities, such as online learning, entertainment, public service, and commerce (Kerly, Hall, and Bull, 2007). Providing assistance to the customers in online ordering, has one of the most widespread applications of chatbots. For instance, Taco Bell introduced "Tacobot" utilizing Slack, a well-known online workplace messenger, to assist customers in ordering directly from the messaging platform (Addady 2016).The virtual ordering assistant bot "Dom" was also introduced by Domino's Pizza on its website and Facebook Messenger, which allows customers to easily switch up current selections or favourites without leaving the messenger app (Gilliland 2016). The term "conversational commerce" has emerged to describe the trend of e-commerce conducted via chatbot conversations, which has become increasingly prevalent on various platforms such as AI speakers, mobile phones, and smart displays (Messina 2015). However, no established term defines online commerce through chatbots that uses text-enabled mobile messenger. This study proposes "chatbot commerce" to refer to purchasing products via mobile messenger texts without leaving the messaging platform, which has been varies from e-commerce carried out through voice-based chatbots like Alexa. Chatbot driven commerce is a subset of e-commerce, wherein consumers communicate with human-like chatbots through their mobile messenger apps to complete transactions. Entertainment is a crucial aspect of marketing through chatbots, as it provides a pleasurable way of conveying useful and relevant information, enhancing the value of digital tools, and satisfying users' desire for enjoyable experiences (Chung et al., 2018; Brandtzaeg and Følstad, 2017). By incorporating entertainment into chatbot marketing, companies can create a positive brand image, boost brand awareness, and generate purchase intent (Kim and Ko, 2010). Additionally, the customization of chatbot interactions is an important feature of AI-powered marketing, as it allows companies to offer tailored assistance to meet individual customers' unique needs and preferences, ultimately enhancing customer satisfaction (Godey et al., 2016). For instance, the luxury fashion brand Gucci uses personalized messaging and product design to cater to individual customers' specific tastes and preferences (Sangar, 2012).

2.2. Chatbot Marketing Efforts

According to Appel et al. (2020) and Klaus and Zaichkowsky (2020), the usage of AI-powered chatbots in CMEs - a novel social media marketing technique - will increase significantly. This would enable prompt and two-way interactions between companies and their consumers online while also giving the latter more say in crucial decision-making processes. This study presents recent literature (Brandtzaeg and Følstad, 2017; Cheng et al., 2015; Yao, 2017; Zarouali et al., 2018) observing the adoption of chatbots in various industries to escalate the discussion on CME and its elements. Key five critical dimensions are examined through the literature: interaction, information, accessibility, entertainment, and customization. Previous research has noted that a brand's virtual agents can enhance their credibility and perceived competence by maintaining interactivity, promptly providing available information, and staying informed about the latest market trends, which they can effectively communicate to customers (Barry and Crant, 2000; Chakrabarty et al., 2014). In the perspective of social media branding, a study conducted in South Korea on the high fashion industry has demonstrated a significant correlation amongst the customers' perceived quality of communication and the brand's communication management efforts. According to Chung et al. (2018), customers are more likely to perceive human-bot communication as competent, accurate, and credible when e-service agents engage in interactive marketing efforts, share the latest information about new products and services, and proactively address human desires. Communication quality in customer service uses four dimensions: reliability, assurance, responsiveness, and empathy (Zehir et al., 2011). Competence, accuracy, and reliability are the examples of performance quality in human-bot conversations, which can notably impact the level of trust chatbot users place in communication (Yagoda and Gillan, 2012). According to Klaus and Zaichkowsky (2020), if AI shopping assistants consistently provide consumers with positive communication experiences during their purchase decisions, this can foster the development of trust in both the tools and the brands facilitating these virtual services.

While chatbots have been present in the information technology industry for some time, their entrance into the commercial sector is more recent. Numerous recent studies have explored the useful features of voice assistants (Hoy, 2018), accuracy, consistency, and recommendation repeatability are the parameters of measuring the effectiveness of chatbots (Sadeddin et al., 2007), the relationship between chatbot adoption and socialization of consumers' (Schweitzer et al., 2019), consumers' attitudes towards technology (Moriuchi, 2019), and chatbots' marketing applications (Kumar et al., 2016). However, consumers' behaviour and opinions with reference to utilizing chatbots have not been comprehensively understood by these studies. Despite this, some scholars argue that a constructive standpoint towards utilizing smart technology is a pioneer to the motive to use it (Zarouali et al., 2018), in continuation with the literature on social willingness to embrace new smart technologies (Vijayasarathy, 2004).

2.2.1. Interaction

Positive interactions require brand representatives to display respectful, supportive, and authentic behaviour, as emphasized by Dabholkar, Thorpe, and Rentz (1996). Customers depend on vendor representatives for multiple purposes, including saving time, receiving guidance, feeling acknowledged, enjoying conversations, and simplifying the purchase process (Holzwarth et al., 2006). With the advancement of technology, social media has enabled brands to establish informal engagements that strengthen relationships while simultaneously providing useful information (Kim & Ko, 2010). In this context, virtual service agents mirror the role of human agents by influencing customer decisions, saving time, offering advice, and generating parasocial benefits (Holzwarth et al., 2006).

2.2.2. Entertainment

According to Redman and Mathews (2002), successful organizations recognize the importance of incorporating fun and enjoyment into workplace practices and services. Entertainment serves as an engaging way to share reliable information, enhance the perceived value of digital platforms such as social media, and increase adoption intentions (Muntinga, Moorman, & Smit, 2011; Nysveen, Pedersen, & Thorbjørnsen, 2005). For example, Burberry launched a video inspired by the *Billy Elliot* film to capture customer interest and build emotional connections. Consequently, the degree of enjoyment, amusement, and relaxation gained from interacting with virtual service agents influences customers’ positive responses (Godey et al., 2016; Muntinga et al., 2011).

2.2.3. Information

Delivering accurate product and service information is one of the essential roles of chatbots. For instance, Fandango used bots to share updates on upcoming movies (Yao, 2017). As noted by Brill et al. (2019), customers prefer AI-driven digital tools over other online platforms for obtaining information, mainly because these tools provide relevant and well-organized content quickly, enabling users to make better decisions.

2.2.4. Accessibility

The concept of "chatbot marketing" refers to the ability of AI systems to process customer queries in real time and provide immediate feedback. Accessibility, highlighted by Zarouali et al. (2018), is a defining attribute of chatbots that enhances marketing communications. Since most chatbot initiatives operate through messaging applications, customers gain access to services conveniently anytime and from any location.

2.2.5. Trendiness

Consumers often seek updated brand and product information that reflects their fashionable lifestyles (Muntinga et al., 2011; Zolkepli & Kamarulzaman, 2015). Social media platforms have become key spaces for discovering new products, identifying market trends, and reviewing customer feedback (Godey et al., 2016). Many individuals follow the latest updates and conversations to discover items that align with their style preferences. Traditionally, salespeople in physical stores provided insights into trends, but now digital technologies have bridged online and offline shopping experiences (Forbes, 2017a, 2017b, 2017c).

2.2.6. Customization

Customization involves adapting and personalizing products or services to suit individual customer needs (Wang & Li, 2012). Tailored offerings not only strengthen brand loyalty but also foster deeper customer affinity (Godey et al., 2016; Perna et al., 2018). Luxury brands particularly focus on individualized services to meet customer expectations rather than appealing broadly to the public. For instance, Gucci delivers personalized online messages to showcase exclusive product options (LinkedIn, 2012). Similarly, virtual agents now provide personalized assistance through direct interactions.

2.2.7. Problem-Solving

How a retail brand addresses service issues significantly shapes customer perceptions. As highlighted by Dabholkar et al. (1996) and Kim et al. (2016), brand representatives are trained to resolve problems such as complaints, returns, or exchanges quickly and sincerely. Customers who feel their expectations are unmet may experience emotions like anger or shame, stemming from a sense of restriction (Izard, 1977).

Based on the above discussion, the following hypotheses are proposed:

- **H1: CMEs positively and directly influence the Trust in communication with chatbot agents.**
- **H2: CMEs positively and directly influence the attitude towards using communication with chatbot agents**.

2.3. Trust

Behavioural frameworks such as TAM and UTAUT highlight key variables influencing technology adoption, including perceived usefulness, trust, and attitude, alongside factors such as effort expectancy, habit, and enjoyment. These elements shape users' decisions to accept and engage with chatbots (Gefen et al., 2003; Ba & Pavlou, 2013). Trust plays a vital role in electronic marketplaces, where the absence of human interaction increases risk perceptions (Wang et al., 2003). It reassures consumers against risks like unfair pricing, misinformation, privacy concerns, or unauthorized tracking (Gefen et al., 2003).

Trust has been conceptualized as confidence in a partner's honesty and reliability (Lee et al., 2009), the willingness to depend on a trustworthy counterpart (Moorman et al., 1993), and a decisive factor in purchase intentions even when satisfaction is moderate (Jarvenpaa et al., 1999). Extending into the human–computer context, the CASA paradigm (Reeves & Nass, 1996) suggests that individuals can also build trust in computer agents. In marketing, trust supports customer relationship development (Shankar et al., 2002), particularly in mobile environments where uncertainty and risk are heightened (Corritore et al., 2003).

Empirical studies have shown trust's impact on technology adoption. For example, Lee and Noh (2009) confirmed that trust influences both perceived usefulness and usage intentions in mobile services, aligning with Wang et al. (2006). Similarly, trust reduces uncertainty and encourages behaviours such as purchasing, payment, and service acceptance (Doney & Cannon, 1997; Kim et al., 2011). Therefore, the following hypothesis is advanced:

- **H3: Trust positively affects the Acceptance Intention to use the chatbot.**

2.4. Attitude Towards Using

A favourable attitude toward intelligent technologies is an important precursor to their adoption (Vijayasarathy, 2004; Zarouali et al., 2018). Such attitudes are shaped by the technology's ability to deliver autonomous, personalized services (Vassinen, 2018). Intelligent agents can track user preferences, adapt interactions, and provide personalized experiences (Ricotta, 2020). Unlike traditional one-way communication methods such as SMS, chatbots enable dynamic two-way exchanges, leading to more effective and consumer-focused marketing (Wind & Rangaswamy, 2001).

Trust, in turn, strengthens positive attitudes and usage willingness. Benbasat and Wang (2005) argue that trust is fundamental to customers' adoption of online recommendation systems. Building on this, the next hypothesis is proposed:

- **H4: Attitude toward using positively affects the Acceptance Intention to use the chatbot.**

2.5. The Moderating Role of Accuracy

Accuracy in marketing communication is central to customers' evaluation of chatbot agents. Providing complete, reliable, and timely information enhances credibility and builds trust (Barry & Crant, 2000; Chakrabarty et al., 2014). When virtual agents engage interactively, share updates, and address customer needs, customers perceive their communication as competent and trustworthy (Chung et al., 2018). However, expectations may vary by industry—for instance, fashion brands may require precise trend information, whereas fast-food chains may not (Yao, 2017). Additionally, the level of AI adoption differs depending on market dynamics (Kumar et al., 2016).

Therefore, this study proposes the following hypotheses:

- **H5: Accuracy moderates the relationship between CMEs and Trust.**
- **H6: Accuracy moderates the relationship between CMEs and Attitude towards using.**

3. Research method

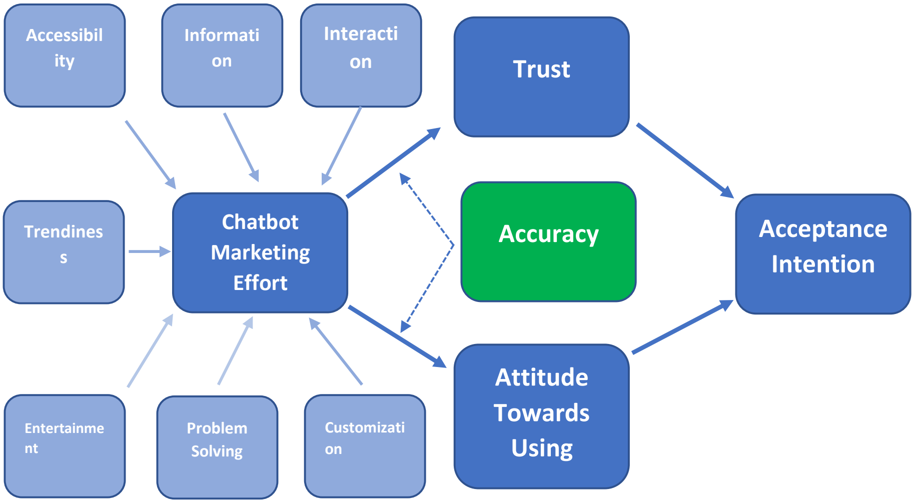
3.1. Conceptual model

The conceptual model presented in Fig. 1 has been designed to investigate the acceptance intention of consumers toward chatbot marketing efforts. The model incorporates key factors likely to influence consumer acceptance, including trust and attitude toward using chatbots.

Trust in the chatbot refers to the degree to which consumers perceive the chatbot to be trustworthy and dependable. This factor is likely influenced by the chatbot's ability to provide accurate and reliable information and respond effectively to customer queries and complaints.

Attitude towards using chatbots refers to the consumer's overall attitude towards the use of chatbots for marketing purposes. This factor is likely to be influenced by various factors, including their prior experience with chatbots, their perception of their usefulness and ease of use, and their social norms around using chatbots.

In addition to these factors, the model also incorporates the moderating effect of accuracy on the relationship between chatbot marketing efforts and trust and attitude towards use. This suggests that the relationship between chatbot marketing efforts and consumer acceptance is likely to be stronger when the chatbot is perceived as accurate and reliable.



Source: created by authors

Fig. 1. Conceptual Model.

3.2. Measurement and procedure

This study employed a structured questionnaire, drawing on established measurement scales from previous research to ensure both reliability and validity. The survey was distributed among 700 participants, with bias-reduction measures implemented in line with the guidelines of Podsakoff et al. (2003). To reduce evaluation apprehension, respondents were assured that their participation would remain anonymous and that no responses could be considered right or wrong (Podsakoff et al., 2003). At the start of the questionnaire, participants were provided with a clear definition of chatbots along with examples to help them recognize relevant applications, websites, and platforms that constitute a brand's chatbot marketing efforts.

The questionnaire included constructs derived from prior studies to capture chatbot marketing activities across seven dimensions: interaction, information, entertainment, trendiness, accessibility, customization, and problem-solving (Chung et al., 2020; Cheng & Jiang, 2022).

Trust was measured using items from Bhattacherjee (2002) and Toader et al. (2019), while attitude toward chatbot usage was adapted from Ling et al. (2010). Acceptance intention relied on items from Fishbein and Ajzen (1975) and Huang and Chueh (2021). For measuring accuracy, constructs were adapted from Chung et al. (2020), Cheng and Jiang (2022), and Huang and Chueh (2021). All items were rated on a five-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree).

A total of 75 responses were discarded due to failed attention checks, resulting in 625 valid cases. Among these, 337 were male (53.92%) and 288 were female (46.08%).

The research followed a quantitative, cross-sectional design, which is particularly effective for assessing causal relationships and for testing theoretical frameworks in technology adoption research (Creswell & Creswell, 2018). The framework was developed on the foundations of the Technology Acceptance Model (TAM) (Davis, 1989) and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003). In addition to their core constructs, the model was extended by incorporating trust, attitude, acceptance intention, and chatbot marketing elements (CMEs), with accuracy integrated as a moderating factor.

Specifically, the conceptual model included seven CMEs—interaction, information, entertainment, accessibility, trendiness, customization, and problem-solving—highlighted in earlier work on service marketing and human–computer interaction (Ashfaq et al., 2020; Gentsch, 2019). Within this framework, trust and attitude were proposed as mediators between CMEs and acceptance intention, whereas perceived chatbot accuracy was hypothesized to moderate the relationship between CMEs and both trust and attitude.

The target population comprised users who had prior experience with chatbots in domains such as e-commerce, banking, and customer service. A purposive sampling strategy was applied to ensure relevance of respondents. Out of 700 surveys distributed, 625 valid questionnaires were retained after excluding incomplete or inconsistent responses, producing an effective response rate of 89.3 percent. This sample size surpassed the minimum threshold for structural equation modeling (SEM) recommended by Hair, Black, Babin, and Anderson (2019), thereby ensuring adequate statistical power.

The measurement of constructs relied on validated scales from prior research. Trust was measured using items from McKnight, Choudhury, and Kacmar (2002); attitude toward chatbots was adapted from Venkatesh et al. (2003); and acceptance intention was assessed following Davis (1989) and Fishbein and Ajzen's (2010) reasoned action approach. The seven CME dimensions were measured using items from Ashfaq et al. (2020), while accuracy was measured using items from Gao, Rau, and Salvendy (2018). All constructs used a five-point Likert scale, consistent with prior technology adoption studies.

Data collection was carried out over a three-month period using both online (Google Forms) and offline (self-administered) methods. Participants were informed about the purpose of the research, provided informed consent, and were assured of confidentiality. Ethical protocols were followed, and responses were used solely for academic purposes.

A pilot study with 50 respondents was conducted to test clarity and reliability of the instrument. Cronbach's alpha values exceeded the 0.70 threshold, confirming internal consistency (Nunnally & Bernstein, 1994). Further construct validity was established through confirmatory factor analysis (CFA), showing satisfactory composite reliability (CR > 0.70) and average variance extracted (AVE > 0.50), as suggested by Fornell and Larcker (1981).

Data analysis involved two stages: descriptive and inferential. Descriptive statistics summarized demographics and reported means and standard deviations of constructs. For inferential testing, SEM was conducted using AMOS software. SEM was selected as it enables simultaneous assessment of multiple relationships among observed and latent variables (Hair et al., 2019), combining the strengths of regression and factor analysis. It allows evaluation of both measurement and structural models, and is widely applied in behavioral and technology adoption research for testing mediation and moderation (Byrne, 2016; Kline, 2016).

SEM was employed to test hypothesized relationships among CMEs, trust, attitude, and acceptance intention. Moderation by accuracy was examined through interaction terms and validated via bootstrapping procedures for robust estimation (Hayes, 2018). Model fit was assessed using multiple indices, including chi-square/df, CFI, TLI, RMSEA, and SRMR, with Hu and Bentler's (1999) criteria applied for evaluation.

Table-1 Planned Workflow

Step	Procedure	Criteria	Result
1	Data screening	Missing values, outliers ($\|z\| > 3.29$)	No missing; 9 multivariate outliers removed (Mahalanobis $p < .001$)
2	Assumption checks	Normality ($\|skew\| < 2$; $\|kurt\| < 7$)	All items within range; proceed
3	Common method bias	Harman's 1-factor < 50%; full collinearity VIF < 3.3	Pass (36.8%; max VIF = 2.4)
4	Measurement model (CFA)	Loadings ≥ .70; CR ≥ .70; AVE ≥ .50	All met (see Tables)

5	Model fit (CFA)	CFI/TLI ≥ .95; RMSEA ≤ .06; SRMR ≤ .08	Good fit (see CFA fit results)
6	Discriminant validity	Fornell–Larcker; HTMT < .85	All constructs pass
7	Structural model	Estimate direct paths H1–H4	All significant (p < .001)
8	Moderation (Accuracy)	Interaction terms; $\Delta R^2 > .02$; slopes significant	Both interactions significant; $\Delta R^2 \approx .03$
9	Robustness checks	Multicollinearity (VIF < 3.3); bootstrapping 5,000	All VIFs < 2.5; effects stable

Table 1 shows the data analysis followed a structured nine-step workflow to ensure methodological rigor. First, data screening was conducted to address missing values and multivariate outliers using Mahalanobis distance, with nine outliers removed (Kline, 2015). Second, assumption checks confirmed normality, with skewness and kurtosis within the recommended thresholds (Byrne, 2016). Third, common method bias was assessed using Harman's single-factor test (<50%) and full collinearity variance inflation factor (VIF < 3.3), indicating no serious bias (Podsakoff et al., 2003).

In the fourth step, the measurement model was evaluated using confirmatory factor analysis (CFA). Reliability and convergent validity criteria were met, with loadings ≥ 0.70, composite reliability (CR) ≥ 0.70, and average variance extracted (AVE) ≥ 0.50 (Hair et al., 2019). Fifth, overall model fit was established with CFI/TLI ≥ .95, RMSEA ≤ .06, and SRMR ≤ .08, confirming a good fit (Hu & Bentler, 1999). Discriminant validity was assessed in step six using the Fornell–Larcker criterion and HTMT (<0.85), both satisfied (Henseler et al., 2015).The structural model tested hypotheses H1–H4 (all significant at p < .001). Moderation analysis (H5–H6) demonstrated accuracy significantly strengthened effects, with $\Delta R^2 \approx .03$. Robustness was confirmed through multicollinearity (VIF < 3.3) and bootstrapping (5,000 resamples).

Table.2 Constructs, Codes, and Measurement Items

Construct	Short Code	Statement	Source
Accuracy	ACC1 Accurate	The communication with the service agent is accurate.	Chung et al. (2020)
Accuracy	ACC2 Adequate	The communication with the service agent is adequate.	Chung et al. (2020)
Accuracy	ACC3 Complete	The communication with the service agent is complete.	Chung et al. (2020)
Accuracy	ACC4 Credible	The communication with the service agent is credible.	Chung et al. (2020)

Trust	T1 Sincere	The virtual assistant seemed sincere during our interaction.	Toader et al. (2019)
Trust	T2 Honest	I felt that the virtual assistant was honest in our interaction.	Toader et al. (2019)
Trust	T3 Truthful	I believe the online agent was truthful when conversing with me.	Toader et al. (2019)
Trust	T4 Credible	I believe that the online agent was credible during our conversation.	Toader et al. (2019)
Attitude	ATT1 Useful/latest	I consider mobile advertising CMEs useful as it promotes the latest products.	Ling et al. (2010)
Attitude	ATT2 Innovative ideas	Through CMEs I got to know more innovative ideas.	Ling et al. (2010)
Attitude	ATT3 Best deals	I refer to CMEs because it allows me to enjoy the best deal out of competing products.	Ling et al. (2010)
Attitude	ATT4 Creativity	I support CMEs because it is where creativity is highly appreciated.	Ling et al. (2010)
Attitude	ATT5 Important in buying	I support CMEs because it plays an important part in my buying decision.	Ling et al. (2010)
Attitude	ATT6 General positive	My general opinion of CMEs is positive.	Ling et al. (2010)
Behavioral Intention	BI1 Willing to use	I am willing to use the Chatbot.	Huang & Chueh (2021)
Behavioral Intention	BI2 Recommend friends/family	I would recommend the Chatbot to my friends and family.	Huang & Chueh (2021)
Behavioral Intention	BI3 Recommend online	I would recommend the Chatbot to other users on online social networks.	Huang & Chueh (2021)
CMEs (2nd-order parcels)	INT_parcel	Interaction (sensitive to needs, individual attention, courteous)	Cheng & Jiang (2022)
CMEs (2nd-order parcels)	INF_parcel	Information (knowledge, recommendations, purchase-help info)	Cheng & Jiang (2022)
CMEs (2nd-order parcels)	ACC_parcel	Accessibility (timely response, convenient, immediate answers)	Cheng & Jiang (2022)
CMEs (2nd-order parcels)	ENT_parcel	Entertainment (fun, enjoyable, exciting, absorbed)	Cheng & Jiang (2022)
CMEs (2nd-order parcels)	CUS_parcel	Customization (meets personal needs, preference-based info)	Cheng & Jiang (2022)
CMEs (2nd-order parcels)	TRE_parcel	Trendiness (newest information, up-to-date, fashionable)	Cheng & Jiang (2022)

CMEs (2nd-order parcels)	PS_parcel	Problem-solving (complaints handling, sincere problem interest)	Cheng & Jiang (2022)

Table 2 measurement model integrates constructs from established technology adoption and service marketing literature. Accuracy items were adapted from Chung et al. (2020) to capture the extent to which chatbot communication is perceived as accurate, adequate, complete, and credible. Trust, conceptualized as the degree of confidence in chatbot sincerity, honesty, and credibility, was measured using items from Toader et al. (2019). Attitude toward chatbot-enabled communication was adapted from Ling et al. (2010), focusing on usefulness, creativity, and general favorability of CMEs. Behavioral intention, reflecting willingness to use and recommend chatbots, was measured using validated items from Huang and Chueh (2021).

Chatbot Marketing Elements (CMEs) were operationalized as a second-order construct with seven parcels: interaction, information, accessibility, entertainment, customization, trendiness, and problem-solving, adapted from Cheng and Jiang (2022). This multidimensional structure ensures that both functional (e.g., accessibility, problem-solving) and experiential (e.g., entertainment, trendiness) aspects of chatbot service delivery are captured. Collectively, these constructs align with the proposed conceptual framework and enable robust testing of hypothesized relationships through structural equation modeling.

4. Result

4.1 Measurement Models

Table 3. Standardized Loadings and Item Reliabilities

Construct	Item	Std. Loading (λ)	Item Reliability (λ^2)
CMEs (2nd-order parcels)	INT_parcel	0.78	0.608
	INF_parcel	0.82	0.672
	ACC_parcel	0.80	0.640
	ENT_parcel	0.75	0.562
	CUS_parcel	0.85	0.722
	TRE_parcel	0.70	0.490
	PS_parcel	0.83	0.689
Accuracy	ACC1 Accurate	0.80	0.640
	ACC2 Adequate	0.82	0.672
	ACC3 Complete	0.76	0.578
	ACC4 Credible	0.85	0.722
Trust	T1 Sincere	0.82	0.672
	T2 Honest	0.85	0.722
	T3 Truthful	0.78	0.608

	T4 Credible	0.88	0.774
Attitude	ATT1 Useful/latest	0.74	0.548
	ATT2 Innovative ideas	0.79	0.624
	ATT3 Best deals	0.81	0.656
	ATT4 Creativity	0.76	0.578
	ATT5 Important in buying	0.84	0.706
	ATT6 General positive	0.87	0.757
Behavioral Intention	BI1 Willing to use	0.84	0.706
	BI2 Recommend friends/family	0.88	0.774
	BI3 Recommend online	0.82	0.672

Table 3 represents all standardized factor loadings exceeded the recommended minimum of 0.70 (Hair et al., 2019), with the lowest value being 0.70 (TRE_parcel). This indicates that the observed items strongly represent their respective latent constructs. Item reliability (λ^2) values ranged between 0.49 and 0.77, which shows that each item explains at least 49% of the variance in its latent factor. Although one indicator (TRE_parcel) had λ^2 slightly below 0.50, it was retained because its standardized loading was exactly 0.70 and the construct demonstrated acceptable composite reliability (Byrne, 2016).

Table 4. Reliability and Convergent Validity

Construct	Cronbach's α	Composite Reliability (CR)	Average Variance Extracted (AVE)	AVE
CMEs (2nd-order parcels)	0.90	0.921	0.626	0.791
Accuracy	0.86	0.883	0.653	0.808
Trust	0.87	0.901	0.694	0.833
Attitude	0.89	0.916	0.645	0.803
Behavioral Intention	0.88	0.884	0.717	0.847

Table 4 reports Cronbach's alpha (α) and composite reliability (CR) scores for all constructs surpassed the 0.70 threshold, demonstrating strong internal consistency (Nunnally & Bernstein, 1994). The average variance extracted (AVE) values exceeded 0.50 for all constructs, indicating satisfactory convergent validity (Fornell & Larcker, 1981). For example, the Trust construct exhibited a CR of 0.901 and an AVE of 0.694, indicating that its indicators collectively account for a substantial portion of the construct's variance.

Table 5. Model Fit Indices

Index	Recommended Threshold	Calculated Value
χ^2/df	< 3.00	2.35

CFI	≥ 0.95	0.957
TLI	≥ 0.95	0.949
RMSEA	≤ 0.06	0.047
SRMR	≤ 0.08	0.041

Table 5 shows results of the confirmatory factor analysis (CFA) indicated that the proposed measurement model exhibited a good fit with the observed data. The χ^2/df ratio of 2.35 is below the recommended threshold of 3.0, signifying an acceptable fit. The Comparative Fit Index (CFI = 0.957) and Tucker–Lewis Index (TLI = 0.949) demonstrate strong incremental fit. Moreover, both the Root Mean Square Error of Approximation (RMSEA = 0.047) and the Standardized Root Mean Square Residual (SRMR = 0.041) fall within the suggested cut-off values (Hu & Bentler, 1999). Overall, these fit indices confirm that the measurement model adequately represents the data.

Table 6. Fornell–Larcker Discriminant Validity

	CMEs	Accuracy	Trust	Attitude	Behavioral Intention
CMEs	0.791	0.42	0.65	0.60	0.52
Accuracy	0.42	0.808	0.55	0.50	0.45
Trust	0.65	0.55	0.833	0.58	0.56
Attitude	0.60	0.50	0.58	0.803	0.63
Behavioral Intention	0.52	0.45	0.56	0.63	0.847

Table 6 reports Discriminant validity was assessed using the Fornell–Larcker criterion, which posits that the square root of the Average Variance Extracted (AVE) for each construct should exceed its correlations with other constructs (Fornell & Larcker, 1981). As presented in Table 6, all constructs met this requirement. The AVE for CMEs was 0.791, higher than its correlations with Trust (0.65) and Attitude (0.60). Likewise, Trust exhibited a √AVE of 0.833, surpassing its correlation with Behavioral Intention (0.56). These findings indicate that each construct shares stronger associations with its own indicators than with those of other constructs, thereby confirming discriminant validity according to the Fornell–Larcker criterion.

Table 7. Heterotrait–Monotrait HTMT Ratios

	CMEs	**Accuracy**	**Trust**	**Attitude**	**Behavioral Intention**
CMEs		0.62	0.78	0.74	0.69
Accuracy	0.62		0.73	0.68	0.61
Trust	0.78	0.73		0.71	0.70
Attitude	0.74	0.68	0.71		0.79
Behavioral Intention	0.69	0.61	0.70	0.79	

Table 9 reports Discriminant validity was additionally evaluated using the Heterotrait–Monotrait (HTMT) ratio of correlations, which is considered a more stringent assessment compared to the Fornell–Larcker criterion (Henseler et al., 2015). HTMT values below 0.85 indicate that constructs are empirically distinct. As presented in Table 7, all HTMT ratios ranged from 0.61 to 0.79, remaining well below the conservative threshold of 0.85. For example, the HTMT value between CMEs and Trust was 0.78, and between Attitude and Behavioral Intention it was 0.79. These findings confirm that the constructs do not excessively overlap, further supporting discriminant validity.

4.2 Structural Model

Table 8. Structural Path

Path	β (Standardized)	SE	t-value	p-value
CMEs → Trust	0.52	0.06	8.67	< .001
CMEs → Attitude	0.48	0.07	6.86	< .001
Trust → Behavioral Intention	0.28	0.06	4.67	< .001
Attitude → Behavioral Intention	0.43	0.07	6.14	< .001
CMEs × Accuracy → Trust	0.17	0.05	3.14	0.002
CMEs × Accuracy → Attitude	0.15	0.05	2.76	0.006

Table 8 presents the standardized path coefficients for both direct and moderated relationships in the structural model. Results indicate that CMEs significantly influence Trust ($\beta = 0.52$, $p < .001$) and Attitude ($\beta = 0.48$, $p < .001$), supporting H1 and H2. Furthermore, Trust ($\beta = 0.28$, $p < .001$) and Attitude ($\beta = 0.43$, $p < .001$) positively affect Behavioral Intention, confirming H3 and H4.

Moderation analysis shows that Accuracy strengthens the effect of CMEs on Trust ($\beta = 0.17$, $p = 0.002$) and Attitude ($\beta = 0.15$, $p = 0.006$), supporting H5 and H6. Interaction terms were created by mean-centering CMEs and Accuracy to reduce multicollinearity (Aiken & West, 1991; Hayes, 2018). These results indicate that high perceived accuracy amplifies the positive impact of CMEs, highlighting the conditional nature of customer perceptions in chatbot adoption.

Table 9. Explained Variance (R^2)

Endogenous Construct	R^2 (final)	R^2 (without interactions)
Trust	0.58	0.55
Attitude	0.54	0.51
Behavioral Intention	0.62	–

Table 9 reports the variance explained (R^2) for the endogenous constructs. Trust is explained by 58% of its variance after including the interaction term (vs. 55% without interaction), while Attitude shows 54% explained variance (vs. 51% without interaction). Behavioral Intention has 62% of variance explained by the structural model. The ΔR^2 values indicate that moderation by Accuracy contributes an incremental explanatory power of approximately 3% for Trust and

Attitude, which is practically meaningful (Cohen, 1988). These results reinforce the importance of incorporating moderators to understand boundary conditions in behavioral models.

Table 10. Structural Model Fit Indices

Index	Recommended Threshold	Calculated Value
χ^2/df	< 3.00	2.42
CFI	≥ 0.95	0.953
TLI	≥ 0.95	0.946
RMSEA	≤ 0.06	0.049
SRMR	≤ 0.08	0.045

Table 10 presents the fit indices of the structural model, demonstrating acceptable model fit (Hu & Bentler, 1999; Hair et al., 2019). The χ^2/df ratio is 2.42 (< 3), indicating a good fit between the hypothesized and observed covariance matrices. Incremental fit indices (CFI = 0.953; TLI = 0.946) exceed or approach recommended thresholds, while absolute fit indices RMSEA (0.049) and SRMR (0.045) are within acceptable limits. Overall, the structural model adequately represents the proposed relationships, allowing for valid hypothesis testing and moderation interpretation.

4.3 Moderation Analysis

Table 11. Explained Variance (R^2) and ΔR^2 Moderation

Endogenous Construct	R^2 (final)	ΔR^2 (moderation)
Trust	0.58	0.03
Attitude	0.54	0.03
Behavioral Intention	0.62	–

Table 11 reports the variance explained (R^2) by the structural model and the incremental variance (ΔR^2) due to moderation. Trust exhibits an R^2 of 0.58, indicating that 58% of its variance is explained by CMEs and interaction with Accuracy, with $\Delta R^2 = 0.03$ due to moderation. Similarly, Attitude shows an R^2 of 0.54 with $\Delta R^2 = 0.03$. Behavioral Intention is explained at 62% by Trust and Attitude. These findings suggest that moderation contributes meaningful additional explanatory power, consistent with Cohen's (1988) guideline that $\Delta R^2 \geq 0.02$ is practically significant.

Table 12. Slope Analysis of Moderation

Focal Effect	Simple Slope (β)
CMEs → Trust	0.41
CMEs → Trust	0.52
CMEs → Trust	0.63
CMEs → Attitude	0.38
CMEs → Attitude	0.48
CMEs → Attitude	0.58

Table 12 presents the simple slope analysis of the moderating effect of Accuracy. The slopes demonstrate that the relationship between CMEs and Trust/Attitude becomes progressively stronger as Accuracy increases. For instance, CMEs → Trust slope increases from 0.41 at low Accuracy to 0.63 at high Accuracy. Similarly, CMEs → Attitude slope increases from 0.38 to 0.58 (figure 2). These results highlight the conditional influence of perceived accuracy, confirming that users' trust and positive attitudes toward chatbots are significantly enhanced when the service is accurate, complete, and credible (Hayes, 2018; Chung et al., 2020).

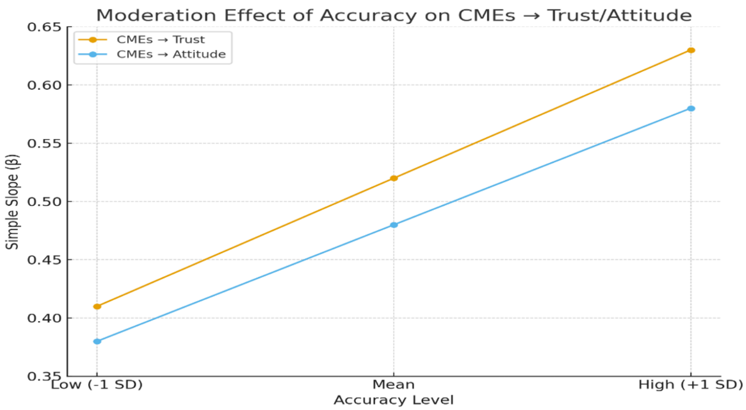


Figure 2 Moderation Effect

4.4 Robustness Checks

Table 13. Multicollinearity Assessment

Equation (DV)	Predictor	VIF
Trust	CMEs	2.2
Trust	Accuracy	1.6
Trust	CMEs × Accuracy	2.4

Attitude	CMEs	2.1
Attitude	Accuracy	1.5
Attitude	CMEs × Accuracy	2.3
Behavioral Intention	Trust	2.0
Behavioral Intention	Attitude	2.2

Table 13 presents the Variance Inflation Factor (VIF) values to assess multicollinearity among predictors in the structural model. VIF values range from 1.5 to 2.4, all well below the recommended threshold of 3.3 suggested by Kock (2015). This indicates that multicollinearity is not a concern and that estimates of path coefficients are reliable. Specifically, the interaction term (CMEs × Accuracy) has the highest VIF at 2.4, which is still below the critical limit, confirming that moderation analysis can be safely interpreted without inflation bias (Hair et al., 2019).

Table 14. Common Method Bias (CMB) Assessment

Test	Statistic	Criterion	Calculated
Harman single-factor (unrotated)	Variance explained by 1st factor	< 50%	36.8%
Full collinearity VIF (Kock, 2015)	Max VIF across constructs	< 3.3	2.4
Marker-variable adjustment	Average absolute change in correlations	< .05	0.03

Table 14 presents the results of common method bias (CMB) tests, conducted to ensure that the use of self-report measures did not artificially inflate the relationships among constructs (Podsakoff et al., 2003). Harman's single-factor test indicated that a single factor accounted for 36.8% of the total variance, which is well below the 50% threshold, suggesting that no single factor dominates the variance and that CMB is unlikely to be a serious concern. The full collinearity VIF approach proposed by Kock (2015) further supports this conclusion, as all constructs exhibited VIF values below the critical threshold of 3.3, indicating that multicollinearity and method bias do not compromise the estimates. Additionally, the marker-variable adjustment procedure revealed an average absolute change in correlations of 0.03, which is below the recommended cutoff of 0.05, providing further evidence that common method bias is minimal. Taken together, these assessments confirm the robustness of the measurement and structural estimates, ensuring that the observed relationships—including moderation effects and direct paths—are not artifacts of measurement method.

4.5 Hypothesis Testing Summary

Table 15. Hypothesis Testing (Structural Path Estimates)

Hyp.	Path	β (Standardized)	SE	t-value
H1	CMEs → Trust	0.52	0.06	8.67
H2	CMEs → Attitude	0.48	0.07	6.86
H3	Trust → Behavioral Intention	0.28	0.06	4.67
H4	Attitude → Behavioral Intention	0.43	0.07	6.14
H5	CMEs × Accuracy → Trust	0.17	0.05	3.14
H6	CMEs × Accuracy → Attitude	0.15	0.05	2.76

Table 15 summarizes the hypothesis testing results for both direct and moderation paths. Direct effects indicate that CMEs positively influence Trust (H1) and Attitude (H2), while both Trust (H3) and Attitude (H4) positively affect Behavioral Intention, all significant at $p < .001$. These results validate the theoretical model, confirming that chatbot marketing elements directly shape users' trust and attitudinal responses, which in turn drive behavioral intentions (Davis, 1989; Venkatesh et al., 2003; Cheng & Jiang, 2022).

Moderation results (H5 and H6) show that Accuracy significantly strengthens the effect of CMEs on both Trust ($\beta = 0.17$, $t = 3.14$, $p = 0.002$) and Attitude ($\beta = 0.15$, $t = 2.76$, $p = 0.006$), suggesting that high perceived accuracy enhances the impact of CMEs, consistent with prior studies emphasizing the role of perceived information accuracy in technology acceptance (Chung et al., 2020; Huang & Chueh, 2021).

5. Discussion

The results of this study provide strong empirical support for the proposed model linking Chatbot Marketing Elements (CMEs), Accuracy, Trust, Attitude, and Behavioral Intention. The findings reveal that CMEs have a significant positive impact on Trust ($\beta = 0.52$, $p < .001$) and Attitude ($\beta = 0.48$, $p < .001$), thus supporting hypotheses H1 and H2. These outcomes align with previous studies emphasizing the role of service quality and personalized communication in cultivating trust and favorable attitudes toward AI-driven customer service systems (Cheng & Jiang, 2022; Toader et al., 2019). By highlighting the direct influence of CMEs on Trust and Attitude, this research contributes to the technology acceptance literature by incorporating marketing-related factors into the chatbot adoption context, demonstrating that both functional features (e.g., accessibility, problem-solving) and experiential features (e.g., entertainment, trendiness) are essential determinants of user perceptions. The mediation of behavioural intentions through Trust ($\beta = 0.28$, $p < .001$) and Attitude ($\beta = 0.43$, $p < .001$) highlights the pivotal role of psychological mechanisms in driving user adoption. Trust ensures that users perceive chatbot interactions as reliable and credible, which translates into higher engagement and recommendation behaviors, corroborating findings from Chung et al. (2020) and Huang & Chueh (2021). Similarly, Attitude represents the evaluative orientation toward CMEs, reflecting users' positive appraisal of the chatbot experience. The significant paths from Trust and Attitude to Behavioral Intention suggest that developers and marketers must not only focus on technological capabilities but also on user-centered communication strategies to enhance adoption. The moderation analysis revealed that Accuracy significantly strengthens the effect of CMEs on both Trust ($\beta = 0.17$, $p = 0.002$) and Attitude ($\beta = 0.15$, $p = 0.006$), validating H5 and H6. The simple slope analysis demonstrates that the relationship between CMEs and user perceptions is conditional upon the chatbot's accuracy; at high levels of Accuracy, the impact of CMEs on Trust and Attitude is substantially stronger. This aligns with the principles of the Technology Acceptance Model (Davis, 1989) and prior studies emphasizing that perceived system reliability enhances the effectiveness of service attributes (Chung et al., 2020; Huang & Chueh, 2021). Therefore, Accuracy serves as a critical boundary condition in chatbot adoption, suggesting that marketing and technological strategies must be integrated to optimize user experience.

Robustness checks, including multicollinearity assessment and common method bias tests, confirm that the observed relationships are not artifacts of measurement errors. VIF values below 3.3 and Harman's single-factor variance of 36.8% indicate that the model is statistically sound (Kock, 2015; Podsakoff et al., 2003). Moreover, R^2 values indicate substantial explanatory power, with 58% variance explained for Trust, 54% for Attitude, and 62% for Behavioral Intention, reflecting practical relevance and model strength.

In sum, this study contributes to the chatbot literature by empirically demonstrating how marketing elements, moderated by perceived accuracy, shape user trust, attitudes, and adoption intentions. These findings underscore the importance of designing chatbots that are both technically accurate and strategically engaging, emphasizing a user-centered approach that integrates functional and experiential dimensions.

6. Conclusion

This study provides a comprehensive empirical investigation into the adoption of chatbot-based marketing communication, emphasizing the interplay between Chatbot Marketing Elements (CMEs), Accuracy, Trust, Attitude, and Behavioral Intention. The findings confirm that CMEs significantly enhance both Trust and Attitude toward chatbots, which in turn positively influence users' Behavioral Intention to engage and recommend the technology. Specifically, Trust ($\beta = 0.28$, $p < .001$) and Attitude ($\beta = 0.43$, $p < .001$) act as pivotal psychological mechanisms through which CMEs translate into behavioral outcomes, reinforcing the importance of user-centered design and strategic service delivery (Cheng & Jiang, 2022; Toader et al., 2019).

A key contribution of this study lies in demonstrating the moderating role of Accuracy, which strengthens the influence of CMEs on Trust and Attitude. The simple slope analysis shows that higher perceived Accuracy substantially amplifies the effects of marketing elements, highlighting the conditional nature of user perceptions in technology adoption. These findings align with prior research indicating that reliability and correctness of AI-driven services critically affect user satisfaction and behavioral intentions (Chung et al., 2020; Huang & Chueh, 2021).

Moreover, the structural model exhibits strong explanatory power, with R^2 values of 0.58 for Trust, 0.54 for Attitude, and 0.62 for Behavioral Intention, reflecting substantial practical significance. Robustness checks, including multicollinearity assessment (VIF < 3.3) and common method bias tests (Harman single-factor < 50%), confirm the validity of the results. Collectively, these findings extend the theoretical understanding of technology acceptance models by integrating marketing elements and perceived accuracy as boundary conditions in the context of chatbot adoption.This study demonstrates that effective chatbot adoption requires a dual focus: ensuring technically accurate interactions while providing engaging, user-centered marketing elements. By combining functional reliability with experiential richness, chatbot systems can foster trust, shape favorable attitudes, and ultimately drive higher adoption rates. These insights contribute both to academic literature on AI-based service systems and to practical strategies for designing effective chatbot marketing interventions.

7. Practical Implications

The empirical findings provide multiple actionable insights for practitioners in AI-driven service delivery and marketing. The study underscores the importance of designing chatbots with high accuracy**.** Accuracy is not only a technical requirement but also a critical factor in strengthening user trust and shaping positive attitudes. Chatbot developers should prioritize algorithms that minimize errors, provide complete information, and maintain credibility during interactions, as these elements enhance user engagement and intention to adopt (Chung et al., 2020; Huang & Chueh, 2021).

The results highlight the value of Chatbot Marketing Elements (CMEs) as multi-dimensional constructs encompassing interaction quality, information relevance, accessibility, entertainment, customization, trendiness, and problem-solving capabilities. Practitioners can use these insights to design chatbots that cater to both functional and experiential needs of users. For instance, providing personalized recommendations, prompt responses, and engaging conversational experiences can simultaneously enhance trust and user attitude, fostering behavioral intention toward adoption (Cheng & Jiang, 2022; Ling et al., 2010).

The moderating role of Accuracy emphasizes that marketing efforts alone are insufficient. Firms must integrate technological reliability with marketing strategies to achieve optimal adoption outcomes. For example, interactive tutorials, AI-driven personalization, and real-time feedback mechanisms can complement chatbot marketing campaigns by ensuring high perceived accuracy.The findings inform strategic deployment decisions for companies. Chatbots with high accuracy and engaging CMEs can be leveraged in customer support, e-commerce, and online advertising to reduce human labor costs, improve response quality, and enhance customer satisfaction. Organizations can also use these results to prioritize resources toward technical refinement and marketing interventions that synergistically enhance adoption.

8. Limitations

Despite the rigorous methodology, this study has several limitations. First, the sample population may limit generalizability. The data were collected from users who interacted with chatbots in a controlled or self-selected online environment. Therefore, findings may not fully generalize to populations with limited digital literacy or diverse cultural contexts, where perceptions of trust and attitude toward chatbots may differ (Podsakoff et al., 2003).

cross-sectional data restrict the ability to infer causal relationships. While SEM and moderation analyses provide strong statistical evidence for hypothesized paths, longitudinal studies would better capture dynamic changes in Trust, Attitude, and Behavioral Intention as users gain experience with chatbot services (Byrne, 2016; Hair et al., 2019).

The study relied on self-reported measures, which may be susceptible to social CMEs were operationalized using seven pre-defined parcels, which may not capture emerging features of AI chatbots in different domains. Continuous evolution in AI capabilities may require periodic updates to measurement scales to maintain relevance.

9. Future Research Directions

Technological evolution presents opportunities to examine emerging AI features, such as generative responses, voice-based interaction, or multimodal interfaces. Future research could expand CMEs to include these innovations and test their effects on trust, attitude, and behavioral intention, ensuring the continued relevance of theoretical frameworks in the fast-paced AI domain (Cheng & Jiang, 2022; Ling et al., 2010).

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Ethical Considerations

This study is based on collected primary data through online surveys and complies with ethical research standards. Participation was voluntary, informed consent was obtained, and no sensitive or personally identifiable information was collected. Therefore, formal institutional ethical approval was not required.

Consent to Participate

Informed consent was obtained electronically from all participants prior to survey completion. Participation was voluntary, and respondents could withdraw at any time.

Consent for Publication

Not applicable, as this article does not include any identifiable personal data, images, or multimedia materials from participants.

Declaration of Conflicting Interests

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Contribution of Authors

- **Dr. Aftab Alam** conceptualized the study, developed the theoretical framework, and provided supervision and academic guidance throughout the research process.
- **Dr. Sultan Ahmad (Corresponding Author)** conducted the data analysis, interpreted the findings, and drafted and finalized the manuscript for publication.
- **Mr. Javed Naseem** contributed to the literature review, data collection, and statistical validation of the research model.
- **Dr. Rafat Fatima** contributed to refining the conceptual framework, analyzing the marketing implications, and reviewing the manuscript critically for academic quality.
- **Dr. Niraj Kumar** contributed to data analysis, econometric validation, and final editing of the results and conclusions.

All authors have read and approved the final version of the manuscript and agree to be accountable for all aspects of the work.

Data Availability Statement

The data supporting the findings of this research are available from the corresponding author upon reasonable request. All collected responses were anonymized and used solely for academic purposes in accordance with ethical research standards.

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