ORIGINAL ARTICLE

OPEN ACCESS

Exploring The Influence of Customer Experience with AI Automated Text Models on Usage Intention: The Moderating Role of Competence, Accuracy, and Credibility.

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Article History:

Submitted: April 16, 2026
Revised: August 22, 2026
Accepted: September 09, 2026
Published online: September 30, 2026

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A B S T R A C T

Purpose— This study examines how customers' experience with AI-assisted chatbots influences their usage intention across application domains, and whether the chatbots' perceived competence, credibility, and accuracy moderate this relationship. It aims to establish a domain-general account of chatbot continuance grounded in expectation-confirmation and source-credibility.

Study Design/methodology/approach—A cross-sectional, quantitative survey was administered to 273 chatbot users selected through convenience sampling. The direct relationship was tested using linear regression with age, gender, and education as control variables, and three moderating effects were tested using Model 1 of the PROCESS Macro in SPSS.

Findings— Customer experience was positively associated with usage intention. Contrary to expectations, none of these attributes- competence, credibility, and accuracy- moderated this relationship. The findings suggest that these attributes operate as direct predictors of usage intention rather than as boundary conditions, and that accuracy may substitute for, rather than reinforce, experiential information.

Practical Implications—Investment in chatbot accuracy and credibility yields greater returns on usage intention than experiential design features do.

Originality/Value—The study repositions competence, credibility, and accuracy as factors that may be directly associated with usage intention rather than moderators of chatbot continuance.

Keywords: Accuracy, chatbots, competence, credibility, customer experience, usage

JEL Classification Codes: G32, G31, G34, G35, G41, L25

1 | INTRODUCTION

1.1 | Background and Context

Artificial-Intelligence chatbots have shifted from a customer-service novelty to an everyday interface, yet their organizational value rests on a fragile condition: users must keep using them. Adoption alone no longer distinguishes competitive firms. By late 2025, ChatGPT reportedly reached roughly 800 million weekly

active users, having doubled from 400 million in February 2025 (Wiggers, 2025), while in the United States, generative-AI adoption rose to 54.6% of those aged 18 to 64 years, a 10 percentage-point increase in a single year (Bick et al., 2026). At the firm level, 88% of organizations reported using generative AI in 2025, up from 78% a year earlier (McKinsey, 2025). These industry statistics, though not peer-reviewed, illustrate the rapid diffusion that motivates closer academic investigation of chatbot adoption. Ubiquity, however, is not the same as durable engagement. Adoption curves say little about whether an individual, having interacted with a chatbot, forms the intention to rely on it again, and it is continued use, not first contact, that determines whether the technology delivers on its promise (Ranieri et al., 2024).

This is where the research problem lies. Sustained chatbot use appears to be gated less by availability than by whether users judge the system worth trusting. Even amid record adoption, roughly ¾ of customers report concern about data security, and workers who trust AI are more than twice as willing to use it, while most non-users remain unclear about its value; comfort with chatbots specifically remains far from universal, with only around 44% of customers reporting they are comfortable using them (Global, 2026). Additionally, a satisfactory experience doesn't automatically convert into an intention to continue; this conversion depends on how the user assesses the chatbot's qualities (Jiang et al., 2022).

In other words, a satisfactory experience doesn't automatically convert into an intention to continue; that conversion seems to depend on how the user appraises the chatbot's qualities (Jiang et al., 2022). It remains unclear which perceived qualities of a chatbot make users want to keep using it, and whether these qualities hold across different domains rather than just one. This study addresses these gaps by drawing on Source Credibility Theory (Hovland et al., 1953), which holds that a source's influence on a receiver's behavior and attitude is conditioned by the source's perceived credibility, conventionally divided into expertise (competence) and trustworthiness. Treating the chatbot as an information source, this lens reframes competence, credibility, and accuracy not as incidental features but as the credibility dimensions that determine how strongly a user's experience translates into continued-use intention. This is consistent with recent evidence that trust is essential for the adoption and continued use of AI systems and that trust significantly mediates the intention to adopt chatbots (Ding & Najaf, 2024). The outcome variable, retention or continuance intention, is further informed by the Expectation-confirmation logic of information-systems continuance, in which a confirmed, satisfactory experience underpins the decision to keep using a technology (Ng & Zhang, 2025).

Prior studies have approached chatbots from two narrower angles. First, much of it concentrates on customer satisfaction as an outcome rather than on the behavioral intention to continue using the chatbot (Abdelkader, 2023; Jan et al., 2023; Wang et al., 2022). Second, findings are typically bound to a single sector such as digital marketing, retail (Aslam, 2023; Jan et al., 2023; Kamoonpuri & Sengar, 2023), banking (Petersson et al., 2023), or customer service (Haugeland et al., 2022), leaving a gap in whether mechanisms generalize. Recent systematic reviews of chatbots and customer experience reinforce this pattern, consolidating domain-specific evidence while calling for different context, theory-driven models. Consequently, little is known about how the perceived characteristics of a chatbot condition the relationship between user experience and continued-usage intention, independent of any particular application, or about the relative strength of those characteristics.

This study addresses this gap. Its objective is to examine, across application domains, how customers' experiences with chatbots shape their usage or retention intention and how the chatbot's accuracy, competence, and credibility moderate that relationship. Accordingly, it is guided by three research questions:

1.3 | Research Questions

RQ1. Does customers' experience with a chatbot influence their usage/retention intention, independent of a specific application domain?

RQ2. Do the chatbot's perceived accuracy, competence, and credibility moderate the relationship between customers' experience and usage/retention intention?

2 | LITERATURE REVIEW

2.1 | Customer Experience with Chatbots and Usage Intention

The relationship between customers' experience with chatbots and their intention to continue using them is best explained through the Expectation-Confirmation Model (ECM) and its related Technology Continuance Theory (Oliver, 1980). These frameworks hold that users form expectations before an interaction, appraise the interaction against those expectations, and when experience confirms or exceeds them, develop the satisfaction that drives the intention to keep using the technology. Applied to conversational agents, a positive chatbot experience operates as post-adoption confirmation, strengthening satisfaction and, through it, usage/retention intention (Rita et al., 2026). Recent information-systems research continues to validate this pathway for AI-driven services, with customer experience emerging as a central factor in continuance usage intention rather than a peripheral one, and with expectation confirmation shaping the satisfaction that predicts continuance (Ngo et al., 2026)

Empirically, a body of knowledge converges that the quality of chatbot experiences raises downstream intention, although studies disagree on which facet matters most. (Haugeland et al., 2022) reported that customer satisfaction and continued-use intention rose when chatbots offered tailored support by efficiently addressing customer issues, concluding that users are more inclined to keep using AI-driven tools when they receive personalized assistance and quick resolution. More recent evidence similarly identifies response relevance and problem resolution as the dominant drivers of chatbot customer experience (Nicolescu & Tudorache, 2022). On the hedonic side, a chatbot's ability to express humor is regarded as a valuable trait that enhances the overall experience by injecting personality and an element of surprise into (Grudin & Jacques, 2019), while human-like design and interactive messaging (Go & Sundar, 2019), self-disclosing behavior (Lee & Choi, 2017), and emotion-or-sentiment-adaptive responses (Diederich et al., 2019) are each reported to heighten perceived anthropomorphism, social presence, satisfaction, and enjoyment.

The evidence is not uniform, however, and this is where prior work leaves the debate unresolved. Ruan and Mezei (2022) found that satisfaction was significantly higher when chatbots conveyed functional product information rather than experiential product attributes. This suggests that the type of information chatbots deliver can influence the customer's experience and, consequently, their intention to use these conversational agents. A study on Generation Z users likewise reported that experiential features primarily influence attitude, while satisfaction is driven by functional performance (Ngo et al., 2025). Cutting across both positions, trust recurs as a decisive condition. Jan et al. (2023) showed that usage intention depends heavily on users' trust in

both the technology and the organization providing it. Customers are more inclined to use AI-driven chatbots when they have faith in their reliability and capability, as well as in the responsible organization. Thereby, and consistent with the confirmation-to-continuance logic of ECM (Monoarfa et al., 2024), we can posit that customer experience with chatbots is closely linked to their usage intention and propose:

H1. *Customer experience with a chatbot is positively associated with usage intention.*

2.2 | Moderating Role of Chatbot Credibility

Under Source Credibility Theory, the influence of any information source on a receiver's attitude and behavior depends on how that source's credibility is appraised, and its two established dimensions are expertise (competence) and trustworthiness (Hovland et al., 1953). Reframing the chatbot as an information source (Sundar, 2008), we treat competence, credibility, and accuracy as the appraisals through which users judge that source: competence reflects perceived expertise (Al-Oraini, 2025; Chung et al., 2020). Credibility reflects perceived trustworthiness or believability (Ohanian, 1990), and accuracy reflects the evidential track record on which both rest (Wang et al., 2026). This is why these three, rather than adjacent constructs, are modeled as moderators. Anthropomorphism, perceived intelligence, and social presence describe how human-like or engaging a chatbot appears rather than how credible its information is (Go & Sundar, 2019; Jin & Youn, 2023); perceived usefulness, trust, and continuance sit downstream of credibility and close to intention itself (Jan et al., 2023); privacy concern and perceived risk. AI anxiety, transparency, explainability, and human oversight are antecedents or risk perceptions that form before the interaction is appraised (Shin, 2021; Wang et al., 2022). Modelling these as moderators would either blur the source-credibility mechanism or create endogeneity with the outcome.

2.2.1. Moderating Role of Competence

Competence reflects the user's appraisal of the chatbot's expertise, that is, the knowledge, skill, and effectiveness it demonstrates in a given domain (Al-Oraini, 2025; Yen & Chiang, 2021). Under Source Credibility Theory (Hovland et al., 1953), when a chatbot is perceived as competent, users attribute a positive interaction to the system's stable ability rather than to chance, so that experience becomes a more reliable signal of future performance and weighs more heavily in the decision to continue using it. Therefore, competence does not create the experience so much as govern how strongly it carries through to intention.

Past studies are largely consistent with a competence effect; chatbot interaction is perceived as comprehensive and accurate, and causes a stronger impression of communication quality (Chung et al., 2020). Customers have more confidence in specialists (domain-specific) than in generalist (capability) agents (Liew & Tan, 2018). Interpersonal communication competence has also been shown to build trust and encourage return use (Skjuve & Brandzaeg, 2018), whereas Nicolescu and Tudorache (2022) found positive links between trust, loyalty, competence, and reuse intention satisfaction. Al-Oraini (2025) discusses perceived competence as one of the strongest predictors of chatbot satisfaction. Nguyen et al. (2023) find that anthropomorphic language increases perceived competence, which drives engagement. However, the same study finds that relational cues, such as social presence, contribute less than competence, suggesting that the expertise-based, functional route is more decisive than the social one (Nguyen et al., 2023), which remains an

imbalance in single-context, cross-sectional design studies. Taken together, a competent chatbot should strengthen the translation of experience into intention.

H2: *Competence moderates the relationship between customer experience and usage intention, such that the relationship strengthens when competence is high.*

2.2.2. Moderating Role of Credibility

Credibility refers to the user's appraisal of the chatbot as believable and trustworthy in what it communicates (Kamoonpuri & Sengar, 2023). It is conceptually distinct from trust: credibility is a property attribute of the source based on its expertise and honesty, whereas trust is the user's willingness to rely on and be vulnerable to the chatbot, a relational state that typically follows from credibility and lies closer to behavioral intention. Therefore, we use credibility, rather than trust, as a moderator. Credibility is a user's early judgement about a chatbot, but trust sits much closer to the decision to use it. Credibility follows Source Credibility Theory; a source seen as believable carries more weight, so users who view a chatbot as credible give greater importance to a positive experience when deciding about continued usage (Hovland et al., 1953).

The literature supports a credibility-based boundary condition. Perceived credibility strengthens usage intention (Kamoonpuri & Sengar, 2023), and the effect of satisfaction on usage intention is greater when the chatbot is seen as credible (Misischia et al., 2022). The effect appears prominently for cautious users, as it is stronger among the risk-averse and requires a higher need for cognitive closure (Huang & Chueh, 2021), aligning with credibility working as uncertainty reduction. Credibility has also been associated with intention through perceived usefulness (Alagarsamy & Mehrolia, 2023). Moreover, contemporary experimental studies found credibility explicitly as a moderator; that brand credibility conditions the influence of a chatbot's anthropomorphic language on engagement and perceived competence, and this effect is significant only when credibility is low (Nguyen et al., 2023). This suggests that higher credibility strengthens how experience supports usage intention.

H3. *Credibility moderates the relationship between customer experience and usage intention, such that the relationship strengthens when credibility is high.*

2.2.3. Moderation of Accuracy

Accuracy refers to the degree to which the chatbot provides correct, relevant, and consistent information (Adamopoulou & Moussiades, 2020; Gao & Xing, 2023). Within Source Credibility Theory, accuracy is the evidential basis on which perceptions of expertise and trustworthiness are built, and this clarifies how it changes the strength of the core relationship. A positive experience is a signal of what future interaction will deliver when accuracy is high, so users allow that experience to more strongly inform their intention. Even a favorable experience is discounted when accuracy is low, deteriorating the path from experience to intention. Accuracy thus operates as a boundary condition rather than a direct cause of intention. Empirically, users report more positive experiences and greater willingness to reuse a chatbot they perceive as accurate (Gao & Xing, 2023), and communication accuracy has been identified as one of the most influential determinants of chatbot usage intention (Adamopoulou & Moussiades, 2020). Accuracy also supports reliability and

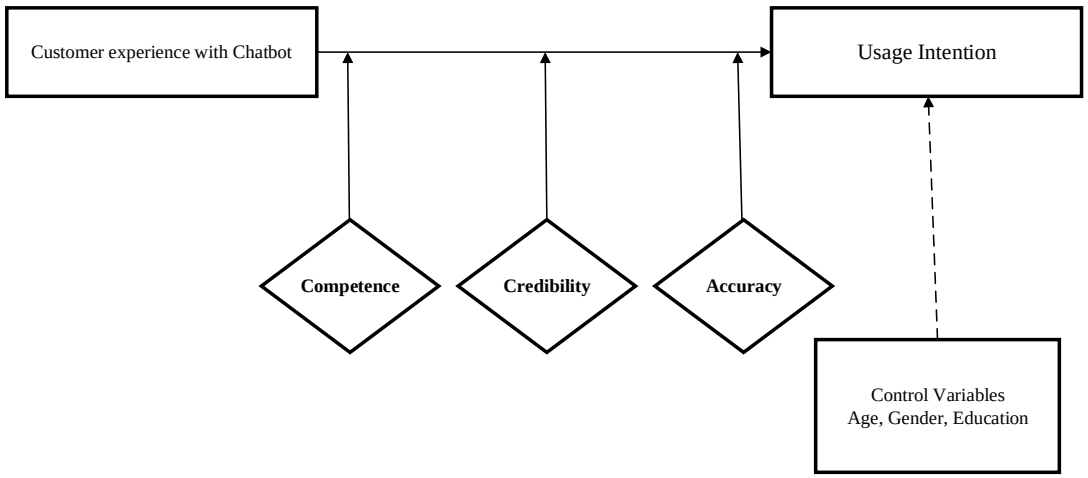
knowledgeability, so persistent chatbots are trustworthy with less error generation, emphasizing a positive experience (Roy & Naidoo, 2021).

Wang et al. (2026) identify accuracy as central to cognitive trust and show that inaccurate or inconsistent responses rapidly erode trust and push users toward human agents, illustrating the fragility of the relationship when accuracy is compromised; relatedly, accuracy-related service-quality dimensions predict whether customers switch away from chatbot agents (Chen et al., 2025). A limitation across this work is its reliance on self-reported, cross-sectional, and largely single-context data, which constrains causal inference about accuracy's conditioning role, precisely the boundary conditions this study tests directly. On balance, higher perceived accuracy should strengthen the experience-intention relationship (see Figure 1). Hence,

H4: *Accuracy moderates the relationship between customer experience and usage intention, such that the relationship strengthens when accuracy is high.*

Figure 1

Conceptual Framework



3 | METHODOLOGY & DESIGN

3.1 | Research Design

The study adopts a quantitative cross-sectional survey design. A quantitative approach is appropriate to test the proposed direct and moderation hypotheses, which requires the measurement of latent constructs and the estimation of relationships among them across samples. In a cross-sectional design, data are collected at a single point in time, which is suited to examining the associations and interaction effects proposed in the conceptual model and is efficient for surveying a dispersed population of chatbot users. We acknowledge that this design measures co-variation rather than temporal sequence, and therefore doesn't permit strong causal claims.

3.2 | Population and Sample

The target population comprised adult users of AI-assisted chatbots. The unit of analysis is an individual AI-powered chatbot user. To be eligible, a respondent had to a) be 18 years or older, b) have used AI-assisted

chatbots, such as customer-service assistants, Generative AI, or any similar conversational agent. Eligibility was confirmed through a screening question at the start of the survey; respondents who reported no recent chatbot use were routed out and excluded, and retained cases could report on an actual chatbot experience. Data were gathered from the Twin Cities of Islamabad and Rawalpindi, Pakistan, using non-probability convenience sampling. Convenience sampling was adopted because no sampling frame of chatbot users exists and because it offers fast access to eligible technology-using respondents within time and resource constraints.

Sample size was determined with reference to the requirements of moderated regression analysis. According to ($N \geq 104 + k$ for testing individual predictors), a model containing the predictor, moderator, interaction terms, and controls requires a minimum of approximately 110 cases. This was validated through a priori power analysis in GPower 3.1 (F-test; R^2 increase, linear multiple regression), with $\alpha = 0.05$, power = 0.80, and a single tested interaction term, assuming a small-to-medium interaction effect ($f^2 = 0.075$); the analysis indicated a minimum of 123 respondents (Faul et al., 2009). The final sample of 273 satisfies both criteria.

3.3 | Variable Measurement

All constructs were measured using multi-item scales adapted from previously validated instruments and reworded to the chatbot context. All variables were mean-centered and standardized before computing coefficients and interaction terms, which renders the differing response ranges immaterial to the moderation estimates.

3.3.1. Customer experience with Chatbots.

Customer experience with chatbots was measured with the scale developed by Chen et al. (2021). The instrument measures customer experience using a five-point Likert scale ranging from 1 = strongly disagree to 5 = strongly agree.

3.3.2. Competence.

Competence was measured using a four-item scale adapted from Akter et al. (2011). The responses were anchored using a seven-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree).

3.3.3. Credibility.

Credibility was assessed with an instrument developed by Kröbel (2022). The responses were anchored using a five-point Likert scale ranging from 1-strongly disagree to 5- strongly agree.

3.3.4. Accuracy

Accuracy was measured using 15 items drawn from the Bot Usability Scale (Borsci et al., 2022). The responses were anchored using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree).

3.3.4. Control Variables.

Age, Gender, and education were included as control variables, as each has been shown to predict technology adoption and usage behavior and therefore confound the proposed hypotheses.

Before data collection, the questionnaire was pre-tested with 20 respondents drawn from the target population for item clarity, wording, and completion time. Minor wording revisions were made based on the pilot. After data collection, the internal consistency reliability of each scale was assessed using Cronbach's Alpha.

3.4 | Data Collection and Ethical Considerations

The survey was conducted via a self-administered online questionnaire (Google Forms) and an in-person paper questionnaire between October 2025 and January 2026. 300 individuals invited/ approached, and 273 usable responses were obtained, yielding a response rate of 91%. Participation was anonymous and voluntary. An informed-consent statement was sent before the questionnaire, explaining the study purpose and voluntary nature of participation, confidentiality, and right to withdraw. The study was conducted in accordance with HEC research guidelines and received approval from the university Research Ethics Committee (REC).

3.5 | Data Analysis Approach

Data were analyzed in IBM SPSS version 27, and moderation effects were tested using Hayes' PROCESS Macro model 1 (Hayes, 2017). The data were screened, and key statistical assumptions were examined: missing data and outliers were assessed; normality (skewness and kurtosis) was checked. Multicollinearity was evaluated using the variance inflation factor (VIF < 5), which ranged from 1.6 to 2.1, well within the conventional threshold. Scale reliability was confirmed using Cronbach's Alpha (Nunnally & Bernstein, 1994).

4 | RESULTS AND ANALYSIS

4.1 | Demographic Profile of Respondents

Our sample size (N=273) ensured comprehensive representation of these demographic categories, and the diverse educational background of our participants further adds to the depth of our analysis. It reveals that 55% of our respondents were male, while 45% identified as female. The majority of our population (49.10%) fell within the age group of 21-30 years old, with the smallest segment (6.20%) aged 31-40 years old. In terms of education, the majority of our respondents (69.20%) held a Bachelor's degree, 19.40% of the population had a Master's degree, followed by Intermediate and Ph.D. holders that comprised 9.50% and 1.80%, respectively.

4.2 | Preliminary Analysis

4.2.1. Reliability and Validity

Table 1

Reliability and validity of the measurement instrument

Constructs	CR	AVE	Fornell-Larcker					VIF
			CE	UI	CP	CD	AC	
Customer Experience (CE)	0.870	0.549	**0.741**					1.60
Usage Intention (UI)	0.825	0.520	0.178***	**0.721**				1.03
Competence (CP)	0.893	0.581	0.153	0.247**	**0.762**			1.22
Credibility (CD)	0.902	0.678	0.203	0.340***	0.419***	**0.823**		1.78
Accuracy (AC)	0.846	0.521	0.198*	0.295***	0.397***	0.465***	**0.745**	2.10

Note. N = 273. Average Variance Extracted = AVE; Composite Reliability = CR; Variance Inflation Factor = VIF. ***p < .001, **p < .01, *p < .05.

To ensure each scale consistently measured its intended construct, internal consistency reliability was measured using Cronbach's Alpha. Table 1 shows all alphas are above the threshold of ≥ 0.70 (Nunnally & Bernstein, 1994), confirming internal consistency reliability. Firstly, the Fornell-Larcker criterion is that the square root of each latent variable's AVE should exceed its correlation with any other latent variable. Secondly, the items should load onto their respective latent variables and be compared with loadings on other latent variables (Sarstedt et al., 2021). Fornell-Larcker criterion in Table 1 confirms that off-diagonal values are less than the square root of the AVE of constructs. Two indices were used to measure convergent validity; each latent construct has composite reliability (CR), which should be more than 0.70 65 (Fornell & Larcker, 1981). Moreover, AVE represents the amount of variance captured by the construct, and ≥ 0.50 signifies good convergent validity. Table 1 shows that all constructs have CR above 0.70 and AVE above 0.50, confirming convergent validity. Multicollinearity was assessed using variance inflation factor (VIF) values.

4.2.2. Regression Assumptions

The independence of regression residuals was assessed using the Durbin-Watson statistic. The obtained values ranged from 1.93 to 2.04, which were close to 2.00 and indicated that residual autocorrelation was not a concern. The VIF values ranged from 1.03 to 2.10 (see Table 1), which were below the recommended threshold of 3.30, indicating that the constructs weren't excessively interrelated and multicollinearity wasn't an issue.

4.2.3. Confirmatory Factor Analysis

Confirmatory factor analysis (CFA) is a form of structural equation modeling used to examine whether observed indicators adequately represent the hypothesized latent constructs. It evaluates the proposed measurement structure and provides evidence regarding construct validity (Brown, 2012). The hypothesized five-factor model demonstrated a satisfactory fit and was substantially superior to the alternative models (see Table 2).

Table 2

Confirmatory Factor Analysis

Indices	χ^2 / df	CFI	TLI	RSMEA	SRMR
5-factor (hypothesized)	1.52	0.965	0.923	0.044	0.041
Recommended value	< 3.00	≥ 0.90	≥ 0.90	≤ 0.08	≤ 0.08
Decision	Acceptable	Good	Good	Good	Good

Note. CFI = Comparative Fit Index; TLI = Tucker-Lewis Index; RMSEA = Root mean square error of approximation; SRMR= Standardized root mean square residual

4.2.4. Common Method Variance (CMV)

Common Method Variance (CMV) refers to systematic measurement variance caused by the data collection method rather than by the construct being studied. It suppresses or inflates relationships among variables and consequently harms the validity of empirical results (Podsakoff et al., 2003). Harman's single-factor test was calculated to examine the presence of CMV. The first unrotated factor accounted for 28.6% of

the total, which was below the threshold of 50%, indicating that common method variance (CMV) was unlikely to be a serious concern in the study.

4.2.5. Correlation Analysis

Table 3 shows that there is no significant effect of control variables on the study variables. Moreover, customer experience with chatbots has a positive and significant association with usage intention. Competence, credibility, and accuracy have a positive association with usage intention.

Table 3

Pearson Correlation Coefficients

Constructs	Mean	α	Age	Gen	Edu	CE	UI	CP	CD	AC
Age	25.345	0511	1							
Gender (Gen)	1.043	0.081	0.090	1						
Education (Edu)	2.761	0.345	0.103	0.189	1					
Customer Experience (CE)	3.971	0.844	0.074	0.042	0.123	1				
Usage Intention (UI)	4.120	0.824	-0.091	0.101	0.023	0.173***	1			
Competence (CP)	3.518	0.890	0.112	0.076	0.082	0.151	0.248**	1		
Credibility (CD)	3.078	0.902	0.080	0.111	0.105	0.201	0.342***	0.421***	1	
Accuracy (AC)	3.421	0.844	0.132	0.092	-0.003	0.199*	0.299***	0.398***	0.468***	1

Note. N = 273. ***p < .001, **p < .01, *p < .05.

4.3 | Hypothesis Testing

4.3.1. Direct Effect

Table 4 presents the results for the direct relationship between customer experience with the chatbot and usage intention. Customer experience reported positive association with usage intention (β = 0.204, SE = 0.044, t = 3.423, p < .001), indicating that one-unit increase in customer experience is associate with 0.204 units change in usage intention, holding control variable constant. by the model accounted for a significant proportion of variance in usage intention (ΔR^2 = 0.038, F-Statistics = 11.714, p < .001), such that customer experience explained an additional 3.8% of the variance beyond the control variables. These results support H1, indicating that a positive relationship exists between Customer Experience and Usage Intention.

Table 4

Direct Effect

Variable	β	S.E.	t	Sig.
Customer Experience	0.204	0.044	3.423	< .001
Change in R^2	0.038			
F-Statistics	11.714			< .001

Note. N = 273; Outcome variable = Usage Intention; SE= standard error; LLCI = lower limit confidence interval; ULCI = upper limit confidence interval.

4.3.2. Moderation Analysis

Table 5 reports the results of three moderated regression models testing whether competence (H2), credibility (H3), and accuracy (H4) condition the relationship between customer experience and usage intention. Each moderator was entered separately using Model 1 of the PROCESS macro (Hayes, 2017). In moderation analysis, hypothesis support depends on the direction and significance of the interaction term, not on the significance of the main effects. The results are therefore interpreted accordingly.

Effect sizes were computed for each interaction term using Cohen's f2 = [ΔR^2 / (1 - ΔR^2)]. The competence interaction produced a single negligible effect (ΔR^2 = .0035, f2 = .004), as did the credibility interaction (ΔR^2 = .016, f2 = .012), both falling below Cohen's threshold of a small effect size (f2 = .020), and consistent with their non-significant status (Cohen, 2013). The accuracy interaction marginally exceeded the small effect threshold, accounting for a small increment in explained variance (ΔR^2 = .0203, f2 = .024).

Competence (H2). The overall model was statistically significant, R^2 = .0714, F (3, 269) = 6.894, p < .001, explaining 7.14% of the variance in usage intention. Competence was positively and significantly associated with usage intention (β = 0.2911, p = .027, 95% CI [0.034, 0.589]), indicating that users who perceive a chatbot as competent report stronger intentions to use it. The direct effect of customer experience was not significant in this model (β = 0.153, p = .290, 95% CI [-0.130, 0.437]). Critically, the interaction term wasn't significant (β = -0.038, p = .315, 95% CI [-0.111, 0.036]), and the interaction didn't meaningfully improve model fit (ΔR^2 = 0.004, F (1, 269) = 1.015, p =.315). The confidence interval contains zero, confirming the absence of a moderating effect. The relationship becomes weaker as competence increases, but the interaction doesn't reach statistical significance (see Appendix, Figure A1). Therefore, H2 wasn't supported.

Credibility (H3). The overall model was statistically significant, R^2 = 0.133, F (3, 269) = 13.703, p < .001, explaining 13.26% of the variance in usage intention. Credibility exhibited a positive and significant effect on usage intention (β = 0.462, p < .001, 95% CI [0.200, 0.723]), confirming that perceived credibility of the chatbot predicts intentions to use it. The direct effect of customer experience was not significant in this model (β = 0.232, p = .075, 95% CI [-0.023, 0.487]). Critically, the interaction term wasn't significant (β = -0.006, p = .071, 95% CI [-0.137, 0.006]), with the confidence interval including zero and the interaction providing a marginal improvement in model fit (ΔR2 = 0.106, F (1, 269) = 3.294, p =.071). The relationship becomes weaker as credibility increases, but the interaction doesn't reach statistical significance (see Appendix, Figure A2). Hence, H3 wasn't supported.

Table 5

Moderation Effects

Variable	β	SE	t	p	LLCI	ULCI
Model 1: Competence as moderator (H2)						
Customer Experience	0.153	0.144	1.061	.289	-0.131	0.437
Competence	0.291	0.131	2.227	.027	0.034	0.548
Customer Experience × Competence	-0.038	0.037	-1.007	.315	-0.111	0.036
R^2 = .0714; F (3, 269) = 6.893***						
ΔR^2 = .0035; F (1, 269) = 1.015, p = .3146 (ns); f^2 = .004						
Model 2: Credibility as moderator (H3)						
Customer Experience	0.232	0.129	1.789	.074	-0.023	0.487
Credibility	0.462	0.133	3.477	.000	0.200	0.723
Customer Experience × Credibility	-0.066	0.036	-1.815	.071	-0.137	0.006
R^2 = .1326; F (3, 269) = 13.703***						
ΔR^2 = .0106; F (1, 269) = 3.294, p = .071 (ns), f^2 = .012						
Model 3: Accuracy as moderator (H4)						
Customer Experience	0.265	0.134	1.974	.049	0.001	0.528
Accuracy	0.631	0.144	4.381	<.001	0.347	0.914
Customer Experience × Accuracy	-0.096	0.038	-2.531	.012	-0.171	-0.021
R^2 = .1470; F (3, 269) = 15.457***						
ΔR^2 = .0203; F (1, 269) = 6.405, p = .012, f^2 = .024						

Note. *N* = 273. SE = Standard error. LLCI = lower limit confidence interval, ULCI = upper limit confidence interval. (95% bias-corrected bootstrap confidence interval with 5000 resamples). All variables were mean-centered before analysis. β is the unstandardized regression coefficient. f^2 = Cohen's effect size for the interaction term

Accuracy (H4). The overall model was statistically significant, R^2 = .147, F (3, 269) = 15.457, p < .001, explaining 14.7% of the variance in usage intention. Both customer experience (β = 0.265, p = .049) and accuracy experience (β = 0.631, p < .001) were positively and significantly associated with usage intention, with accuracy emerging as the significant predictor across all three models. The interaction term was statistically significant (β = -0.096, p = .012, 95% CI [-0.1705, -0.0213]), and the interaction accounted for a significant increment in explained variance (ΔR^2 = 0.020, F (1, 269) = 6.405, p =.012). The relationship becomes weaker as accuracy increases (see Appendix, Figure A3); moderation is significant, but in the opposite direction to our hypothesis. Therefore, H4 wasn't supported.

4.3.3. Robustness Check

A robustness check was carried out to assess the stability of the findings. The analyses were repeated using demographic control variables, exclusion of potentially influential observations, bootstrapped confidence intervals, and heteroscedasticity-robust standard errors (Öner, 2026). The magnitude and the statistical significance of the main relationships remained largely unchanged, indicating that the findings were robust across alternative analytical specifications (see Appendix A, Table A1).

Table 6

Summary of Results

Hypothesis	Test Results
H_1. Customer experience with a chatbot is positively associated with usage intention.	Supported
H_2. Competence moderates the relationship between customer experience and usage intention, such that the relationship strengthens when competence is high.	Not Supported
H_3. Credibility moderates the relationship between customer experience and usage intention, such that the relationship strengthens when credibility is high.	Not Supported
H_4. Accuracy moderates the relationship between customer experience and usage intention, such that the relationship strengthens when accuracy is high.	Not Supported

5 | DISCUSSION

The current study examines the impact of customer experience with chatbots on usage intention with the moderating role of chatbot competence, accuracy, and credibility. For H1, there is a positive relationship between customer experience with chatbots and usage intention. This aligns well with the expectation-confirmation logic underpinning the hypothesis (Oliver, 1980), whereby an interaction confirming prior expectations generates the satisfaction that motivates continued use. The result aligns with Haugeland et al. (2022), who found that personalized support and rapid issue resolution raise continued-use intentions, and with the evidence identifying experiential quality as a determinant of reuse (Nicolescu & Tudorache, 2022). The literature also points out that factors like the type of information provided by chatbots or their ability to engage users through humor and human-like characteristics play a very important role in improving overall customer experience. Ruan and Mezei (2022) found that conveying information about functional product features is associated with higher levels of customer satisfaction.

For H2, competence exerted a significant positive direct effect, but the interaction was non-significant; H2 is not supported, indicating that competence acts as an antecedent rather than a boundary condition. This diverges from Source Credibility Theory (Hovland et al., 1953), which perceived expertise as more diagnostic of future performance. The direct effect nevertheless aligns with previous research; Nicolescu and Tudorache (2022) link competence to satisfaction, reuse intention, and trust. Skjuve and Brandzaeg (2018) find interpersonal communication competence builds rapport and encourages return use; and Al-Oraini (2025) identifies it among the strongest predictors of satisfaction. Taken together, competence is a determinant of usage intention in its own right. Additionally, the research conducted by Jin and Youn (2023) emphasizes the importance of adding the social presence of chatbots to foster their perceived competence and increase intention to use.

For H3, Credibility produced the second strongest direct effect, confirming that believability raises usage intention. Moreover, this finding supports the idea that credibility predicts users' ability to use chatbots by improving their perception of their usefulness. However, the interaction was non-significant. This suggests that while users value chatbot competency, it might not play a significant role in deciding whether to continue using it or not. This sits uneasily with Kamoonpuri and Sengar (2023), and Misischia et al. (2022) reported

that credibility amplifies the effect of experience on usage intention. But Alagarsamy and Mehrolia (2023) suggest that credibility enhances perceived usefulness and is thereby associated with intention directly rather than the experiential pathway.

For H4, Accuracy was the strongest predictor of customer usage intention of the chatbot. Customers place a high value on chatbot accuracy and believe it to be an important consideration in determining how well they interact with the bot, as proven by the literature. The interaction is negative, indicating that accuracy weakens rather than strengthens the experience-intention relationship. We interpret it cautiously; this is theoretically logical rather than unusual. It is consistent with a substitution logic, where a chatbot is perceived as highly accurate, accuracy itself furnishes a sufficient basis for continued use, and the broader experiential appraisal becomes less diagnostic. When accuracy is uncertain, users fall back on overall experience as the primary cue. This is compatible with evidence that accuracy underpins cognitive trust and that inaccurate responses erode it (Wang et al., 2026), and that accurate chatbots make fewer errors and appear more knowledgeable (Roy & Naidoo, 2021).

5.1 | Theoretical Implications

The findings answer the study's research questions unexpectedly. Customer experience does predict usage intention across domains. Patterns across H2 to H4 carry a coherent implication. The three credibility dimensions specified by Source Credibility Theory appear to predict usage intention rather than shaping the experience-intention relationship. All produced significant positive direct effects, and the two largest, accuracy and credibility, exceeded the effects of customer experience itself. This suggests users judge whether to continue using a Chatbot primarily on what the system is, rather than how a single interaction felt. Source Credibility Theory may therefore work better in the conversational-agent context as an explanation of what directly drives usage intention, rather than what shapes the effect of experience on it. The negative accuracy interaction further suggests credibility cues may substitute for experiential information rather than reinforce it, an inversion meriting dedicated theoretical development. Our study highlights theoretical gaps that will have to be filled in order to fully account for the complex nature of customer interactions with chatbots.

5.2 | Practical Implications

The practical significance of our research lies in providing useful insights for business units seeking improvement in their Chatbot strategies. It can guide designers to improve chatbot features, enabling them to offer better user experiences by understanding the impact of chatbot attributes on user behavior. By identifying the relationship between user intention and customer experience, businesses may find it appropriate to shift their approaches to engagement, focusing on the positive impact of user experiences on engagement. Investment in accuracy and credibility yields larger returns in usage intention than experiential design features. Business entities can improve their Chatbot ROI by strategically allocating resources to areas having a major impact on customer satisfaction and engagement. The negative accuracy interaction adds nuance, i.e., experiential design matters most when accuracy is imperfect, so firms operating chatbots of uncertain reliability may also benefit from improving the interaction experience.

5.3 | Limitations and future Directions

Several limitations qualify these findings. Convenience sampling was used with a sample size of 273 respondents from a single geographical context, constraining generalizability. The cross-sectional design

captures co-variation at one point in time and doesn't permit causal inference. Moderated regression is underpowered for detecting interactions, so the non-significant results for H2 and H3 may reflect insufficient power rather than true null effects, a concern particularly relevant to H4, where the interaction approached significance but in the opposite direction from the proposed hypothesis. Self-reported and closed-ended measures introduce possible common-method, response bias, and social-desirability biases. Finally, the study is domain-general and doesn't account for industry-specific or cultural moderators.

The limitations discussed above prime several significant future research directions. First, a longitudinal design that can monitor user-chatbot interaction over a long period of time can provide valuable insights about actions and perceptions to determine the long-term significance of chatbot technology. Moreover, this will address concerns about response and common method bias. Second, future studies can replicate with probability-based larger samples, which would clarify whether the non-significant interaction reflects insufficient power or a true null hypothesis. Third, a qualitative or mixed-method research design may allow for more comprehensive research of user-chatbot interactions, including other aspects such as perceived values, trust, and emotions. Finally, domain-specific and cross-cultural replication would better describe the boundaries of these findings.

7 | CONCLUSION

This study tested four hypotheses concerning customer experience with AI-powered chatbots, usage intention, and the moderating roles of competence, credibility, and accuracy. Customer experience positively predicted usage intention (H1, supported). Competence (H2) and credibility (H3) didn't moderate this relationship, and accuracy (H4) moderated it significantly but in the hypothesized direction. All three moderation hypotheses are therefore rejected. Rather than diminishing the contribution, this reframes it. The attributes examined shape usage intention directly and, for accuracy, appear to substitute for rather than amplify experiential information. Resting on cross-sectional data from a single sampling context, these conclusions invite further investigation rather than setting the question.

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Acknowledgment: The authors would like to express their sincere thanks to the editor and the anonymous reviewers for their helpful comments and suggestions.

Author Contributions: Conceptualization: Juniad, S. and Khan, S.; Data curation: Juniad, S. and Malik, A.N.; Formal analysis: Juniad, S. and Liaqat, M.; Methodology: Juniad, S. and Khan, S.; Software: Juniad, S. and Ameer, S.M.; Supervision: Khan, S.; Validation: Juniad, S. and Malik, A.N.; Writing – original draft: Juniad, S. and Khan, S.; Writing – review & editing: Juniad, S. and Khan, S. All authors approved the final version of the manuscript for publication.

Declaration of Conflicting Interest: The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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Funding: The author(s) received no financial support for the research, authorship, and/or publication of this article.

Data Availability Statement: The data supporting the findings of this study were collected through a self-administered survey of adult users of AI-assisted chatbots in the Twin Cities of Islamabad and Rawalpindi. Owing to ethical restrictions and to protect the confidentiality and privacy of participants, who were assured that their responses would be used solely for research purposes, the data are not publicly available and cannot be shared.

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Appendex

Table A1.

Robustness Check

Relationship	Main model β	Bootstrap β	Model with controls β	Robust SE result	Conclusion
CE→UI	0.173***	0.174***	0.168***	Significant	Robust
CP→CE	0.051	0.053	0.048	Not Significant	Stable
CD→CE	0.123	0.127	0.119	Not Significant	Stable
AC→CE	0.121	0.124	0.116	Not Significant	Stable

Note. CE = Customers Experience; UI = Usage Intention; CD = Credibility; AC = Accuracy; CP = Competence; SE= standard error

Figure A1

Interaction plot of customer experience and competence on usage intention

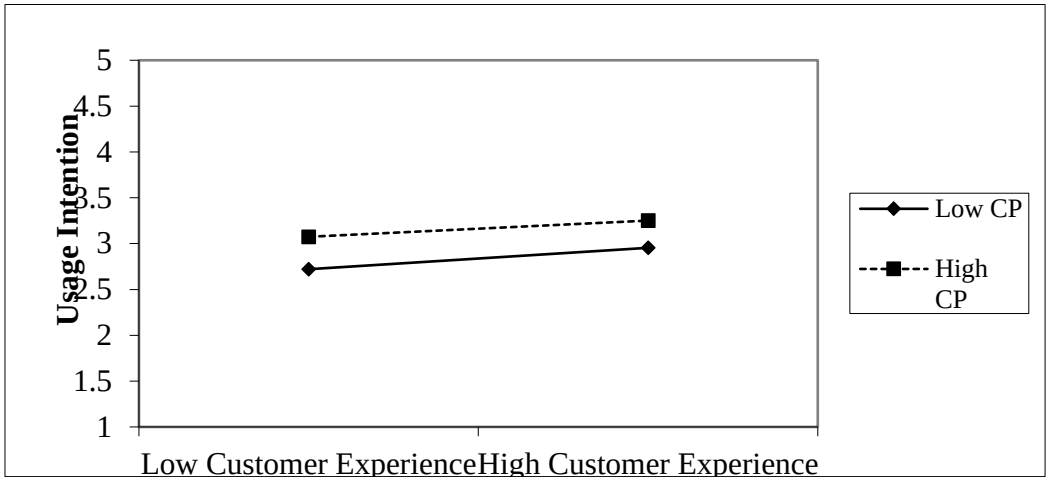


Figure A2

Interaction plot of customer experience and credibility on usage intention

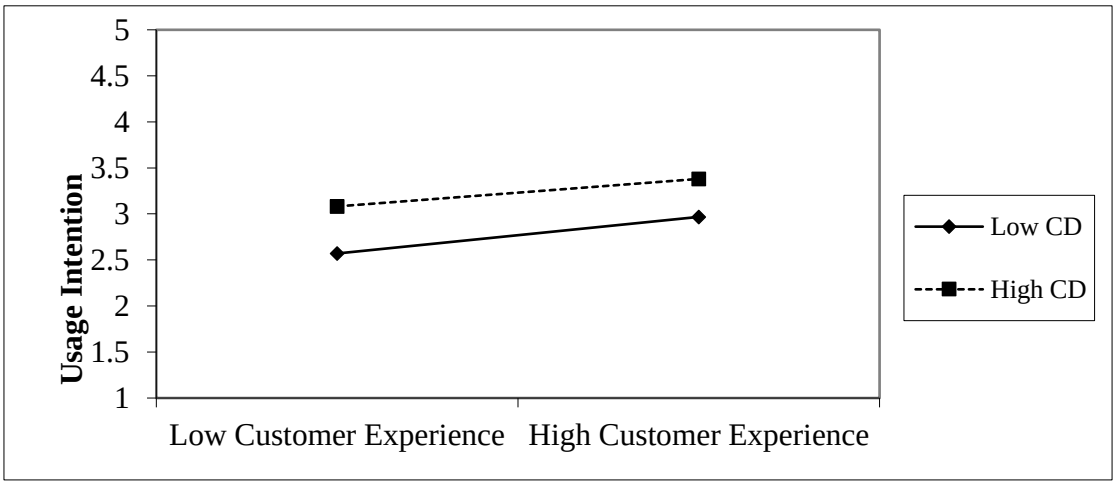


Figure A3

Interaction plot of customer experience and accuracy on usage intention

