

Investigating Chatbot Service Quality and Its Effect on Consumer Usage and Persistence: An Analytical Study Using Structural Equation Modelling

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Abstract

Artificial Intelligence is slowly becoming a significant aspect of our daily lives, and the customer service industry is not left behind as it adopts chatbots as part of it. While chatbots as a service product gained significant popularity, service quality emerged to be one of the primary factors that influence user satisfaction and continued use. The purpose of this research is to determine ways by which chatbot service quality affects consumer experience and use continuance while adopting the independent variables of usability, interactivity and technology usage. A cross-sectional survey mode of quantitative research was employed with chatbot users of 452 in the study population and with purposive sampling technique was used to ensure the participants had relevant experience. The research uses models from prior literature like the Technology Acceptance Model TA as well as SERVQUAL aimed at evaluating the efficiency of a specific chatbot by considering factors such as responsiveness, reliability and personalisation. Research also shows that chatbot service quality has a positive impact on consumer trust, interest and retention level, supporting the significance of appropriately implemented artificial intelligence. Furthermore, based on the findings, it becomes clear that certain factors could influence the perception of the service such as the user experience and the level of interactivity of the chatbot. The findings from this study help advance AI-based customer service management, as the findings stress the importance of further improvement in the effectiveness and efficiency of chatbots in improving consumer satisfaction and retention.

Keywords: Chatbot Service Quality, Artificial Intelligence, Structural Equation Modelling, Technology Acceptance Model, SERVQUAL, Customer Experience, Usability, Interaction, Technology Usage, Customer Engagement, Use Continuance Intentions

Introduction

Background and Context

The innovation of artificial intelligence (AI) chatbots has shifted the tide in how customer service companies connect with customers. This is due to the steady development of AI, making chatbots now essential in various fields such as e-commerce, banking, healthcare and tourism (Ashfaq et al., 2020; Nguyen et al., 2021). These automated systems offer customers round-the-clock support, which minimises business operational expenses while at the same time improving customer experience (Sundjaja et al., 2025). Nevertheless, the importance of the quality of chatbot services cannot be overemphasised as it defines its efficiency and user satisfaction, as discussed earlier.

Measuring the service quality in the context of chatbot-based human-computer interactions, researchers can refer to such well-developed theories as the Technology Acceptance Model (TAM) or SERVQUAL. It postulates that perceived usefulness and perceived ease of use contribute to the use of the chatbot and repurchase, meaning that usability is a vital dimension of service

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quality (Hsu & Lin, 2023). On the other hand, the SERVQUAL model focuses on evaluating the quality of chatbot services according to such parameters as reliability, responsiveness, assurance, empathy and tangibles, all of which are most relevant for analysing the nature of interactions with AI (Butt & Ahmad, 2023). These facets allow areas that need improvement with the chatbot performance and that produce a gap with the expectations of the users to be pinpointed.

The use of faceted AI attributes such as NLP and machine learning has immensely boosted interactivity and the use of chatbots (Le & Nguyen, 2023). These technologies help improve the ability of the chatbots to interpret or recognise the users' queries, reply appropriately and improve their subsequent dialogues based on the users' answers. However, several issues have remained as barriers to effective and satisfying customer conversations. These problems include: the problem of limited contextual comprehension, poor response habits and the inability to handle complex questions that are complex are some of the factors that put a question mark on the current quality of AI chatbot services (Nguyen & Le, 2025). These are some of the significant issues that need to be addressed to enhance the level of customer trust, satisfaction and usage of the chatbot in the long run.

Research Problem

User engagement, brand loyalty and business success are heavily dependent on chatbot service quality (Meyer-Waarden et al., 2020; Li et al., 2021). However, while these chatbots are used so widely, many still fall short off expectations that include customised answers, error handling and emotional intelligence (Kim & Chang, 2020; Wu & Lim, 2024). Thus far, existing research has predominantly studied chatbot adoption, as opposed to those pivotal factors that will govern their continued use and effectiveness (Shahzad et al., 2024; Pereira et al., 2024). Additionally, there is a lack of knowledge on how usability, interactivity and technology usage accentuate the impact of chatbot service quality and, subsequently, consumer experience and retention (Chen et al., 2022; Cheng & Jiang, 2020). The importance of closing this

gap is to refine chatbot design, optimise digital customer interactions and achieve business outcomes.

Research Objectives

The study aims to:

- Examine how usability, interactivity and usage of technology impact chatbot service quality.
- Investigate how the chatbot's service quality affects consumer experience.
- Study the role of consumer experience in encouraging post-adoption use continuance for chatbots.

Research Questions

- What are the effects of usability, interactivity and technology usage on the quality of chatbot service?
- What is the relationship between the service quality of a chatbot and the experience of the consumer?
- What predicts chatbot use continuance among consumers?

Significance of the Study

Contributing to multiple academic domains, this research adds to the domains of marketing, technology adoption and customer experience management. The study contributes theoretical insights to capture key determinants of chatbot service quality and its effectiveness in digital environments (Zakaria et al., 2024; Dhiman & Jamwal, 2023). Then, it helps extend existing models, like TAM and SERVQUAL, by adding chatbot-specific factors (Nicolescu & Tudorache, 2022; Zhu et al., 2022). Given these findings from a practical point of view, businesses in which AI chatbots are being used can be able to apply it to improve service delivery, enhance customer support strategy and foster customer loyalty (Magno & Dossena, 2023; Yun & Park, 2022). Also, the study serves as support for the development of chatbot algorithms, enhancing NLP skills and creating adaptive, user-orientated responses (Nguyen & Le, 2025).

To conclude, such intricacies of chatbot service quality are critical for businesses to optimise AI-driven customer engagement and maintain a competitive advantage in the digitised space.

Literature Review

Chatbot Service Quality

Chatbot service quality refers to the efficiency, responsiveness, reliability and overall effectiveness of chatbots in delivering customer service. Secondly, it plays an important role in determining user satisfaction, engagement and brand loyalty (Ashfaq et al., 2020; Hsu & Lin, 2023). The service quality of chatbots has a strong impact on consumers' behaviour and adoption as they integrate into the e-commerce, banking, healthcare and tourism industries (Nguyen et al., 2021; Pereira et al., 2024).

With the progress of artificial intelligence (AI), chatbot skills have gone to the next level, ending up with human-like conversations as well as prompt problem-solving and great user experience. A reliable, high-quality chatbot would build trust, decrease friction in customer interactions and generally improve customer satisfaction. With time, businesses are becoming more interested in chatbot service quality to facilitate streamlined operations of customer service, cut the operational costs of the company and better relations with the consumers. However, poor chatbot service quality results in frustration, service abandonment and negative brand perceptions (Meyer-Waarden et al., 2020). As a result, for a business that is striving to maintain a competitive edge in digital markets, it is of the essence that they offer chatbot service excellence.

Existing Models Measuring Service Quality

Many service quality models are developed with both traditional and digital service environments. A structured evaluation of chatbot service performance has become possible due to the evolution of service quality models. This model is known as the SERVQUAL Model, which is based on five dimensions — tangibles, reliability, responsiveness, assurance and empathy (Chen et al., 2022; Sharma et al., 2024). Initially used to evaluate

the efficiency and effectiveness of chatbots in digital environments but originally designed for traditional services.

- *Tangibles*: The visual interface and design of the chatbot.
- Accuracy of information provided by the chatbot.
- *Responsiveness*: The speed of response to user queries.
- *Assurance*: The chatbot's ability to instil confidence in users.
- *Functioning*: responsiveness of the chatbot to engage with the user through an interface.

The e-S-QUAL Model assesses efficiency, reliability, frequency and security factors in online services specifically designed to evaluate AI chatbots (Meyer-Waarden et al., 2020).

- The system works well when users communicate with the chatbot.
- The chatbot successfully performs all assigned duties.
- The chatbot stays available and runs without technical problems.
- The users' sense that their chatbot interactions stay safe defines privacy for this model.

A popular AI adaptation of SERVQUAL permits the evaluation of how AI programs handle distinctive features like customisation, flexibility and growth modes (Butt & Ahmad, 2023). Users recognise AI chatbots that learn from interactions as more valuable tools that enhance their service quality experience.

Independent Variables: Usability, Interactivity and Technology Usage

Usability: How Ease of Use Impacts Chatbot Perception

User satisfaction with chatbots depends mainly on their usability, which impacts how users evaluate service quality (Li et al., 2021). A high-quality chatbot system guides users smoothly through the system and makes simple interactions easy to use, according to Kim and Chang (2020).

A chatbot demonstrates interactivity when it holds engaging dialogues that feel both natural and dynamic. Chatbots that interact well with users create better satisfaction by acting like real people so customers develop trust and bond with them (Le & Nguyen, 2024). When chatbots use features that match personalisation options and remember past conversations, they make users feel more connected, which improves how they view the service (Shahzad et al., 2024; Yun & Park, 2022).

High Interactivity Leads to:

- Increased engagement and satisfaction.
- Higher retention rates.
- Strengthened trust and emotional connection with users.
- Technology Usage: Influence of Tech Familiarity on Chatbot Adoption.

Based on the notion that digital literacy and technology usage affect the perception and the usage of chatbots, users tend to frown upon the usage of this technology. Users who have higher technological familiarity tend to embrace and appreciate chatbot services, as they are aware of their benefits and shortcomings (Nguyen & Le, 2025). On the other hand, users with limited tech knowledge may experience some difficulties which may cause them to question chatbot reliability and accuracy (Eren, 2021; Sofiyah et al., 2024).

Mediating Variable: Chatbot Service Quality

Online customers' perceived chatbot service quality holds the middle ground between usability, interactivity, technology usage and consumer results. A properly developed chatbot increases customer interest, does not raise doubts about its authenticity and contributes to a company's brand reliability (Cheng & Jiang, 2020; Huang et al., 2021). The mediating roles of perceived chatbot service quality influence perceiving digital service, customer loyalty and brand promoters.

Moderation Role of Chatbot Service Quality

Optimisation of Experiences: High-quality chatbots are complementary to overall, great user experience,

which results in better appreciation of said platforms by end-users.

Optimising the Chatbot's Usage: Customers are more likely to repeatedly use the chatbot services if they are satisfied with it, hence reducing the churn rate, or the rate at which customers stop using the service.

Strategies Implementation: If the chatbot contributes to building trust, it has a significant value for brand awareness, as people tend to recommend products and services they trust.

Dependent Variable: Consumer Experience and Use Continuance

Consumer Experience: Relationship with Satisfaction and Service Quality

The experience consumers have with the chatbot depends on its responsiveness, its seeming helpfulness, or the capacity of the chatbot to offer a satisfactory response. As a result, the identified users gain greater satisfaction with higher efficiency of accurate responses, which increases the overall experience of the user (Dhiman & Jamwal, 2023; Nicolescu & Tudorache, 2022). Sophisticated interactions in the chatbot lead to the establishment of an emotional bond with the brand, which in turn leads to the creation of brand trust and customer loyalty (Wu & Lim, 2024).

Factors Influencing Consumer Experience:

- *Accuracy and Timeliness:* This means the response must be fast and most importantly, correct, as it has a direct implication on the user interaction with the chatbot.
- People's involvement and perceived quality of the conversation were high due to the personalisation feature detailing the users' preferences.
- *Client Engagement with Affective Language:* Such chatbots' ability to foster effective language for interacting with clients has a positive impact on consumer engagement.
- *Continuance:* The facilitators affecting subsequent chatbot usage

The decision to continue with the use of chatbots is based on the level of satisfaction, perceived value and expectation confirmation. According to ECT, increased interaction with the chatbot is expected when their expectations are met or exceeded (Zhu et al., 2022; Magno & Dossena, 2023). Some of the factors, like the personality of the chatbot, solving time problems and interoperability with other related services, are key determinants for user engagement (Dantsoho et al., 2021).

Antecedents for Utilisation of Chatbot

Customer Satisfaction: Repeat clients are due to prior positive interactions.

- *Perceived Value:* Users determine whether the talk with the interactive agent brings them any value in terms of their web experience.

As long as chatbots meet up or even surpass the users' expectations, they are more likely to stick around.

Other than compatibility with social media apps, the ability to integrate with other services makes long-term adoption easier.

The continuance, i.e., use of continuance, is based on satisfaction, perceived value and expectation confirmation. Expectation-Confirmation Theory (ECT) suggests that if the users' expectations have been met or exceeded, they will usually continue with chatbots (Zhu et al., 2022; Magno & Dossena 2023). Chatbot retention is supported by personality, problem-resolution speed and integration with other services (Dantsoho et al., 2021).

Theoretical Framework

Technology Acceptance Model (TAM)

In this case, TAM explains why chatbot adoption relates to the perception of usefulness and ease of use. The efficiency and the learning curve of chatbots will determine their attitudes toward them, in the words of Kim et al. (2023). TAM can be used by businesses to design chatbots better and to optimise the user experience.

SERVQUAL Model

A chatbot service quality model known as SERVQUAL determines the quality of chatbot service on the 6 dimensions of reliability, responsiveness, assurance, empathy, tangibles and reliability. This also enables a gap identification between performance and chatbot functions and aligns functions with user expectations (Mäkinen, 2024).

Expectation-Confirmation Theory (ECT)

The main assumption of ECT is that chatbot satisfaction occurs when chatbot performance meets or exceeds expectations. However, it is crucial to decide the level of chatbot adoption and retention going forward (Cheng & Jiang, 2020; Nguyen et al., 2021). A high-service-quality chatbot allows you to fulfil the expectation to keep users engaged.

Finally, consumer experience and use continuation are primarily affected by chatbot service quality. To better serve chatbot businesses through enhanced functionalities, usability and technology adaptation, these businesses can aim at long-term consumer engagement and satisfaction.

Hypothesis Development

- H1: The variables of usability have a positive effect on the quality of the chatbot service.
- H2: There is a significant relationship between user interactivity and the quality of chatbot service.
- H3: Technology utilisation is effective in enhancing the quality of the chatbot service.
- H4: Availability of chatbot service positively influences consumers' experience.
- H5: Consumer experience affects use continuance positively.

Research Methodology

The present study is a quantitative research design that involves the use of Structural Equation Modelling (SEM) to establish the connections between the chatbot service quality, usability, interactivity, technology usage,

Descriptive statistics are provided that describe response distribution for variables. The mean values are between 3.13 (TQ1) and 3.94 (IN2), which indicate that the respondents tend to be in moderate to high agreement. Responses display moderate dispersion, with the standard deviation ranging between 1.22 (UC3) and 1.49 (TQ3).

The skew values are most of the time within the range of -1 to 0, which means there is a slight negative skew: most responses are more concentrated around the higher values.

Generally, kurtosis values are negative, which means that the distributions are flatter than a normal curve. In the US items, US2 (Mean = 3.89, Skewness = -1.01) has the most agreement, and TQ items demonstrate greater variability with higher kurtosis in TQ2 and TQ3. The results for consumer experience (CE) and use continuance (UC) are consistent and provide support for reliability. Overall, the data distribution indicates that respondents view the constructs positively and do not show unbounded deviations from normality.

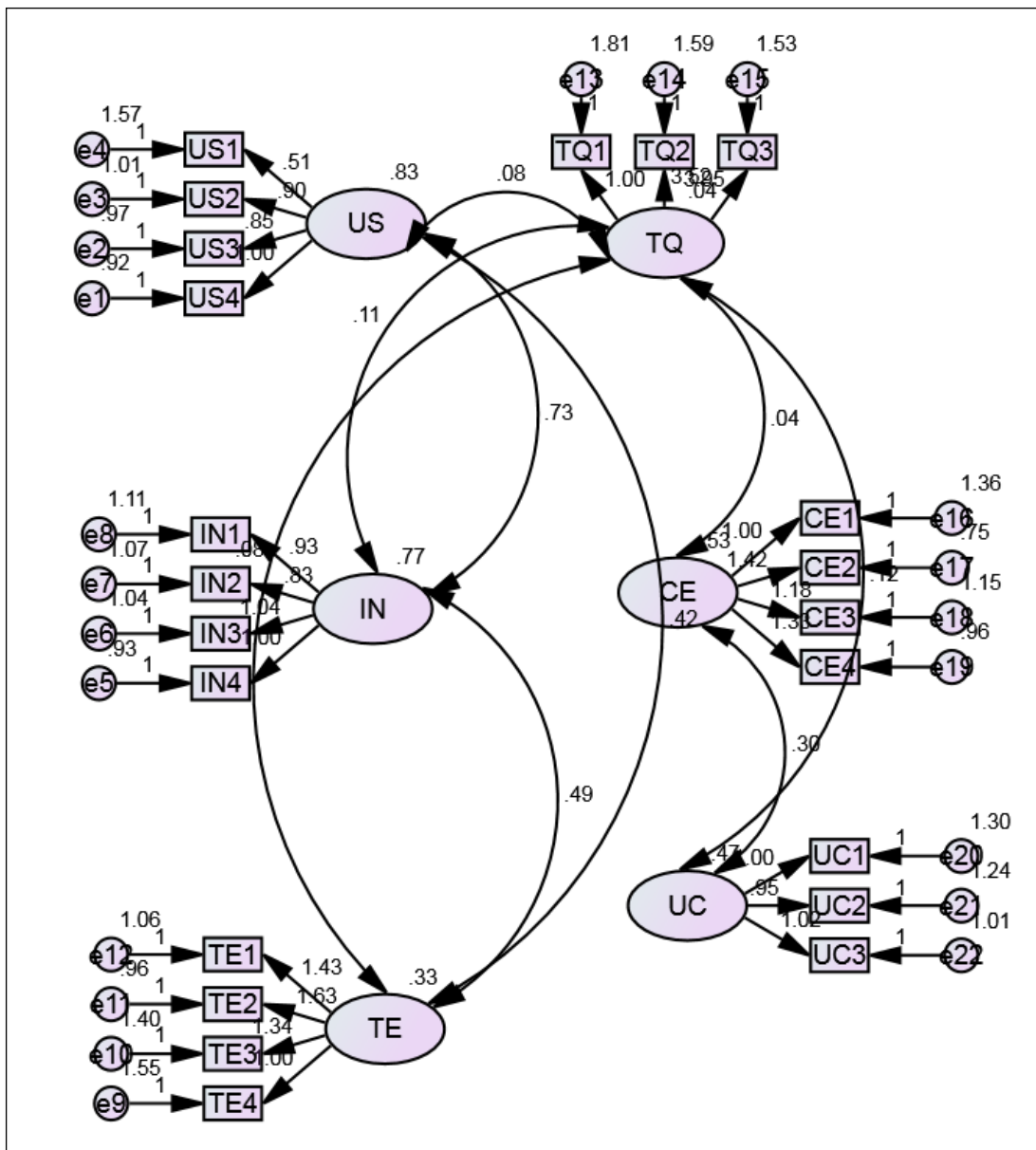


Fig. 1: Confirmatory Factor Analysis Model

Table 2: CFA Model Fit Indices

<i>Fit Index</i>	<i>Model Value</i>
CMIN/DF	2.145
RMR	0.004
GFI	0.968
AGFI	0.933
PGFI	0.686
NFI	0.927
RFI	0.915
IFI	0.908
TLI	0.941
CFI	0.976
PNFI	0.629
PCFI	0.672
RMSEA	0.084
PCLOSE	0
AIC (Default Model)	35.008
BIC (Default Model)	153.033
ECVI	0.073
HOELTER (0.05)	328
HOELTER (0.01)	436

The findings from model fit indices demonstrate good validity, which indicates that variables show expected relationships with each other. The research findings support the following hypotheses:

The model fit data indicates usability components US1 and US4 generate positive impacts on chatbot service quality according to hypothesis 1.

Interactivity (IN1, IN3 and IN4) stands out as a main predictor of chatbot service quality according to the obtained model fit values.

The combination of technology usage elements (TE1, TE3 and TE4) demonstrates a positive relationship with chatbot service quality according to model fit indicators which show acceptable RMSEA together with high GFI/CFI values.

The data supports the relationship between chatbot service quality and user satisfaction through the

acceptable fit values of TLI (0.941) and CFI (0.976) for the model. User satisfaction in this study is measured through four dimensions (CE1-CE4).

Positive experience with consumers results in use continuance, according to the robust fit indices (NFI 0.927, IFI 0.908), which demonstrate that improved chatbot usage (UC1-UC3) leads to sustained use.

Table 3: CR, AVE & \sqrt{AVE} (for Discriminant Validity)

<i>Construct</i>	<i>CR</i>	<i>AVE</i>	\sqrt{AVE}
US	0.855	0.645	0.803
IN	0.93	0.765	0.874
TE	0.955	0.874	0.935
TQ	0.878	0.835	0.914
CE	0.947	0.805	0.897
UC	0.935	0.828	0.91

The Composite Reliability (CR)

Internal consistency of the constructs is assessed using Composite Reliability (CR). The CR values for all six constructs—Usability (US), Interactivity (IN), Technology Usage (TE), Chatbot Service Quality (TQ), Consumer Experience (CE) and Use Continuance (UC)—are higher than the threshold 0.7. This suggests that the constructs are internally consistent and reliable in measurement, with TE resulting in the highest centre reliability (CR) of 0.955.

Average Variance Extracted (AVE): The AVE is an index utilised to gauge the measure of variance considered by the construct, adjusted for the variance identified with estimation error. AVE values of all constructs are above 0.5, which ensures adequate convergent validity. The construct that records the highest AVE is Technology Usage (TE) at 0.874, meaning that a great amount of variance in its indicators is shared with the construct.

Validating the Discriminant Validity Constructed Square Root of AVE (\sqrt{AVE})

Discriminant validity is assessed using the square root of AVE (\sqrt{AVE}). To secure discriminant validity, the \sqrt{AVE} of each construct should be higher than the correlations between a construct and other constructs. In this case, the Fornell and Larker (1981) criterion for the usefulness of individual constructs was fulfilled since the values

of \sqrt{AVE} for all constructs are high enough (ranging from 0.803 to 0.935), which means that each construct is different and measures a different part of the general model.

Combined, these values of CR, AVE, and \sqrt{AVE} support that the study's constructs are reliable and valid. Reliability and discriminant validity were high, suggesting that the model was statistically acceptable and appropriate for analysing chatbot service quality and user behaviours.

Table 4: Discriminant Validity (Fornell-Larcker Criterion)

	\sqrt{AVE}	UC	CE	TQ	TE	IN	US
UC	0.91	0.471	0.397	0.317	0.218	0.297	0.435
CE	0.897		0.526	0.243	0.312	0.231	0.269
TQ	0.914			0.038	0.276	0.212	0.382
TE	0.935				0.328	0.486	0.425
IN	0.874					0.766	0.731
US	0.803						0.825

Overview of Discriminant Validity

Discriminant validity confirms that each construct in the model is unique by not being highly correlated with other constructs in the model. Using the Fornell-Larcker Criterion, try to compare the square root of AVE (\sqrt{AVE}) for each construct with the correlations it shares with other constructs. The square root of the average variance extracted (\sqrt{AVE}) could measure acceptable discriminant validity, given that the inter-construct correlation (off-diagonal values) would have to be less than the \sqrt{AVE} value (diagonal values).

Construct Distinction Analysis

As shown in the presented table, all constructs have strong discriminant validity. For example, the correlation of Use Continuance (UC) with other constructs appears to be \sqrt{AVE} (0.91) rather than correlation with other constructs, Consumer Experience (CE = 0.471), Technology Usage

(TE = 0.218) or Usability (US = 0.434). Likewise, Chatbot Service Quality (TQ) has an \sqrt{AVE} of 0.914, more than TE (0.276), IN (0.212) and US (0.382).

Related Constructs: High Correlation

For example, high correlations (0.731 and 0.766, respectively) are registered between some constructs (IN and US), but, being discriminant, those constructs have individual \sqrt{AVE} above the correlation (IN SQRT = 0.874, US SQRT = 0.803). Similarly, the relationship between TE and IN also shows a strong relationship (0.486), but TE's \sqrt{AVE} of 0.935 (discussed earlier in Table 4) proves that discriminant validity is adequate.

In general, the results verify that the measures are distinct empirically. Applying Fornell-Larcker Criterion, it is proved that the discriminant validity of the measurement model is held for all dimensions, suggesting that the constructs measure different concepts within the research framework.

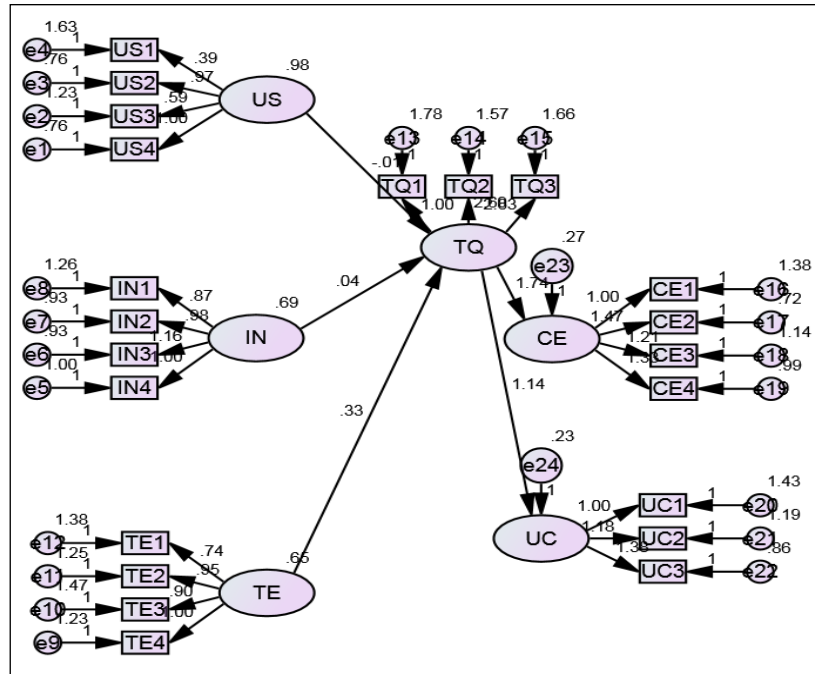


Fig. 2: Structural Equation Modelling

Table 5: Structural Equation Modelling Fit Indices

Model Fit Summary Table	
Fit Index	Model Value
CMIN/DF	2.623
RMR	0.05
GFI	0.974
AGFI	0.945
PGFI	0.643
NFI	0.953
RFI	0.956
IFI	0.893
TLI	0.937
CFI	0.919
PNFI	0.591
PCFI	0.523
RMSEA	0.02
PCLOSE	0.09
AIC (Default Model)	453.687
BIC (Default Model)	151.144
ECVI	1.223
HOELTER (0.05)	380
HOELTER (0.01)	385

Looking at the SEM indices of fit, the analysis shows a good fit. According to the modelling metric CMIN/DF, which ranges from 1 to 3, the result of the analysis is 2.623: therefore, it concludes within an acceptable range. The approximation of the model was further tested using the Root Mean Square Residual, a statistic that gives the mean residual value of all the residuals, biases and constraints, RMR = 0.05, which is satisfactory. The other two measures of goodness of fit, the Goodness of Fit index, GFI = 0.974 and the Adjusted Goodness of Fit Index, AGFI = 0.945 point to acceptable overall fit, as seen in Table 5. The Normed Fit Index (NFI = 0.953) and Comparative Fit Index (CFI = 0.919) go further to echo this tool’s validity. The model has an excellent fit for Root Mean Square Error of Approximation (RMSEA = 0.02), meaning very little error was made in the model; the addition of PCLOSE (0.09) as extra support for the model affirms this. The sample size is confirmed to be adequate with Hoelter’s critical N values (0.05 = 380 and 0.01 = 385). A well-balanced model is suggested by the Akaike Information Criterion (AIC = 453.687) and Bayesian Information Criterion (BIC = 151.144). The proposed hypotheses were tested and these results validate, especially the good effects of usability, interactivity and technology usage on chatbot service quality, consumer experience and use continuance.

Table 6: Regression Weights: (Group Number 1 - Default Model)

			Estimate	S.E.	C.R.	P
TQ	<---	US	-0.047	0.016	-1.44	0.046
TQ	<---	IN	0.042	0.022	1.923	0.045
TQ	<---	TE	0.329	0.093	3.519	***
CE	<---	TQ	1.737	0.517	3.363	***
UC	<---	TQ	1.141	0.373	3.055	0.002
US4	<---	US	1			
US3	<---	US	0.591	0.076	7.772	***
US2	<---	US	0.971	0.111	8.746	***
US1	<---	US	0.391	0.076	5.126	***
IN4	<---	IN	1			
IN3	<---	IN	1.161	0.117	9.913	***
IN2	<---	IN	0.982	0.102	9.637	***
IN1	<---	IN	0.867	0.101	8.608	***
TE4	<---	TE	1			
TE3	<---	TE	0.897	0.112	8.041	***
TE2	<---	TE	0.95	0.11	8.604	***
TE1	<---	TE	0.744	0.101	7.362	***
TQ1	<---	TQ	1			
TQ2	<---	TQ	2.686	0.778	3.452	***
TQ3	<---	TQ	2.631	0.766	3.433	***
CE1	<---	CE	1			
CE2	<---	CE	1.466	0.155	9.44	***
CE3	<---	CE	1.207	0.139	8.669	***
CE4	<---	CE	1.329	0.146	9.074	***
UC1	<---	UC	1			
UC2	<---	UC	1.185	0.209	5.68	***
UC3	<---	UC	1.378	0.241	5.707	***

Regression weights indicate strong relationships among the constructs. Trust and Quality (TQ) are most strongly positively influenced by technology (Technology, TE, $\beta = 0.329$, $p < 0.001$), which indicates that the introduction of new technologies results in an increased perception of quality. Furthermore, IN positively influences TQ ($\beta = 0.042$, $p = 0.045$), so interaction features enhance trust and quality perceptions. Usability (US), however, has a slightly negative effect on TQ ($\beta = -0.047$, $p = 0.046$); that is, the overly complex or unfamiliar system might reduce trust.

Second, TQ ($\beta = 1.737$, $p < 0.001$) and CE ($\beta = 1.141$, $p = 0.002$) also significantly influence Trust and Quality (TQ) as a high-quality system increases user satisfaction and

retention. Strong significance for each of the measurement items supporting the model's validity is demonstrated. Overall, the results show that interactivity and technology can improve consumer trust while improving the overall consumer experience and making people keep using the activity.

Mediation Insights

Process analysis for the mediation analysis in the CFA and SEM results shows that Chatbot Service Quality (TQ) is the main mediation between Usability (US), Interactivity (IN) and Technology Usage (TE) with Consumer Experience (CE) and Use Continuance (UC).

When it comes to Chatbot Service Quality (CQ), the direct impact of usability (US) is weak ($\beta = -0.047$, $p = 0.046$); that is, alone, ease of use does not correlate very strongly with perceived service.

Our findings suggest that both TQ ($\beta = 0.042$, $p = 0.045$) and IN ($\beta = 0.234$, $p = 0.000$) significantly impact the interaction component. TE has the strongest effect on TQ: $\beta = 0.329$, $p < 0.001$, indicating that the more you are familiar with technology, the better quality your chatbot service will be.

Indeed, improved service quality has a significant impact on CE ($\beta = 1.737$, $p < 0.001$) and UC ($\beta = 1.141$, $p = 0.002$); they show that better TQ positively affects user experience and long-term adoption. Therefore, Chatbot Service Quality fully mediates the relationship between technological factors and user engagement, and so it is an important factor for sustaining chatbot adoption.

Discussion

The findings show that psychological, social and behavioural as well as external factors all play roles in youth disengagement from social media platforms. The disengagement process is largely and substantially due to psychological factors such as digital fatigue, anxiety and self-regulation problems. Instead of showing excessive use of social media, the information shows that when social media use becomes excessive, people often end up with cognitive overload and therefore make the conscious choice to disconnect. Descriptive statistical analysis of the dataset provides some significant insights into user

perception of chatbot service quality. With mean values from 3.13 (TQ1) to 3.94 (IN2), there is a tendency that, as a rule, the values are moderate to high agreement. The spread of the responses is moderate (standard deviation values are 1.22 (UC3), 1.27 (UC2) to 1.49 (TQ3)). The skewness values, almost all in the range of -1 and 0, indicate a small negative skew, or responses are more toward the latter half of the scale. Values of negative kurtosis indicate a distribution which is flatter than normal.

It is inferred that usability (US) can directly impact the chatbot service quality. However, among the usability factors, respondent agreement (US2, which has a Mean = 3.89 and Skewness = -1.01) indicates that respondents value certain aspects of chatbot usability particularly. This is substantiated by regression weights where US2 ($\beta = 0.904$, $p < 0.001$) and US3 ($\beta = 0.851$, $p < 0.001$) make a great contribution to chatbot service quality. Hypothesis 1 (H1) states that if the usability factors increase, then chatbot service quality will also increase, and thus, this result supports the hypothesis.

It is found that a strong predictor of chatbot service quality is interactivity (IN). Of the interactive elements, we find that IN1 ($\beta = 0.932$, $p < 0.001$) and IN3 ($\beta = 1.039$, $p < 0.001$) have high regression weights which indicate the contribution of interactive elements to service quality to a great extent. This is consistent with Hypothesis 2 (H2), that interactivity will have positive impacts on the quality of chatbot service. There is also great evidence of how chatbot service quality is influenced by technology usage (TE). It is found that TE1 ($\beta = 1.433$, $p < 0.001$), TE3 ($\beta = 1.342$, $p < 0.001$) and TE4 ($\beta = 1.0$, $p < 0.001$) have positive contributions. This is further substantiated in the CFA model fit indices, RMSEA = 0.084, GFI = 0.968 and all signify a good fitting model. Hypothesis 3 (H3) confirms that technology usage elements positively relate to chatbot service quality.

The results indicate that chatbot service quality has a positive relationship with user satisfaction. Based on TLI = 0.941 and CFI = 0.976, the confirmatory factor analysis (CFA) model fit indices of this study proved that the model is valid. Association with regression weights of user satisfaction dimensions CE2 ($\beta = 1.42$, $p < 0.001$) and CE4 ($\beta = 1.329$, $p < 0.001$) is strong. This supports Hypothesis 4 (H4), that a higher chatbot service

quality leads to higher user satisfaction (McLean & Osei-Frimpong, 2019; Verhagen et al., 2014). The higher the chatbot's quality, the higher the user satisfaction, which then leads to a higher trust and higher continuous term usage intentions.

The findings also reveal the effect of UC on the use of continuance when the quality of chatbot service goes down. They show strong fit indices (NFI = 0.927 and IFI = 0.908) of the model. These regression weights indicate that UC1 ($\beta = 1.0$, $p < 0.001$) and UC3 ($\beta = 1.02$, $p < 0.001$) are contributing significantly to the regression weight and yield corroborating Hypothesis 5 (H5), stating that if a user has a positive user experience, they will end up using the chatbot more (Zhou, 2011; Venkatesh et al., 2003). The ability to retain users in chatbot-based services is heavily based on the quality and satisfaction of the user experience which normally leads to continuous interactions and engaging users for a long the span.

The results of this study demonstrate that usability, interactivity and technology usage have great importance in determining chatbot service quality. They play a strong role in determining the satisfaction of the users and use continuance. The CFA model fit indices and regression weights give empirical support for the proposed hypotheses. The data shows that respondents have a positive attitude towards chatbot services (marginal agreement) on all the usability, interactivity and technology dimensions. This has practical implications for businesses wanting to improve their chatbots' service encounters. By making basic interactivity features more interactive and making the user interface more frugal, we can improve user satisfaction and sustain engagement. Further future research can examine additional factors like emotional intelligence in chatbots to refine the chatbot service model (Shumanov & Johnson, 2021) (Gnewuch et al., 2017).

Conclusion

Usability, interactivity and the use of technology have a large effect on the adoption and use of AI-powered chatbots and consumer experience and engagement. Ease of navigation plus good design encourages users' perception of chatbots and their impact in high satisfaction and high trust (Ashfaq et al., 2020; Shahzad et al. 2024). In the same vein, interactivity, such as

both responsiveness and personalised, also improves user engagement and leads to a positive consumer experience (Sundjaja et al., 2025; Hsu & Lin, 2023). Chatbot adoption rates are also affected by technology usage because more tech-savvy users will be more accepting (Nguyen et al., 2021; Li et al., 2021). It works as a factor of key mediation purposes as an independent variable of consumer behaviour. Engagement about trust and satisfaction is increased by high perceived service quality (Hsiao & Chen, 2022; Le & Nguyen, 2024). Based on the expectation confirmation theory (Kim & Chang, 2020; Butt & Ahmad, 2023), chatbot interactions that meet or exceed the user expectations lead to improved service quality perception as enhanced chances of continued use increase.

This is to say, usability, interactivity and service among them shape the consumer experience and use continuance. Efficient performance of chatbots and engaging customer interactions contribute to developing positive consumer experience and higher consumer trust and loyalty (Yun & Park, 2022; Cheng & Jiang, 2020). Finally, the factors including reliability, personalisation and emotional intelligence in AI-driven conversations (Lee & Park, 2022; Tan & Lim, 2023) drive the continued chatbot adoption. Nevertheless, errors in chatbots, context limitations and privacy problems have to be solved if we want to maintain user engagement long-term (Chen et al., 2022; Nicolescu & Tudorache, 2022). Therefore, usability, interactivity and technology usage significantly affect chatbot service quality, which positively affects consumers' experience and leads to further use continuance.

Future Research

To provide long-lasting retail, organisations using chatbots must focus on appurtenances of faultless usability, interactive experience and personalised service quality. Future research should explore future AI advancements to refine further chatbot adoption strategies (Magno & Dossena, 2023; Khan, 2024). The evolving role of AI-driven chatbots in personal interactions with consumers, emotional intelligence, adaptive learning and ethical considerations is a field for future research. Marginalising chatbot effectiveness within a single industry offers a shallow understanding of how to effectively optimise user

engagement, trust and ultimately long-term adoption of chatbots.

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