

PARTICIPANT EMOTIONAL INTELLIGENCE AND EVALUATIONS OF AN
IT SERVICE MANAGEMENT CHATBOT IN HIGHER EDUCATION

by

MIA JOLLY

B.S., Johnson C. Smith University, 1990
M.S., Georgia Institute of Technology, 1992
M.S., Augusta University, 2018

A Research Paper Submitted to the School of Computing Faculty of
Middle Georgia State University in
Partial Fulfillment of the Requirements for the Degree

DOCTOR OF SCIENCE IN INFORMATION TECHNOLOGY

MACON, GEORGIA

2026

Participant emotional intelligence and evaluations of an IT service management chatbot in higher education

Mia Jolly, *Middle Georgia State University, mia.jolly@mga.edu*

Abstract

This study examines the relationships among participants' emotional intelligence, trust in automation, user satisfaction, and perceived service quality during a standardized information technology service management chatbot interaction. The researcher used a quantitative, non-experimental, correlational design. Participants reviewed a standardized chatbot scenario involving an access denial issue and completed survey measures of emotional intelligence, trust in automation, user satisfaction, and perceived service quality. The results showed that participants' emotional intelligence was positively related to trust, user satisfaction, and perceived service quality. Trust remained strongly associated with user satisfaction. These findings suggest that participants' emotional intelligence may help explain why users respond differently to the same automated support interaction. The study contributes to the literature on chatbot-based support in higher education and similar institutional settings by identifying that emotional intelligence is a meaningful individual factor in user evaluations of chatbot interactions and by reinforcing the relationship between trust and user satisfaction.

Keywords: emotional intelligence, trust in automation, user satisfaction, perceived service quality, IT service management chatbots

Introduction

Information technology service management teams play an important role in supporting teaching, research, and daily operations in colleges and universities. As support needs continue to grow, many institutions have turned to chatbots and other automated tools to help address routine technical problems. Artificial intelligence is playing an increasingly important role by improving the flexibility and efficiency of service delivery (Mao et al., 2021). When users interact with chatbot support, they do not focus solely on technical accuracy. They also consider that the interaction feels reliable, useful, and appropriate to the situation. Prior research has shown that trust, perceived intelligence, and user comfort shape user evaluations of automated service systems (Pillai et al., 2024; Urbani et al., 2024). Recent research has also examined emotional intelligence in relation to chatbot use and found a positive association between chatbot utilization and emotional intelligence in a higher education setting (Mosleh et al., 2024). Even with this growing body of work, research has not clearly established whether participant emotional intelligence is associated with trust, satisfaction, and perceived service quality in response to a standardized IT service chatbot interaction. This study addresses that gap by examining participant emotional intelligence as a user-level factor associated with evaluations of automated support in a higher education IT service context.

A final review of the instrument clarified that the Wong and Law Emotional Intelligence Scale measures participants' self-reported emotional intelligence, not the chatbot's attributes. Consequently, the study was reframed to focus on whether participants' emotional intelligence is related to their evaluation of the chatbot-based IT support interaction. This adjustment ensures the study aligns with the instrument and clarifies that user differences in responses may stem from variations in emotional intelligence.

This study specifically investigates whether participants' emotional intelligence is associated with trust in automation, user satisfaction, and perceived service quality during chatbot-based IT support interactions in higher education. While past research has examined chatbot adoption and service evaluations, it has not specifically addressed how emotional intelligence impacts evaluations of standardized IT service chatbots

in higher education settings. This study addresses that gap by clarifying emotional intelligence's role as a user-level factor shaping trust, satisfaction, and perceived service quality. The findings may help institutions understand user interpretations of automated support, informing chatbot design, service escalation, and support strategy.

The following research questions guide this study:

RQ1: To what extent does participant emotional intelligence predict trust in an IT service management chatbot?

RQ2: To what extent does participant emotional intelligence predict user satisfaction with an IT service management chatbot interaction?

RQ3: To what extent does participant emotional intelligence predict perceived service quality in an IT service management chatbot interaction?

RQ4: To what extent does trust predict user satisfaction in an IT service management chatbot interaction?

Literature Review

In the following literature review, the relationships among emotional intelligence as an individual difference, chatbots as an aspect of information technology service management, and research on technology adoption, trust, and service quality are explored. Together, these works provide the necessary groundwork for the current study. The key amendment to the previous framework is to conceptualize emotional intelligence as a characteristic of the participants, not the chatbots.

Emotional Intelligence as an Individual Difference

By definition, emotional intelligence is the ability to understand and regulate one's emotions (Goleman, 2005; Mayer et al., 2016). It helps people communicate effectively, show empathy, and stay composed in stressful situations. This is crucial in service-based environments. Users in service settings often experience urgency, uncertainty, or frustration.

This definition matches how emotional intelligence was measured in the survey. The survey focused on people's skills in emotional awareness, sensing others' emotions, regulating emotions, and self-control. Emotional intelligence was defined by respondents' skills, not chatbot features. People with different levels of emotional intelligence perceive the same chatbot interaction differently (Wong & Law, 2002).

The academic literature supports this position. For example, people with high emotional intelligence may show patience even when conversations lack warmth. They may focus more on the conversation's practical value or manage frustration better when a bot does not work well. Others may find chatbot interactions less valuable or trustworthy. Emotional intelligence also affects technology adoption (Abu-Shanab & Abu Shanab, 2022).

Chatbot Experience in Information Technology Service Management

Chatbots are used in IT service management during stressful periods, especially when access issues disrupt workflow. Users judge not just the correctness of answers, but also their clarity, appropriateness, and usefulness. Prior research highlights factors such as tone, clarity, and perceived understanding, all of which can affect satisfaction and trust. Recent findings also show that both functional and relational aspects—like trust, competence, and communication style—impact chatbot evaluations.

The chatbot scenario used reflects a typical IT support situation. All participants saw the same scenario: a user received an "access denied" error before a meeting, interacted with the chatbot, tried a password change, cleared the browser cache, and was advised to create a ticket. Because all participants reviewed the

same chatbot scenario, differences in trust, satisfaction, and perceived service quality were more likely to reflect participant-level differences than differences in exposure.

All three constructs—trust, satisfaction, and perceived service quality—were dependent variables in the chatbot scenario. The trust questionnaire items addressed reliability, dependability, predictability, confidence, and trustworthiness, and followed definitions from prior automation-related trust studies (Jian et al., 2000). Satisfaction questions involved clarity, usefulness, communication, problem-solving, and overall impressions, based on findings about chatbots (Diederich et al., 2022). Perceived service quality used a SERVQUAL-inspired framework with reliability, responsiveness, and assurance dimensions (Parasuraman et al., 1988).

Technology Adoption, Trust, and Service Evaluation

It is widely documented that individual assessments of automated systems, as well as choices regarding technology use, are influenced by factors such as trust, intelligence, and comfort (Pillai & Sivathanu, 2020; Urbani et al., 2024). Such knowledge is highly relevant to the current investigation, as trust and satisfaction have been selected as primary outcomes. Furthermore, recent studies have shown that individual emotional intelligence can play an essential role in decision-making, especially in technology contexts (Abu-Shanab & Abu Shanab, 2022). However, this aspect has not been considered in the current investigation; specifically, no effort has been made to investigate emotionally intelligent chatbots. Rather, this project seeks to identify whether emotional intelligence plays any role in users' evaluations of their interactions with the given tool.

The significance of trust in IT support is difficult to ignore, given the extent to which users rely on institutional technological solutions across various spheres of life, from learning and work to interpersonal communication. If automated systems are viewed as dependable and predictable, users are more likely to continue using them. On the other hand, unreliable or unhelpful support tools will likely prompt users to seek alternatives. According to recent studies, trust is one of the main predictors of customers' satisfaction, and chatbots' reliability, competence, integrity, and effectiveness in information handling determine positive evaluations (Syamsudin & Ratnapuri, 2024). In the current study, trust in automation was assessed using 12 items, half of which used negative phrasing.

Satisfaction and service quality make suitable dependent variables in projects on service technologies. Satisfaction refers to the overall user perception of an interaction, while service quality concerns the user's evaluation of aspects such as reliability and responsiveness. Recent studies in the field of chatbots demonstrate that trust and service quality have a significant impact on user satisfaction; in particular, service quality shows very high predictive power. As for reliability, responsiveness, empathy, and problem-solving ability, these factors positively influence users' perception of AI-driven services (Syamsudin & Ratnapuri, 2024). Both measures under consideration have been calculated following the interaction in the chatbot scenario. Although previous studies have highlighted the importance of trust, satisfaction, and service quality perception in chatbot assessment, recent studies have examined the outcomes of unsuccessful chatbot encounters. This area of study is relevant since the service failure process can affect user trust and overall chatbot assessment.

Chatbot Service Failure, Escalation, and Trust

The literature suggests that chatbots can either positively or negatively affect the customer experience in service interactions, depending on how well the customer experience is delivered. According to Ranieri et al. (2024), chatbots influence the customer experience during interaction with the firm along the relational, cognitive, affective, and behavioral dimensions. Specifically, Ranieri et al. (2024) demonstrated that chatbots can enhance the service encounter by providing information and procedural guidance to customers, supporting task completion, building trust, reducing stress, and enabling the completion of the service journey. On the other hand, chatbot service failures can lead to increased confusion, loss of trust, stress, and service journey abandonment due to confusing, repetitive, and unhelpful responses from the system.

Chatbot service failures were also associated with negative emotional responses, such as anger, betrayal, frustration, and passive defeat, as well as coping behaviors, including support seeking, active coping, acceptance, and withdrawal, according to Zhang et al. (2024). Moreover, according to Zhang et al. (2024), such failures are characterized by a lack of understanding of the user's request, the provision of information that is useless to the client's needs, difficulty in resolving the customer's problem, and poor integration with human agents. Furthermore, chatbots became increasingly problematic when escalation to a human agent was not provided quickly and efficiently enough. This aspect is important because it demonstrates that customers' experience and perception of the company's service can be shaped by the chatbot's performance and the efficiency of its escalation management. Castillo et al. (2021) offer another important perspective on the issue and emphasize that failed AI service interactions are likely to lead to customer resource loss and value co-destruction. The authors describe authenticity problems, cognition problems, affective problems, functionality issues, and integration issues as contributing to this problem. Thus, this literature review offers an important framework for exploring chatbot failure and the role of trust in service quality and service recovery.

Higher Education as the Context

In addition, higher education represents a relevant background for the proposed research. Disruptions with technology in this case will be related to learning, researching, teaching, or accessing any institution-related system. Thus, providing information technology (IT) support services is vital. It is even more important to ensure high quality when denying people access to some crucial systems or information resources.

The situation presented in the survey is realistic, as it is set against the backdrop of a higher education institution and concerns gaining access to systems for a meeting. It might help reveal why people with different levels of emotional intelligence perceive chatbot interactions similarly by showing whether the same processes in a chatbot are evaluated equally across individuals.

The literature suggests that trust, satisfaction, and service quality are important outcomes of automated service encounters and that emotional intelligence may influence these processes. Some research has examined the impact of emotional intelligence on chatbot interactions in higher education institutions and found a significant correlation (Mosleh et al., 2024). Other research has shown that satisfaction with AI chatbots depends on trust and perceived service quality (Syamsudin & Ratnapuri, 2024). Also, some researchers claim that there is a clear connection among trust, competence, and communication in automated interactions, leading to satisfaction (Al-Oraini, 2025). However, no clear relationship has been found between participants' emotional intelligence and their experience using the IT service chatbot in higher education settings.

Methodology

Research Design

This study used a quantitative, non-experimental correlational design to examine the relationships among participants' emotional intelligence, trust in the chatbot, satisfaction with the interaction, and perceived service quality. Because all participants reviewed the same chatbot exchange, differences in evaluation could be attributed to participant characteristics rather than to differences in exposure.

Ethical Considerations and IRB Approval

The study received Institutional Review Board approval before data collection began. After the survey was administered, a closer review of the instrument showed that the WLEIS measured participants' own emotional intelligence rather than emotional intelligence attributed to the chatbot. The findings were therefore interpreted as reflecting participants' emotional intelligence. This clarification did not change how participants completed the survey, how anonymity was protected, or how the data were handled.

Participants and Setting

Participants were adults aged 18 or older who had prior experience using IT support services in the workplace or institutional settings. Recruitment took place through online outreach, direct contacts, higher education IT communities, and a CloudResearch panel. Higher education provided the setting for the chatbot scenario because technology disruptions in that environment can affect teaching, learning, research, and access to institutional systems.

Instrumentation

The survey included a standardized chatbot scenario followed by Likert-type items rated on a 7-point scale ranging from 1 (strongly disagree) to 7 (strongly agree). Emotional intelligence was measured with the 16-item Wong and Law Emotional Intelligence Scale, which assesses self-emotional appraisal, others' emotional appraisal, use of emotion, and regulation of emotion. Trust in automation was measured with a 12-item chatbot-focused scale informed by Jian et al. (2000), including both positively worded and reverse-coded items. User satisfaction was measured with five chatbot-focused items informed by Diederich et al. (2022). Perceived service quality was measured with a six-item SERVQUAL-based scale adapted from Parasuraman et al. (1988). After the data were screened and the negatively worded trust items were reverse-coded, composite scores were calculated for each construct. See Appendix A for the survey.

Subjects and Procedure

After providing informed consent, participants reviewed a standardized transcript of an IT helpdesk chatbot conversation involving an access denial problem before a meeting. The chatbot suggested basic troubleshooting steps, such as resetting the password and clearing the browser cache, before directing the user to submit a support ticket. Participants then completed the measures of emotional intelligence, trust, satisfaction, and service quality. No identifying information was collected, and the survey took about 10 to 12 minutes to complete.

Data Analysis

The data were analyzed in IBM SPSS Statistics. The dataset was screened for missing values, incomplete responses, out-of-range values, and potential outliers. Descriptive statistics were calculated for participant characteristics and the main study variables. Internal consistency for each scale was assessed using Cronbach's alpha. Bivariate correlations were used to examine relationships among participant emotional intelligence, trust in automation, user satisfaction, and perceived service quality. Linear regression analyses were then used to examine whether participant emotional intelligence was associated with trust, satisfaction, and perceived service quality, and whether trust was associated with user satisfaction. Regression assumptions, including linearity, normality, homoscedasticity, and multicollinearity, were evaluated before the findings were interpreted.

Limitations

Several limitations should be considered when interpreting the findings. One limitation was the need to reframe the study conceptually after data collection. The original proposal described emotional intelligence as a chatbot characteristic, whereas the administered WLEIS measured participants' self-reported emotional intelligence. The study was interpreted according to the instrument that was actually used, although the original consent language did not fully reflect that distinction. The study also relied on a convenience sample, which limits generalizability. In addition, all measures were based on self-report following a single standardized scenario, so the responses may not fully capture how users react in live support settings. The cross-sectional correlational design allows for the examination of relationships among variables, but it does not support causal conclusions. Responses to a hypothetical scenario may also differ from reactions to an actual real-time chatbot interaction in a working service environment.

Results

This section reports the statistical results of the study. The analyses examined the association between participants' emotional intelligence, their trust in automation, their user satisfaction, and their perception of service quality after reviewing a standardized IT Service Management chatbot case study. The software used for these purposes was IBM SPSS Statistics. Data screening, descriptive statistics, reliability, Pearson's correlation, and simple linear regression were performed using IBM SPSS Statistics.

Preliminary Data Screening

Before the actual statistical tests, the data set underwent an initial data integrity check in SPSS to verify accurate variable coding and the preparation of composite measures. The means of composite scores for emotional intelligence, trust, user satisfaction, and perceived service quality for the participants were determined. Reverse-coded trust questions were added to the composite trust measure before running the analysis. SPSS results were obtained from item frequency distributions, descriptive statistics, tests for normality, reliability estimates, a correlation table, and four simple linear regressions. The final data set included 207 cases for the regressions. Descriptive demographic profiles of the subjects were reported based on respondents' information, while correlations and regression analyses were conducted using 207 cases with complete data for the key independent and dependent variables.

SPSS regression outputs included a histogram, normal probability plot, and scatterplot for each regression. By visual inspection, the simple linear regression assumptions seemed to be fulfilled. Since there is only one predictor in each model, multicollinearity did not exist in any model.

Participant Characteristics and Descriptive Statistics

Table 1 summarizes the demographic characteristics of the participants included in the study. The demographic features provide a background against which the sample used in the analysis is placed. The sample consisted of adults from different demographic groups, with the vast majority reporting prior interaction with chatbots.

Table 1
Participant Characteristics

Variable	Category	n	%
Gender	Female	117	56
	Male	90	43.1
	Other / Prefer not to say	2	.9
Age Group	18 to 24	17	8.1
	25 to 34	45	21.5
	35 to 44	65	31.1
	45 to 54	49	23.4

Descriptive statistics were calculated for the four major variables studied. The respondents' emotional intelligence had a mean score of 5.52 and a standard deviation of 0.78. Chatbot trust had a mean score of 4.54 and a standard deviation of 1.22. The user satisfaction scores had a mean value of 4.65 and a standard deviation of 1.43. Users' service quality perceptions had a mean score of 4.77 and a standard deviation of 1.30. On average, the data suggests that respondents had high emotional intelligence and moderately positive perceptions of the chatbot's trustworthiness, satisfaction, and service quality. Table 2 shows the descriptive statistics for the four variables of interest.

Table 2

Descriptive Statistics for Main Study Variables

Variable	M	SD
Participant Emotional Intelligence	5.52	0.78
Trust in the Chatbot	4.54	1.22
User Satisfaction	4.65	1.43
Perceived Service Quality	4.77	1.30

Scale Reliability

The emotional intelligence scale demonstrated strong internal consistency, with a Cronbach's alpha of .908 across 16 items. The trust scale also demonstrated strong internal consistency, with an alpha of .928 across 12 items. The user satisfaction scale demonstrated strong internal consistency, with an alpha of .900 across 5 items. The perceived service quality scale demonstrated strong internal consistency, with an alpha of .901 across 6 items.

Table 3 summarizes the reliability coefficients for the four multi-item scales. The Cronbach's alpha coefficients were determined before undertaking the correlation and regression analysis.

Table 3

Internal Consistency Reliability of Study Scales

Scale	Number of Items	Cronbach's Alpha	Correlations Among Study Variables
Emotional Intelligence	16	.908	
Trust	12	.928	
User Satisfaction	5	.900	
Perceived Service Quality	6	.901	

The correlations among the variables of emotional intelligence, trust toward the chatbot, user satisfaction, and perceived service quality are presented in Table 4 below. All the variables had significant positive correlations. The emotional intelligence variable had positive correlations with trust ($r = .289, p < .001$), user satisfaction ($r = .209, p = .002$), and perceived service quality ($r = .304, p < .001$). The trust variable had positive correlations with user satisfaction ($r = .816, p < .001$) and perceived service quality ($r = .840, p < .001$). There was a strong correlation between user satisfaction and perceived service quality variables ($r = .897, p < .001$).

Table 4

Pearson's Correlations Among Study Variables

Variable	1	2	3	4	M	SD
1. Emotional Intelligence	1.00				5.52	0.78
2. Trust	.289***	1.00			4.54	1.22
3. User Satisfaction	.209**	.816***	1.00		4.65	1.43
4. Perceived Service Quality	.304***	.840***	.897***	1.00	4.77	1.30

Note. $p < .01$. $p < .001$

Emotional Intelligence and Trust

Participant emotional intelligence was examined as a predictor of trust in the chatbot. The results showed a significant positive relationship, $F(1, 205) = 18.83$, $p < .001$. Emotional intelligence explained 8.4% of the variance in trust, $R^2 = .084$. Participants with higher emotional intelligence tended to report greater trust in the chatbot, $B = 0.452$, $SE = 0.104$, $\beta = .289$, $t = 4.34$, $p < .001$.

Emotional Intelligence and User Satisfaction

Participant emotional intelligence was examined as a predictor of user satisfaction with the chatbot interaction. The results also showed a significant positive relationship, $F(1, 205) = 9.44$, $p = .002$. Emotional intelligence explained 4.4% of the variance in satisfaction ($R^2 = .044$). Participants with higher emotional intelligence reported greater satisfaction with the chatbot ($B = 0.382$, $SE = 0.124$, $\beta = .209$, $t = 3.07$, $p = .002$).

Emotional Intelligence and Perceived Service Quality

Participant emotional intelligence was examined as a predictor of perceived service quality in the chatbot interaction. The analysis showed a significant positive relationship, $F(1, 205) = 20.96$, $p < .001$. Emotional intelligence explained 9.2% of the variance in perceived service quality ($R^2 = .092$). Participants with higher emotional intelligence were more likely to report favorable perceptions of service quality ($B = 0.504$, $SE = 0.110$, $\beta = .304$, $t = 4.58$, $p < .001$). Among the models that used emotional intelligence as the predictor, this was the strongest relationship.

Trust and User Satisfaction

Trust was examined as a predictor of user satisfaction with the chatbot interaction. This analysis showed a strong positive relationship, $F(1, 205) = 409.65$, $p < .001$. Trust explained 66.5% of the variance in satisfaction ($R^2 = .665$). Participants who reported greater trust in the chatbot also reported greater satisfaction, $B = 0.953$, $SE = 0.047$, $\beta = .816$, $t = 20.24$, $p < .001$. This was the strongest relationship observed among the regression models.

Table 5
Summary of Simple Linear Regression Results

Section	Predictor	Outcome	<i>B</i>	<i>SE</i>	β	<i>t</i>	<i>p</i>	R^2	<i>F</i>
Emotional Intelligence and Trust	Emotional Intelligence	Trust	0.452	0.104	.289	4.34	< .001	.084	18.83
Emotional Intelligence and User Satisfaction	Emotional Intelligence	User Satisfaction	0.382	0.124	.209	3.07	.002	.044	9.44
Emotional Intelligence and Perceived Service Quality	Emotional Intelligence	Perceived Service Quality	0.504	0.110	.304	4.58	< .001	.092	20.96
Trust and User Satisfaction	Trust	User Satisfaction	0.953	0.047	.816	20.24	< .001	.665	409.65

Summary of Findings

The analyses revealed a consistent overall pattern. The collected data were reliable enough for analysis. Emotional intelligence, trust, user satisfaction, and perceived service quality were all positively correlated. Users with high emotional intelligence also reported high levels of trust, user satisfaction, and perceived

service quality. The variable most strongly correlated with user satisfaction was trust. The findings suggest that emotional intelligence and trust influenced how users evaluated their experience with the chatbot for IT support.

Discussion

The results of this study indicated that participants' emotional intelligence was positively associated with trust, user satisfaction, and perceived service quality in response to a standardized IT service management chatbot scenario. Trust also demonstrated a particularly strong positive relationship with user satisfaction. The discussion that follows interprets these findings in relation to literature, the higher education IT context, and the practical implications of chatbot-based support.

Interpretation of the Findings

This study examined whether participants' emotional intelligence was associated with trust in automation, user satisfaction, and perceived service quality during a standardized IT service management chatbot interaction, and whether trust was associated with user satisfaction. The findings indicated that participant emotional intelligence was positively related to trust, user satisfaction, and perceived service quality, while trust demonstrated a particularly strong positive relationship with user satisfaction. Taken together, these results suggest that user-level emotional differences may influence how automated support interactions are interpreted and evaluated, even when all participants are exposed to the same chatbot scenario. They also suggest that trust plays a central role in shaping satisfaction with chatbot-based IT support in higher education and similar institutional settings.

The findings regarding participants' emotional intelligence support the view that emotional intelligence functions as an individual difference that may shape responses to technology-mediated interactions. Prior literature has linked emotional intelligence to communication effectiveness, emotional regulation, and the ability to manage stressful interactions (Goleman, 2005; Mayer et al., 2016). In this study, participants with higher emotional intelligence reported greater trust in the chatbot, higher user satisfaction, and more favorable perceptions of service quality. Because all participants reviewed the same chatbot scenario, these findings suggest that users may bring different emotional and interpretive capacities to the same automated support exchange. This interpretation is also consistent with prior work suggesting that emotional intelligence may influence technology-related judgments and adoption behavior (Abu-Shanab & Abu Shanab, 2022).

The relationship between participant emotional intelligence and trust is especially meaningful because trust reflects judgments about reliability, predictability, and confidence in an automated system (Jian et al., 2000). In the present study, participants with higher emotional intelligence tended to report greater trust in the chatbot. One possible explanation is that emotionally intelligent individuals may be better able to regulate frustration, interpret the support process more favorably, or remain attentive to the procedural value of the chatbot interaction even when the issue is not resolved immediately. This finding extends prior research on chatbot trust by showing that trust may be shaped not only by the system's design but also by the characteristics of the user evaluating it (Pillai et al., 2024; Urbani et al., 2024).

Participant emotional intelligence also positively predicted user satisfaction and perceived service quality. These findings suggest that emotional intelligence may shape broader judgments about whether a chatbot interaction feels useful, responsive, and satisfactory. The strongest of the three emotional intelligence models was the relationship with perceived service quality. That pattern may indicate that emotional intelligence is particularly relevant to how users assess the overall quality of a support process, including whether it appears reliable, responsive, and assuring (Parasuraman et al., 1988). In the standardized scenario used in this study, the chatbot provided troubleshooting guidance and then directed the user to submit a support ticket. Participants with higher emotional intelligence may have been more likely to view that exchange as structured and appropriate, even though it did not provide immediate resolution. This

interpretation aligns with service-oriented chatbot research that has emphasized the roles of communication quality, competence, and responsiveness in user evaluations (Al-Oraini, 2025; Diederich et al., 2022).

The strongest finding in the study was the relationship between trust and user satisfaction. Trust explained a substantial proportion of the variance in satisfaction and represented the strongest relationship observed across the regression models. This result reinforces prior research identifying trust as a major factor in favorable evaluations of automated service encounters (Pillai et al., 2024; Syamsudin & Ratnapuri, 2024; Urbani et al., 2024). In practical terms, the finding suggests that users are far more likely to report satisfaction when they perceive the chatbot as dependable and trustworthy. For IT service environments, this means that technically accurate responses alone may not be sufficient. Users must also feel confident in the chatbot's guidance and in the support process it represents.

These findings should also be considered alongside the correlational results as a whole. All four primary study variables were positively and significantly related, which supports the broader interpretation that evaluations of chatbot-based support are interconnected. Emotional intelligence, trust, satisfaction, and perceived service quality did not operate as isolated constructs in this study. Instead, the pattern of findings suggests that users who responded more positively in one area were also more likely to respond positively in others. This pattern strengthens the argument that user evaluations of chatbot interactions reflect an overall interpretive process rather than a series of disconnected judgments.

Implications for Higher Education IT

These findings are especially relevant in the higher education IT context. Colleges and universities depend on IT services to support teaching, learning, research, and institutional operations. Users often seek help during stressful moments, such as when access problems interfere with work or time-sensitive responsibilities. In these situations, support interactions are likely to be evaluated not only on whether the problem is solved, but also on whether the support feels dependable, clear, and appropriate to the situation. The present findings suggest that both participant emotional intelligence and trust influence those judgments. This has important implications for higher education IT leaders, as chatbot performance may need to be assessed as a service experience rather than solely as a technical tool.

The study contributes to the literature by focusing on participant emotional intelligence as a user-level characteristic associated with chatbot evaluation. Much of the prior literature has examined chatbot adoption, trust, or service quality, while emotional intelligence research has often centered on human interaction or broader behavioral processes (Abu-Shanab & Abu Shanab, 2022; Goleman, 2005; Mayer et al., 2016). This study adds to that literature by showing that participants' emotional intelligence may help explain why users respond differently to the same automated IT support encounter. That contribution is useful because it shifts attention toward the interpretive role of the user in chatbot evaluation and highlights the importance of considering user-level differences in studies of automated support.

Several practical implications follow from these findings. First, institutions should recognize that chatbot success depends in part on trust. Automated support systems should therefore be designed to communicate clearly, provide consistent guidance, and offer transparent next steps when an issue cannot be resolved immediately. Second, escalation practices matter. In this study, the chatbot ultimately directed the user to submit a support ticket, and the user's evaluation of that process may depend on whether the escalation appears timely, credible, and useful. Third, higher education IT organizations may benefit from evaluating chatbot effectiveness using user-centered measures, such as trust, satisfaction, and perceived service quality, rather than relying solely on efficiency-oriented metrics. Together, these implications support a broader view of chatbot deployment as part of an institutional service strategy rather than only as a technical automation tool.

From an operational standpoint, the findings suggest that higher education institutions should be cautious about judging chatbot value only through resolution rate, speed, or ticket deflection. Those measures may be useful, but they do not fully capture users' experience with automated support. If users do not trust the

chatbot, they may remain dissatisfied even when the system provides technically appropriate information. Institutions may therefore benefit from incorporating user perception measures into chatbot evaluation and governance processes, particularly when automated support is deployed in areas that affect access, productivity, and continuity of work.

Limitations

The results have to be considered in light of several limitations. First, the research design was non-experimental and purely correlational. In such a case, the research can only reveal correlations between variables but cannot prove causation. Specifically, the discovered positive associations between emotional intelligence and higher levels of trust, satisfaction, and service quality perception cannot be taken as evidence of the former's influence on these aspects. Equally, trust could not be concluded to cause increased user satisfaction.

The convenience sample and reliance on self-report also limit generalizability. Participant selection through convenience sampling makes it impossible to determine whether they are representative of the general public. Moreover, self-reports can bias participants' responses depending on their response set or how they interpret certain survey questions. Moreover, answers were collected after participation in a standard chatbot scenario rather than a real-life interaction with a support bot. While this ensured consistent conditions for participants, it is possible that real-life interactions would be evaluated differently due to urgency, potential risks, or back-and-forth exchanges.

A further limitation involves the post hoc conceptual reframing of the study. As noted in the methodology and limitations sections, the administered instrument measured participant emotional intelligence through self-report rather than chatbot-attributed emotional intelligence. Although the research was conducted using the instrument, it is important to note that this is significant for understanding its impact, as this paper analyzes users' emotional intelligence rather than chatbots'.

Recommendations for Future Research

Potential areas for future research could build on this study by exploring the equivalent relationships in live chatbot support settings in higher education institutions. Investigating real-world scenarios would reveal whether the identified relationships persist when participants encounter real-time situations with consequences for their interactions. In this way, it would be possible to determine how relationships among chatbot tone, escalation language, and trust operate in practice and whether they influence users' perceptions of chatbot-based services.

Future studies could compare chatbot-based support across different higher education user segments, such as students, professors, and administrative personnel. Different expectations regarding support processes, technological capabilities, or willingness to utilize chatbots could lead to divergent opinions about their use and potential benefits. For instance, comparing the effects of chatbot tone or escalation language on trust and user satisfaction in users with high and low emotional intelligence could help institutions decide on their chatbot design and support escalation protocols.

Another useful direction for future research would be to explore more complex relationships among the variables discussed in this paper. Given the high correlation between trust and user satisfaction found in this study, future research could examine whether trust mediates the relationship between participants' emotional intelligence and satisfaction with chatbot-based support. Another potentially valuable area of future investigation is the role of perceived service quality in shaping general user evaluations of chatbot-based services.

Conclusion

Overall, the study has established a positive relationship between participants' emotional intelligence and their perceptions of trust in automation, user satisfaction, and service quality in a standardized IT service management chatbot setting, with trust being particularly strongly correlated with participants' satisfaction levels. Based on the findings of the research, it can be concluded that chatbot assessment is not solely determined by the support provision process but is also influenced by the qualities of the participants involved. In higher education IT settings, where such processes are often conducted under pressure and with operational implications, it becomes evident that trust and user interpretation are particularly crucial.

References

- Abu-Shanab, E. A., & Abu Shanab, A. (2022). The influence of emotional intelligence on technology adoption and decision-making process. *International Journal of Applied Decision Sciences*, 15(5), 604–622. <https://doi.org/10.1504/IJADS.2022.125485>
- Al-Oraini, B. S. (2025). Chatbot dynamics: Trust, social presence and customer satisfaction in AI-driven services. *Journal of Innovative Digital Transformation*, 2(2), 109–130. <https://doi.org/10.1108/JIDT-08-2024-0022>
- Castillo, D., Canhoto, A. I., & Said, E. (2021). The dark side of AI-powered service interactions: Exploring the process of co-destruction from the customer perspective. *The Service Industries Journal*, 41(13–14), 900–925. <https://doi.org/10.1080/02642069.2020.1787993>
- Diederich, S., Brendel, A. B., Morana, S., & Kolbe, L. M. (2022). On the design of and interaction with conversational agents: An organizing and assessing review of human-computer interaction research. *Journal of the Association for Information Systems*, 23(1), 96–138. <https://doi.org/10.17705/1jais.00724>
- Goleman, D. (2005). *Emotional intelligence: Why it can matter more than IQ*. Bantam.
- Jian, J., Bisantz, A. M., & Drury, C. G. (2000). Foundations for an empirically determined scale of trust in automated systems. *International Journal of Cognitive Ergonomics*, 4(1), 53–71. https://doi.org/10.1207/s15327566ijce0401_04
- Mao, H., Zhang, T., & Tang, Q. (2021). Research framework for determining how artificial intelligence enables information technology service management for business model resilience. *Sustainability*, 13(20), 11496. <https://doi.org/10.3390/su132011496>
- Mayer, J. D., Caruso, D. R., & Salovey, P. (2016). The ability model of emotional intelligence: Principles and updates. *Emotion Review*, 8(4), 290–300. <https://doi.org/10.1177/1754073916639667>
- Mosleh, S. M., Alsaadi, F. A., Alnaqbi, F. K., Alkhzaimi, M. A., Alnaqbi, S. W., & Alsereidi, W. M. (2024). Examining the association between emotional intelligence and chatbot utilization in education: A cross-sectional examination of undergraduate students in the UAE. *Heliyon*, 10(11), e31952. <https://doi.org/10.1016/j.heliyon.2024.e31952>
- Parasuraman, A., Zeithaml, V. A., & Berry, L. L. (1988). SERVQUAL: A multiple-item scale for measuring consumer perceptions of service quality. *Journal of Retailing*, 64(1), 12–40.
- Pillai, R., Ghanghorkar, Y., Sivathanu, B., Algharabat, R., & Rana, N. P. (2024). Adoption of artificial intelligence (AI) based employee experience (EEX) chatbots. *Information Technology & People*, 37(1), 449–478. <https://doi.org/10.1108/itp-04-2022-0287>
- Pillai, R., & Sivathanu, B. (2020). Adoption of AI-based chatbots for hospitality and tourism. *International Journal of Contemporary Hospitality Management*, 32(10), 3199–3226. <https://doi.org/10.1108/ijchm-04-2020-0259>

- Ranieri, A., Di Bernardo, I., & Mele, C. (2024). Serving customers through chatbots: Positive and negative effects on customer experience. *Journal of Service Theory and Practice*, 34(2), 191–215. <https://doi.org/10.1108/jstp-01-2023-0015>
- Syamsudin, D. Q., & Ratnapuri, C. I. (2024). Analysis of the influence of trust and service quality on customer satisfaction in using AI chatbot as customer service Veronika. In *2024 International Conference on Informatics, Multimedia, Cyber and Information System (ICIMCIS)*, 277–282. <https://doi.org/10.1109/icimcis63449.2024.10957031>
- Urbani, R., Ferreira, C., & Lam, J. (2024). Managerial framework for evaluating AI chatbot integration: Bridging organizational readiness and technological challenges. *Business Horizons*, 67(5), 595–606. <https://doi.org/10.1016/j.bushor.2024.05.004>
- Wong, C., & Law, K. S. (2002). The effects of leader and follower emotional intelligence on performance and attitude. *The Leadership Quarterly*, 13(3), 243–274. [https://doi.org/10.1016/s1048-9843\(02\)00099-1](https://doi.org/10.1016/s1048-9843(02)00099-1)
- Zhang, R. W., Liang, X., & Wu, S.-H. (2024). When chatbots fail: Exploring user coping following a chatbots-induced service failure. *Information Technology & People*, 37(8), 175–195. <https://doi.org/10.1108/ITP-08-2023-0745>

Appendix A

Instructions:

Please review the following IT helpdesk exchange. All participants will view the same scenario to ensure a consistent interaction before completing the survey.

Standardized Chatbot Scenario:

User:

I keep getting an “access denied” message when I try to log in. I need to get into the system as soon as possible because I have a meeting starting shortly.

Chatbot:

Hello. I can help you with that.

Please make sure you are entering the correct username.

If the issue continues, try resetting your password using the “Forgot Password” link.

User:

I reset it yesterday, so I’m not sure why this is happening.

Chatbot:

Please confirm that your new password meets all system requirements.

You may also need to clear your browser cache.

Here are instructions that may help: [link].

User:

I cleared the cache, but the login still isn’t working.

Chatbot:

If you continue having trouble, please submit a support ticket.

A technician will review the issue and contact you.

After reviewing the scenario, continue to the survey items below.

Likert Scale:

1 = Strongly Disagree

2 = Disagree

3 = Slightly Disagree

4 = Neither Agree nor Disagree

5 = Slightly Agree

6 = Agree

7 = Strongly Agree

Survey Instrument

Source: Wong & Law (2002); Jian et al. (2000); Diederich et al. (2022); Parasuraman et al. (1988)

Perceived Emotional Intelligence (WLEIS – 16 items)

(Defines emotional awareness, understanding of others’ emotions, use of emotion, and emotion regulation)

Self-Emotional Appraisal (SEA)

1. I can recognize my emotions when they arise during a conversation.

2. I can clearly express my feelings when interacting with others.
3. I have a good sense of why I feel the way I do.
4. I can describe my emotions accurately.

Others' Emotional Appraisal (OEA)

5. I can tell when others are feeling upset even if they do not say it directly.
6. I can sense when someone feels confused during an interaction.
7. I am good at noticing emotional cues in others.
8. I can understand how others feel based on how they communicate.

Use of Emotion (UOE)

9. I can stay positive even when a situation becomes difficult.
10. I can use my emotions to motivate myself to address a problem.
11. I can focus on a task even when I am frustrated.
12. I can direct my emotions to help me perform better in challenging situations.

Regulation of Emotion (ROE)

13. I can stay calm when things do not go as expected.
14. I am able to control my temper when I feel irritated.
15. I can recover quickly after feeling upset.
16. I can manage my emotions so they do not negatively affect my decisions.

Trust in Automation (12 items)

(Defines reliability, dependability, predictability, and confidence—reverse-coded items marked “R”)

17. The chatbot behaved in a reliable manner.
18. I felt comfortable relying on the chatbot.
19. The chatbot's responses were dependable.
20. I believed the chatbot acted in my best interest.
21. I felt confident in the chatbot's ability to help me.
22. The chatbot responded in a consistent way.

Reverse-coded items (R):

23. I felt uneasy about depending on the chatbot. (R)
24. I worried that the chatbot might provide incorrect information. (R)
25. The chatbot's behavior seemed unpredictable. (R)
26. The chatbot made me feel unsure about its recommendations. (R)

Positive items:

27. I believed the chatbot provided a trustworthy experience.
28. I believed the chatbot was competent in handling the issue.

User Satisfaction (5 items)

(Defines clarity, usefulness, communication quality, and overall experience)

29. The chatbot's responses were clear.
30. The guidance the chatbot provided was helpful.

31. The chatbot communicated in a way that made sense for the situation.
32. I felt the chatbot handled my issue effectively.
33. Overall, I was satisfied with the interaction.

Perceived Service Quality (SERVQUAL-Based, 6 items)

(Defines reliability, responsiveness, and assurance)

Reliability

34. The chatbot provided accurate information.
35. The chatbot offered guidance that I could rely on.

Responsiveness

36. The chatbot responded to my issue in a timely manner.
37. The chatbot addressed my concern without unnecessary delay.

Assurance

38. The chatbot made me feel confident that my issue could be resolved.
39. The chatbot appeared knowledgeable about how to handle the problem.

Demographic and Experience Questions

40. What is your age range?
- 18–24
 - 25–34
 - 35–44
 - 45–54
 - 55–64
 - 65+
41. What is your gender?
- Female
 - Male
 - Nonbinary
 - Prefer to self-describe: _____
 - Prefer not to answer
42. How often do you use IT support services?
- Rarely
 - A few times per year
 - Monthly
 - Weekly
 - More than once per week
43. Have you used a chatbot for IT support before?
- Yes
 - No
44. How comfortable are you using chatbots for support?
- 1 = Not at all comfortable ... 7 = Very comfortable