

Trust in Human-Chatbot Interaction: An Integrated Model of Performance Expectancy and Decision Making

Dr. Anindya Deb, Associate Professor, Department of Mass Communication and Media, Central University of South Bihar, Bihar

Alisha Pathak, Research Scholar, Department of Mass Communication and Media, Central University of South Bihar, Bihar

Abstract

The communicative behaviour of users has changed with the evolution and advancements of technology, significantly altering the dynamics of human machine interactions. The rapid integration of chatbots into everyday life, particularly in healthcare, has intensified the need to understand the role of trust in human-computer interaction. While existing models of technology adoption—such as the Unified Theory of Acceptance and Use of Technology (UTAUT) and the Technology Acceptance Model (TAM)—emphasize performance expectancy and ease of use, they often overlook the socio-psychological construct of trust that shapes users' willingness to depend on conversational agents. This study integrates UTAUT, TAM, and the Human-Computer Trust Model (HCTM) to examine how trust influences performance expectancy and decision-making in human-chatbot communication.

A web-based survey of 255 users aged 18–45 in South Asia was analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The results demonstrate that trust has a strong and direct positive effect on both performance expectancy and decision-making. Model evaluation indicated robust predictive power (R^2 values above 0.89) and acceptable fit indices (SRMR = 0.042, NFI = 0.929). These findings highlight trust as a central determinant in chatbot adoption, shifting the discourse from purely functional acceptance to relational and affective dynamics. By empirically validating trust as a key predictor of technology use outcomes, this study extends current acceptance models and provides actionable insights for the design of reliable, transparent, and ethically responsible chatbots. The findings have particular relevance for healthcare and other high-stakes domains, where user trust is indispensable for effective decision support and engagement.

Keywords: *Human Machine Communication, Chatbot, Decision Making, Performance Expectancy, Trust, TAM*

Introduction

Trust has emerged as a pivotal concern with the growing use of conversational agents across sectors, particularly in healthcare where chatbot-provided advice can carry significant consequences for users' well-being. Existing research has largely emphasized system-centered factors such as accuracy, transparency, anthropomorphism, and persona design (Bach et al., 2022; Seitz et al., 2022), yet less attention has been given to how users themselves define, experience, and act upon trust during real-time interactions with chatbots. While multiple definitions and operationalizations of trust exist, and antecedents such as reliability, perceived humanness, and interaction quality have

been identified, a critical gap remains in developing user-centered models that link trust to cognitive and behavioral outcomes (Alagarsamy & Mehroliya, 2023).

This gap is particularly consequential in health-related contexts. Studies show that while clinicians increasingly integrate AI tools into their workflows, patients and vulnerable populations often exhibit hesitancy or conditional acceptance, driven by concerns about privacy, safety, responsibility, and personalization (Wu et al., 2024). These concerns often hinder the translation of “intention to use” into actual reliance on chatbot-provided advice. Moreover, trust is not static but dynamic, negotiated during ongoing interactions, where features such as empathy and social cues can either strengthen or repair user confidence (Tsumura & Yamada, 2024).

Addressing this gap, our study adopts a user-centered approach to examine trust as a direct antecedent of two underexplored outcomes in human–chatbot communication: performance expectancy—the belief that chatbots can enhance users’ ability to achieve health-related goals—and decision making—the willingness to rely on chatbot-generated recommendations. By integrating elements of the Unified Theory of Acceptance and Use of Technology (UTAUT), the Technology Acceptance Model (TAM), and the Human–Computer Trust Model (HCTM) into a unified framework, and empirically testing it through Partial Least Squares Structural Equation Modeling (PLS-SEM), this study advances understanding of how trust operates across psychological and behavioral dimensions in health contexts. In doing so, it addresses the need to integrate social and technical explanations of trust, offering evidence that interactional cues and perceived empathic competence meaningfully shape user trust and adoption behaviors (Ding & Najaf, 2024; Gu et al., 2024).

By linking trust to both cognitive expectations (performance expectancy) and behavioral outcomes (decision making), this research clarifies how user-centered trust emerges in health chatbot interactions, develops an integrated theoretical account that bridges utility, trust, and adoption, and provides actionable insights for designers and stakeholders aiming to foster appropriate trust in chatbot technologies. The hypotheses derived from this framework position trust as a direct antecedent of both performance expectancy and decision making—marking a shift from studying mere intention to use toward understanding deeper cognitive and behavioral dimensions of trust.

The increasing use of machines and artificially intelligent tools for the purpose of communication and dissemination of information by different age groups across the globe suggests that we have come a long way in making machines more communicative. Earlier, machine mediated communication used to be a centre of attention but 2020 onwards we are seeing a rise in direct human to machine communication. However, irrespective of how advanced machines and artificial intelligence become, one question stays unaltered: whether it will ever be able to provide us the safe communicative spaces that our relationships with other human beings do. As we dive in to study human machine communication, we find multidimensional phenomena operating in the process of communication. One such phenomena is the role of abstract values like trust in human machine communication process. This study focuses on the role of trust as a major component in influencing the decision making of chatbot users and also their expectations of performance from chatbots.

Review of existing literature

In order to understand the existing status of trust in human chatbot communication, a thorough literature review was conducted using various sources. The available work has been organised below using thematic literature review under two broad themes. (Torraco, 2005)

Human Chatbot Communication

Chatbots are software driven robots capable of interacting with its users through instant messaging via text or voice. (Brandtzaeg and Følstad, 2018; de Greeff and Belpaeme, 2015) There are many categories of chatbots like menu or button based chatbots, rules-based chatbots, AI-powered chatbots, voice chatbots and generative AI chatbots. (IBM,2023) Button based chatbots are the simplest chatbots that operate with a fixed set of menu. Rules based chatbots use a predefined conversational path to answer any asked questions; these are commonly used for FAQs. AI-chatbots come with Natural Language Understanding (NLU) capability, they have the ability to understand the questions of users irrespective of how they are framed mostly, they possess an ability to remember users' interactions and act like a friend to them. Voice chatbots or voice bots are another category of chatbots that simply deal with voice as an input than text. Siri, Alexa, etc. come under this category of voice bots and they are extensively being used to get rid of monotonous IVR calls. The most latest category of chatbots is called as generative AI chatbots which not only act as conversational agents but also possess the ability to generate nascent content based on the database they have. ChatGPT4 is a prominent example of generative AI chatbots.

The idea of communication between humans and chatbots dates back to the 1960s, when Joseph Weizenbaum developed ELIZA, an early natural language processing program at MIT. ELIZA created the illusion of conversation by employing pattern matching and substitution techniques to replicate a psychotherapist's dialogue. Despite its simplicity, ELIZA showcased the ability of computers to participate in human-like conversations. In the 1980s, attention turned to more sophisticated systems such as PARRY, which was created by Kenneth Colby and aimed to simulate a patient suffering from schizophrenia. These pioneering chatbots established a foundation for future developments in AI and human-computer interactions.

Trust in Human Chatbot Communication

The emergence of chatbots has greatly changed the way humans interact with computers, allowing for more intuitive and efficient communication. As user expectations change, chatbots are increasingly crafted to be empathetic and aware of context, integrating emotional intelligence to improve user experience. The emphasis has now shifted from mere functionality to establishing trust and nurturing meaningful interactions.

As conversational agents advance with ChatGPT, comprehending their influence on user experience, trust, and engagement has become essential. User perception regarding chatbots significantly affects their functionality. Research conducted by Hancock et al. (2011) indicates that users' readiness to engage with chatbots is influenced by perceived social presence and anthropomorphism. When chatbots demonstrate human-like characteristics, users are more inclined to form a sense of trust and emotional connection. However, studies by Lee et al. (2020) reveal that excessive human-like qualities may create a situation called the "uncanny valley," where users experience discomfort if a chatbot appears overly human yet does not meet their expectations.

Trust is a vital element that impacts interactions with chatbots. Trust has been conceptualised in different ways across all the disciplines. Rousseau et al. in 1998 defined trust as a positive expectations about the intentions and behaviours of others. As per social capital theory (Putnam, 2000), the existence of trust plays a vital role in every relationship. Trust enables one to connect better with their fellows and the presence or absence of trust significantly guides their cooperative behaviour with others. Gefen (2000) emphasises that perceived trustworthiness, competence, and benevolence significantly influence users' readiness to depend on chatbots for information. Additionally, Wang et al. (2021) discovered that transparency in chatbot replies boosts user trust, as individuals prefer agents that clarify their reasoning and data sources.

There are multiple factors that influence trust- past experiences, competence, reliability and communication being some of them. The rise of technology, especially artificial intelligence and automation, has brought about changes in trust dynamics. Users' trust in technology influences their acceptance and dependence on these systems for making decisions (Lee & See, 2004). Studies show that individuals are more inclined to trust technology that showcases reliability, transparency, and performance. Trust shapes the methods and styles of decision-making. When trust is high, collaborative decision-making is more common (McAllister, 1995). In contrast, low levels of trust can create a competitive atmosphere, where individuals may withhold information and behave defensively, resulting in slower decision-making processes (Zand, 1972).

Chatbots are utilized in numerous fields, such as customer service, healthcare, and education. In healthcare, chatbots like Woebot reveal promise in offering support for mental health. Studies by Fitzpatrick et al. (2017) indicate that users often value the anonymity and accessibility provided by chatbot-based interventions, resulting in higher engagement in mental health practices. Yet, concerns surrounding the accuracy of information and the absence of human empathy continue to be substantial obstacles. Human-chatbot interaction is an evolving domain that carries important consequences for both technology and society. Grasping user attitudes, enhancing design, and tackling obstacles are crucial for creating successful conversational agents. As technology advances, continuous research will be important for influencing the future of human-chatbot exchanges, making sure they are not just effective but also reliable and engaging.

As evident in existing literature on chatbots, relationship with conversational chatbots has a significant impact on decision making and performance expectancy by the users. The role of trust in these relationships is significant in strengthening the bond between the user and chatbot. (Skjuve, 2021) However, most of the studies that we encountered dealt with machine mediated perspective of trust in human chatbot communication. Currently, this study attempts to bridge the existing gap in literature and provide a users' perspective of trust in human chatbot communication. This builds up on existing theoretical frameworks to explore how trust navigates decision making and performance expectancy when users interact with chatbots.

Theoretical Framework

This study built upon from three widely acclaimed theoretical models namely UATAT, TAM and HCTM.

Unified Theory of Acceptance and Use of Technology (UTAUT) model

Venkatesh et al. in 2003 introduced a conceptual framework to provide a comprehensive account of acceptance of information technology by an individual. This theory builds up on eight different models proposed for different disciplines like sociology, psychology, information technology, etc. These theories include Personal Computer Usage Model; Innovation Diffusion Theory; Technology Acceptance Model; Theory of Reasoned Action; Combined TAM-PBT; Theory of Planned Behavior; Social Cognitive Theory and Motivational Model. This theory proposes four main factors that influence behavioural intention and use behaviour. These factors are performance expectancy, social influence, effort expectancy and facilitating conditions. (Venkatesh et al., 2003) UATAT is generally used to study the acceptance of latest technology and usage patterns among a population. Since its proposal, it has been used by many researchers across the globe for studying the effect of these four factors on user behaviour and their intention to use. However, literature suggests that out of proposed factors, performance expectancy influences behavioural intention the most. (Mosweu et al., 2016; Afonso et al. 2012) Hence, for maintaining the relevance of our study we have selected performance expectancy as one of the elements on the basis of this theory.

Technology Acceptance Model (TAM)

TAM was proposed by Fred Davis in 1986 at the University of Michigan. This model explains how the users accept and use technology. According to this theory the factors that influence acceptance of any new technology and intention to use by an individual are perceived usefulness and perceived ease of use. Perceived usefulness refers to the extent upto which the user thinks using a technology will enhance their performance and perceived ease of use refers to the degree to which a technology is expected to be straightforward and effortless while using. According to TAM, technology acceptance is a three stage process where external factors (features of system design) stimulate cognitive responses in the form of perceived ease of use and perceived usefulness. This cognitive response ultimately leads to affective an response that is intention towards using a technology. This model suggests that if a user thinks something is easy to use, they are more likely to accept that technology and use it for their work. On the contrary, the technology that seems complex and difficult to use has a tough time being accepted by the users.

Human Computer Trust Model

For years human computer interactions were studied by the researchers but no empirical study was available to measure trust between the two. In 2020, Gulati et al. developed a socio-technical model to evaluate the construct of trust between human and computer during their interactions. They used seven attributes of trust and proposed a model using Partial Least Square Structural Equation Modelling. These attributes were Benevolence, Competence, Honesty, Motivation, Predictability, Reciprocity and Willingness. This model bridged a major gap surrounding the literature that dealt with trust in human computer interactions. It was one of the pioneering works that focussed directly on human- IT artefact interactions rather than studying relationships between human beings mediated by technology. Hereby, this model played an instrumental role in establishing the relevance of trust in human machine interactions which are otherwise considered as mechanical and devoid of any abstraction. From this model, we picked up our independent element to study Human

Chatbot Interactions that is trust. This model was an empirical modification of Human Computer Trust Model originally proposed by Sousa et al. (2014). The study by Sousa et al. was based on participatory design sessions and was a combination of unification of the work done by Davis and Venkatesh et al.

Hypotheses Development

This paper is an attempt to introduce trust as one of the major determinants of decision making and performance expectancy by the users. In order to develop hypothesis, we began by defining each of the elements of this study namely performance expectancy, decision making and trust.

Performance Expectancy

Performance expectancy is defined as the belief of a user that a particular technology will be beneficial to them and help them enhance their performance during a task. Performance expectancy is one of the major elements in Unified Theory of Acceptance and Use of Technology proposed by Fred Davis. In context of this study, we operationally define performance expectancy as the degree upto which a user thinks that using chatbots for resolving their health related queries will help them achieve their goals and reduce their workload.

Decision Making

Decision Making is defined as the process by which an individual reaches a conclusion about what actions should be taken in order to fulfil their set of objectives within the given set of limitations. According to Russo and Schoemaker (2002), decision making is done in four phases that begins with learning from experiences and ends at coming to conclusions with framing of issues and intelligence gathering as intermediary steps. In this study we define decision making as the behaviour of users where they are willing to use chatbots for seeking and acting upon health related advices provided by chatbots.

Trust

Trust can be defined as a socio-psychological construct embedded in personalities and social relations. (Misztal, 1996) We operationally define trust as the degree of security chatbots are able to provide to its users while they use it for getting any sort of information. Trust itself is a latent construct influenced by multiple factors but for this study we see it as an independent variable that influences decision making and performance expectancy by chatbot users.

Based on the above operational definitions and available literature on performance expectancy, decision making, and trust; we frame the following hypothesis.

H1: Trust is positively related to performance expectancy.

H01: Trust is not positively related to performance expectancy.

H2: Trust has a direct positive affect on decision making for chatbot users.

H02: Trust has no direct positive affect on decision making for chatbot users.

Research Methodology

The researcher conducted a web based survey among the population aged between 18-45. The respondents of the survey hailed from different parts of south Asia. The questionnaire for the survey was designed based on UATAT and HCTM. In total, 12 questions were selected by the researchers keeping the purpose of measuring latent constructs of performance expectancy, decision making and trust. The survey was circulated among 800 individuals out of which 255 responses were received. Forced four point Likert scale was used to collect responses in order to stimulate a clarity in thinking among respondents. The collected response was analysed using Smart PLS 4 software where PLS SEM model was developed using the measured constructs. This model was analysed in two stages as suggested by Gulati et al. (2017). The first stage evaluated the measurement model using the parameters of outer loading and cronbach's alpha. In the second stage, structural model was evaluated using Variance Inflation Factor and R square values. Overall model fitness was assured by an acceptable range of Standardized Root Mean Square Residual (SRMR) and Normed Fit Index (NFI).

Data Analysis

The collected data for the study was analysed using Partial Least Square Structural Equation Modelling using SmartPLS 4 software. PLS SEM is a non-parametric method hence bootstrapping is used to get statistical significance. (Chin, 1998) The rationale behind using PLS SEM over other techniques stems from its relevance in exploratory studies. PLS-SEM is a robust multivariate analytical technique that enables researchers to evaluate intricate cause-and-effect connections between latent constructs and their associated indicators. This approach was selected for its capacity to manage small to medium sample sizes and its appropriateness for exploratory studies. (Shahsavari et al.,2023) The proposed PLS SEM model was analysed in two stages as suggested by Gulati et al. (2017) - evaluation of measurement model and evaluation of structural model.

Evaluation of measurement model

For evaluating the measurement model, outer loading of the constructs was calculated. The measurement model was evaluated based on two parameters including indicator loadings and internal consistency reliability (Cronbach's alpha). In the initial analysis, some factors were found to have a outer loading of less than 0.4, such factors were removed for their insignificance. The final instrument had eight measures including exogenous and endogenous constructs. Table 1 demonstrates the outer loadings of eight indicators that we have used for measuring the endogenous constructs of decision making, performance expectancy and trust. For internal consistency reliability, we used Cronbach's alpha (CA) values. Performance expectancy showed a value of 0.733, decision making had a value of 0.683 and trust had a value of 0.605. All these values fall under acceptable range. Based on the above obtained values, the first stage of evaluating measurement model was successfully crossed.

Table 1. Outer loadings of elements being studied

	Outer loadings
DM1 <- Decision Making	0.726
DM2 <- Decision Making	0.715
PE1 <- Performance Expectancy	0.673
PE2 <- Performance Expectancy	0.663
PE3 <- Performance Expectancy	0.736
T1 <- Trust	0.656
T2 <- Trust	0.673
T3 <- Trust	0.627

Evaluation of structural model

On stage two, in order to evaluate the structural model, we used two values : Variance Inflation Factor and R square. The Variance Inflation Factor (VIF) is utilised to identify multicollinearity within regression analysis, such as Partial Least Squares Structural Equation Modeling (PLS-SEM). Multicollinearity takes place when independent variables exhibit strong correlations, potentially increasing the variance of coefficient estimates and leading to instability in the model's predictions. Kock (2015) highlights the need for studying VIF in order to assure that they fall under acceptable limits. Any value lower than 5 is considered acceptable for PLS SEM models (Hair et al., 2015). For our study, the significantly low VIF values showed that there was no multicollinearity between the variables taken into account for study.

	VIF
DM1	1.368
DM2	1.368
PE1	1.454
PE2	1.492
PE3	1.409
T1	1.262
T2	1.142
T3	1.269

In the comprehensive guide to PLS SEM provided by Hair et al., they claim that R square values are essential for assessing the quality of any model. R-square ranges between 0 and 1 for PLS SEM. Ideally, a value lesser than 0.25 is considered weak, from 0.25 to 0.25 moderate and anything above 0.50 is considered a strong fit. The R square and R square adjusted values for our endogenous constructs showed a promising value of 0.892 and 0.908 emphasising that our independent variable of Trust is highly predictive of decision making and performance expectancy. Thus, based on this, our model has a good predictive power, which essentially means that the

exogenous variables predict the endogenous variables with a high degree of accuracy. Table 2 demonstrates the aforesaid values as calculated by the smartPLS 4 software.

Table 2. R-square values of endogenous variables

	R-square	R-square adjusted
Decision Making	0.892	0.891
Performance Expectancy	0.908	0.908

Overall model fitness evaluation

For overall fitness of model, the parameters used were Standardized Root Mean Square Residual (SRMR) and Normed Fit Index (NFI). SRMR serves as a measure of goodness-of-fit in structural equation modelling, including Partial Least Squares Structural Equation Modeling (PLS-SEM). It measures the discrepancy between the observed correlations and those predicted by the model. NFI evaluates how well a model aligns by contrasting the chi-square statistic of the designated model with that of a baseline model, usually a null model where no correlations exist among the variables. Typically, the values for SRMR should be less than 0.08 (Hu and Bentler,1999) and for NFI any value greater than 0.90 (Lohmoller,1989) is considered a good fit. For the proposed model, SRMR turned out to be 0.042 and NFI was 0.929 both of which suggest that the model is acceptably fit.

	Saturated model	Estimated model
SRMR	0.042	0.042
NFI	0.929	0.929

Hypotheses Testing

Based on the available literature and theoretical underpinnings, the researcher had proposed the following hypotheses that correlated trust with performance expectancy and decision making.

H1: Trust is positively related to performance expectancy.

H01: Trust is not positively related to performance expectancy.

H2: Trust has a direct positive affect on decision making for chatbot users.

H02: Trust has no direct positive affect on decision making for chatbot users.

For validating our hypotheses, a two tailed t-test was performed whose results are shown in Table 3. We checked the p-values for both the relationships. P-values are essential in statistical hypothesis testing, acting as a means for researchers to assess the level of evidence opposing a null hypothesis. A smaller p-value (for instance, $p < 0.01$) indicates strong evidence opposing the null hypothesis, pointing to a significant effect or relationship. Conversely, a larger p-value (such as $p > 0.05$) indicates weak evidence, suggesting that any observed effect may just be a result of chance. For this study, $p=0.00$ that is strongly suggestive of the fact that both of our null hypotheses should be rejected and alternate hypotheses ought to be accepted. A high level of t-statistics also reaffirms acceptance of both the hypotheses. For H1, t-statistics is 11.276 and for H2, T statistics is 12.973 explaining a strong positive relationship between variables in both the cases.

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics ((O/STDEV))	P values
Trust -> Decision Making	0.944	0.948	0.084	11.276	0.000
Trust -> Performance Expectancy	0.953	0.957	0.073	12.973	0.000

Findings and discussions

Based on the above statistical evaluations, we reaffirm that trust plays a vital role in influencing human chatbot communication. The expectations of users are highly dependent on the level of trust that chatbots are able to gain by their responses and the rapport they are able to establish in general. A contemporary user who is familiar with technology already knows that chatbots function with a humongous database. They can answer any question that is posed to them as long as it is in synchronisation with what they have been fed. On the same line, when a user is making the decision to use chatbots, the only thing that they look for is whether the tools they are going to use are trustworthy or not. Our findings from this study strongly emphasise the undeniable influence of trust in human chatbot communication and provide strong empirical evidence to support this point.

This study explored how trust shapes user perceptions and behaviors in human–chatbot interaction by integrating constructs from UTAUT, TAM, and HCTM into a single structural model. The results indicate that trust strongly predicts both performance expectancy and decision making, suggesting that user-centered trust is not merely a secondary consideration but a central determinant of how people evaluate and rely on chatbots. These findings contribute to ongoing efforts in HCI to move beyond system-centric accounts of trust toward relational and socio-psychological explanations of human–machine communication.

At the theoretical level, the study demonstrates the value of synthesizing adoption models with trust frameworks. While TAM and UTAUT have long highlighted perceived usefulness and performance expectancy as drivers of adoption, they have rarely been examined alongside explicit measures of trust. Our findings suggest that trust may serve as a psychological filter through which users interpret chatbot utility, thereby linking cognitive appraisals of usefulness with behavioral willingness to act on chatbot advice. This integrated approach aligns with recent calls to account for both social and technical determinants of trust in conversational agents. At the same time, the unusually strong effect sizes observed in this study underscore the need for caution. Although robustness checks indicated that common method bias was unlikely to fully explain the results, conceptual overlap between constructs may have amplified the relationships. This highlights the importance of refining measurement models to better capture the multidimensional nature of trust and to reduce redundancy across items. Future research using longitudinal or experimental designs would provide stronger evidence for causal ordering between trust, expectancy, and decision

making. Practically, the findings reaffirm that fostering appropriate trust is essential for sustainable chatbot adoption, particularly in healthcare where advice carries heightened risk. Users who perceive chatbots as competent, reliable, and transparent are more likely to evaluate them positively and to incorporate their recommendations into decision making. This implies that design strategies should go beyond technical accuracy to include mechanisms that signal empathy, explainability, and accountability. However, designers must also guard against unwarranted over-trust, which could expose users to misinformation or bias.

Taken together, these findings support the argument that trust is foundational to human–chatbot communication. While this study provides exploratory evidence for trust as a direct antecedent of performance expectancy and decision making, further research is needed to test the robustness of these relationships across contexts, populations, and trust dimensions. By treating trust as both a relational and functional construct, future work can advance a more comprehensive and ethically grounded understanding of chatbot use. We propose the following model in Fig.1 to elaborate the influence of trust on performance expectancy and decision making by chatbot users. This model comprises three elements : Trust, Performance Expectancy and Decision making. It shows that trust directly and positively influences performance expectancy and decision making by the chatbot users. The higher is the level of trust, the more is the performance expectancy and probability of users using chatbot for their work.

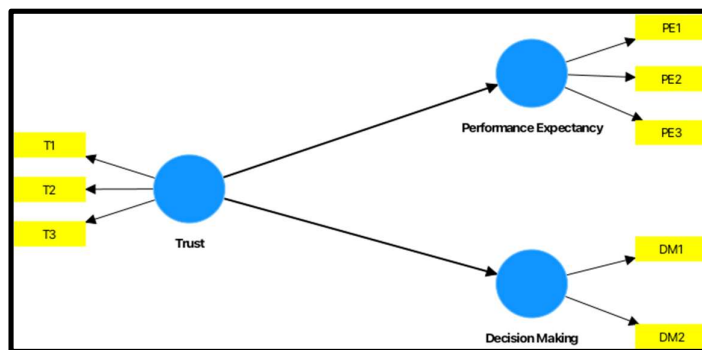


Fig.1. Trust in decision making and performance expectancy by chatbot users

Theoretical contribution

By integrating UTAUT, TAM and HCTM, this study advances human computer interaction theory in three ways. Firstly, it empirically validates trust as a central construct that predicts performance expectancy as well as decision making. This expands the existing models which treat trust as a peripheral construct. Secondly, it put forward trust not as a static belief but as a relational dynamic that shapes interactions and its outcomes. Lastly, it provides evidence from a South Asian context that diversifies the geographical scope of human chatbot communication research, which otherwise is majorly dominated by western settings. These contributions align with the need for more contextualised and relationally oriented approaches in human-computer interactions.

Implications of the study

Transparency in reasoning, accuracy, and clear communication of limitations can improve user confidence in chatbots. This study underscored the need of incorporating trust-building mechanisms in chatbot designs for developers. In healthcare and other sensitive field, attention to privacy, data protection, and accountability is particularly important. Organisations adopting chatbots must also acknowledge that trust is dynamic and evolves through consistent interactions. Continuous refinement, user-centred design, and ethical governance are therefore needed for sustaining trust over time.

Conclusion

Based on the findings of this study, the researchers provide strong evidence for the relationship of trust with performance expectancy and decision making in the context of human-chatbot communication. Higher is the level of trust in chatbots, higher is the performance expectancy by the users and higher are the probability of users going to chatbots for their work.

This study was one of the pioneering attempts to establish the relevance of abstraction in human chatbot communication and explore further ways of widening the existing scholarship which, as inferred during the study, seems to be limited in the context of abstraction at present. Trust, empathy, understanding, co-operation and collaboration stay undeterred when it comes to communication and in order to foster technological development, each one of these should be given importance. From this study, we suggest the human machine communication scholarship to emphasise more on abstract values like one we did in this study in order to strengthen the relationship between human beings and machines while keeping both the humane perspectives and mechanical perspective of communication into consideration.

Limitations and recommendations

This research enhances the understanding of how trust affects performance expectancy and decision-making during interactions with chatbots. However, there are several limitations that should be recognized and present opportunities for future investigation. To begin with, trust was treated as a singular dimension in this study. Although this method provides clarity, it fails to account for the various factors that may influence trust, such as perceived transparency, reliability, empathy, privacy guarantees, and cultural alignment. Subsequent studies should consider a multidimensional approach to identify and evaluate these factors and their significance in building user trust.

Additionally, the cross-sectional design restricts the ability to capture the dynamic nature of trust. Trust in interactions between humans and chatbots is not fixed; it can strengthen or weaken over time as users engage more frequently, encounter errors, or witness enhancements in chatbot capabilities. Longitudinal or experimental research could offer important insights into the processes involved in trust development, maintenance, and decline, thereby expanding the current findings.

References

1. Afonso, C. M., Roldan Salgueiro, J. L., Sanchez Franco, M. J., & Gonzalez, M. d. I. O. (n.d.). [Title not provided].
2. Broussard, M. (2019). *Artificial unintelligence: How computers misunderstand the world*. MIT Press.
3. Chin, W. W. (1998). The partial least squares approach to structural equation modeling. In G. A. Marcoulides (Ed.), *Modern methods for business research* (pp. 295–336). Erlbaum.
4. Etzrodt, K., Gentzel, P., Utz, S., & Engesser, S. (2022). Human-machine communication: Introduction to the special issue. *Publizistik*, 67. <https://doi.org/10.1007/s11616-022-00754-8>
5. Fitzpatrick, K. K., et al. (2017). Delivering cognitive behavioral therapy to young adults with depression using an automated conversational agent: A randomized controlled trial. *Journal of Medical Internet Research*, 19(4).
6. Gefen, D. (2000). E-commerce: The role of familiarity and trust. *Omega*, 28(6), 725–737.
7. Gulati, S., Sousa, S., & Lamas, D. (2017). Modelling trust: An empirical assessment. In *16th IFIP TC 13 International Conference on Human-Computer Interaction—INTERACT 2017* (pp. 40–61). Mumbai, India.
8. Hancock, J., et al. (2011). The effect of anthropomorphism on trust and compliance. *Computers in Human Behavior*, 27(1), 129–136.
9. Hu, L.-T., & Bentler, P. M. (1998). Fit indices in covariance structure modeling: Sensitivity to underparameterized model misspecification. *Psychological Methods*, 3(4), 424–453.
10. Jurafsky, D., & Martin, J. H. (2019). *Speech and language processing*. Pearson.
11. Kleinberg, J., et al. (2020). Conversational agents: A review of the literature. *Artificial Intelligence Review*, 53(3), 1753–1795.
12. Lee, J. J., et al. (2020). The uncanny valley in human-robot interaction: A review. *International Journal of Social Robotics*, 12(2), 289–303.
13. Lohmöller, J.-B. (1989). *Latent variable path modeling with partial least squares*. Physica.
14. Luger, E., & Sellen, A. (2016). Like having a really bad PA: The gulf between user expectation and experience of conversational agents. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems* (pp. 5286–5297).
15. Misztal, B. A. (1996). *Trust in modern societies: The search for the bases of social order*. Polity Press.
16. Mosweu, O., Bwalya, K. J., & Mutshewa, A. (2016). A probe into the factors for adoption and usage of electronic document and records management systems in the Botswana context. *Information Development*, 33(1), 97–110.
17. Nielsen, J. (2019). The principles of user experience. *Nielsen Norman Group*.
18. Octavianus, A. W., Wijaya, E. A., & Andajani, S. R. (2020). Menguji determinan individual intention to use pada aplikasi Traveloka. *Journal of Business and Banking*, 10(1), 71–89. <https://doi.org/10.14414/JBB.V10I1.2230>
19. Roekel, D. V. (n.d.). *Preparing 21st century students for global society*. National Education Association. <http://www.nea.org/assets/docs/A-Guide-to-Four-Cs.pdf>
20. Skjuve, M., Følstad, A., Fostervold, K. I., & Brandtzaeg, P. B. (2021). My chatbot companion—A study of human-chatbot relationships. *International Journal of Human-Computer Studies*, 149, 102601. <https://doi.org/10.1016/j.ijhcs.2021.102601>

21. Topping, K. J., et al. (2020). Chatbots as learning companions: Evaluating the effectiveness of chatbot interactions in education. *Computers & Education*, 156, 103931.
22. Torraco, R. J. (2005). Writing integrative literature reviews: Guidelines and examples. *Human Resource Development Review*, 4(3), 356–367.
<https://doi.org/10.1177/1534484305278283>
23. Türetken, O., et al. (2018). Customer service chatbots: A framework for understanding their role in customer service. *Journal of Business Research*, 92, 373–380.
24. Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 27(3), 425–478.
25. Wang, Y., et al. (2021). Trust in chatbots: A systematic review and future research directions. *Computers in Human Behavior*, 121, 106803.