

EFFECT OF TRUST IN AI ON HUMAN AI RELATIONSHIP AMONG UNIVERSITY STUDENTS

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KEYWORDS:

Trust in AI, Human AI
Relationship, University Students

CITE THIS ARTICLE:

Noor, M., & Batool, N., & Zaheer, M. (2026). Effect of trust in AI on human AI relationship among university students. Pakistan Journal of Positive Psychology, 3(1), 150-157.

ABSTRACT

The study aimed to examine the effect of trust in AI on Human-AI relationship among university students. A cross-sectional survey research design was used. The sample comprised 300 university students (150 males and 150 females) selected through convenient sampling technique. Measures included the General Attitude toward AI Scale (GAAIS) by Schepman and Rodway (32 items, Positive $\alpha = .84$, Negative $\alpha = .73$), Short Trust in Automation Scale (S-TIAS) by McGrath et al. (3 items, $\alpha = .88$), and Experiences in Human-AI Relationships Scale (EHARS) by Yang and Oshio (7 items). Correlation analysis showed that trust in AI was positively correlated with Human-AI relationship. The study contributed to the growing literature on Human-AI relationships by highlighting the role of trust in AI in Human-AI interactions among university students. The findings have important implications for AI literacy, technology acceptance, and the development of educational interventions aimed at fostering healthy and effective Human-AI relationships.

I. INTRODUCTION

The construct of trust in AI technologies has been conceptualized from different perspectives within academic literature, owing to the interdisciplinary of the topic of human-technology interaction research. Trust in automation was conceptualized as "an attitude that an agent will aid in achieving one's goals in a situation involving uncertainty and vulnerability" (Lee & See, 2004, p. 51). Such a conceptualization highlights how the notion of trust is a psychological process allowing people to cope with uncertainties and risks while leveraging technological agents to accomplish certain tasks or make decisions for them. Uncertainty and vulnerability are key components of AI interactions due to the probabilistic nature of systems' behavior. Mayer et al. (1995) also provide a famous definition of interpersonal trust when they say that "trust is a willingness of a party to be vulnerable to the actions of another party based on the expectation that the other will perform a particular action important to the trustor, irrespective of the ability to monitor or control that other party" (p. 712). Although the definition was formulated in relation to human interactions, it has found broad application to human-computer interaction because the psychological element of vulnerability under conditions of uncertainty is transferable to the human-technology relationship.

Furthermore, Hoff & Bashir (2015) introduced a tripartite model of trust in automation with dispositional trust, situational trust, and learned trust. Dispositional trust is related to the inherent tendency of individuals towards trusting technology, which is affected by personality, cultural background, and past experiences. Situational trust can be formed due to the context of interaction that includes features of the system, tasks, and environment. Learned trust is formed in a dynamic process where users form their beliefs regarding system reliability through experience with the system. The tripartite model received considerable empirical validation. The recent academic

focus has been on the difference between appropriate and inappropriate trust. Appropriate trust is characterized by the alignment of users' trust in AI systems with the real capacity of those systems. Inappropriate trust includes both overtrust (over-reliance when the system is unreliable) and undertrust (under-reliance when the system is reliable). Schemmer et al. (2023) define appropriate reliance as “human beings’ capability to discriminate right and wrong advice from AI and act upon that discrimination” (p. 410) referring to the metacognitive aspect of trust adjustment. In this research, trust in AI technology will be understood as acceptance of vulnerability to the actions of AI systems due to expectations about their competence, benevolence, and integrity.

Theoretical Foundations of Trust in AI

Trust Theory

The basic conceptual model for explaining trust in artificial intelligence lies with the Integrative Model of Organizational Trust proposed by Mayer, Davis, and Schoorman (1995). In this theory, trust is defined as a readiness of a person to take risks and be vulnerable because of his or her positive attitude towards other parties' intentions, abilities and behaviors. Despite the fact that the model was designed in order to describe the relationship between people and organizations, it is often used to understand how human interacts with intelligent technologies because the model gives an opportunity to analyze the way in which people create trust in relation to intelligent technologies. Trustworthiness is characterized by such features as ability, benevolence and integrity. Mayer et al. (1995).

Human Automation Trust Theory

Trust theories in relation to automation were introduced by Lee and See (2004) with the Human Automation Trust Theory. Lee and See define trust as confidence in the contribution of an automated system towards achieving the individual's goals under uncertainty and vulnerability conditions. The theory focuses on that trust is not static but develops dynamically through interactions between the user and the automated system. A number of factors which determine the formation of trust have been identified in the theory, and these include performance, process, and purpose. Performance entails how well the system performs the task at hand. Process involves the user's perception of the workings of the system and how decisions are made in the system. Purpose involves the perception of the motives that have guided the designing of the system. Trust impacts on the reliance behavior, and for optimal results to be achieved, trust should match the ability of the system.

Three-Stage Model of Trust in Automation

In Hoff and Bashir's (2015) tripartite model of trust in automation, the process of trust formation is discussed in terms of its development at multiple time scales. According to Hoff and Bashir's theory, trust can be either dispositional, situational, or learned. The former refers to personality-related tendency of an individual to trust technological systems. Situational trust is determined by context, which includes such aspects as task, environment and system features. Finally, learned trust is formed on the basis of experience as users observe how reliable, predictable and effective the system in question is. The importance of the theory in relation to AI technologies lies in the necessity for individuals to interact with intelligent systems repeatedly. Trust, therefore, is not defined by initial perceptions but continually updates as a result of further experiences.

Socio-Technical Trust Framework

The socio technical model for AI trust has been developed by Siau and Wang (2018), which involves aspects of technology, humans, and environment. Under this model, trust in artificial intelligence depends on three broad classes of determinants. The first class consists of technological attributes such as performance, explainability, transparency, reliability and accuracy. The second class refers to human attributes including personality, experience with technology, and trust propensity of individuals. The third class includes the environmental aspects like culture, organization, rules, and task. It is noteworthy that under this model, trust in artificial intelligence cannot be assessed by only considering technological attributes. Rather, it is based on interactions among technological system, individual user, and environmental aspects.

Model of Appropriate Trust and Reliance

Schemmer et al. (2023) define appropriate trust as the ability of users to recognize the difference between good and bad AI advice and adapt themselves accordingly. This approach focuses on trust calibration where users can set their expectations regarding the system's capabilities realistically. An overestimation of trust will cause the users to accept bad advice without criticism, while underestimating trust will not allow them to get any benefit from good advice. The notion of appropriate trust has gained its significance because of using AI in high-stakes settings like healthcare, education, finance, and public administration.

Demographic Differences of Trust in AI

The issue of age has often been considered as a characteristic that affects people's trust in AI systems and other automated technologies. According to earlier research, younger people are likely to show higher trust and readiness for accepting innovations in the sphere of technology because of their higher level of familiarity with digital technologies and higher awareness of technological changes. Therefore, increased familiarity may be associated with an increased perception of the effectiveness and reliability of AI systems. In case, younger people may perceive AI as an extended technology and, therefore, may have higher likelihood of relying on the results of AI systems. On the contrary, older people may have low trust in AI systems because of the lack of exposure to innovative technologies, problems with reliability, or problems with the understanding of AI system. Nonetheless, the results concerning age effects are inconsistent. Some researchers state that older adults can also build high trust in AI systems if they are reliable, transparent, and user-friendly. Therefore, age has indirect influence on trust through other characteristics (Lee & See, 2004).

Trust in AI has also been studied in relation to gender as a variable that might affect trust in AI. Based on past literature, it can be concluded that men have higher levels of trust and readiness to adopt AI technology than women. Such differences have been usually explained by differences in terms of technology experience, risk perception, and confidence in adopting new technologies but not always consistent. Such differences have usually been explained by differences in terms of risk perception, technology acceptance, and confidence in interaction with technology. Women have been found in some cases to pay more attention to privacy issues, ethical concerns, transparency, and possible risks from AI technologies. Men, in their turn, may be more interested in usefulness and performance of AI. At the same time, modern studies indicate that gender differences in trust tend to diminish as individuals gain direct experience with AI systems and become more familiar with their capabilities (Glikson & Woolley, 2020).

Educational achievement has been linked to differences in trust for AI. People who have higher levels of education tend to be technologically literate and thus have a better understanding of what is achievable using AI technology. Through this understanding, they become capable of forming more accurate trust without over or under-trusting. People with higher education levels are likely to be more aware of ethical, legal, and social ramifications of AI. This makes them capable of critically evaluating AI while being aware of the advantages that come from the use of the same (Siau & Wang, 2018). Cultural factors significantly contribute to building trust in AI systems. Every culture holds its views on technology, uncertainties, power, and innovation. People from cultures that have high levels of technological optimism tend to be more trusting of AI and more ready to incorporate such technologies into their daily routines. On the contrary, cultures with high levels of uncertainty avoidance tend to be more skeptical of autonomous technologies and value transparency and accountability more. Culture also shapes people's views on privacy, fairness, and ethics, which impact the building of trust in AI systems (Siau & Wang, 2018).

The experience of a user with technology has been found to be among the most powerful predictors of their trust in AI. Those who engage with technologies on a regular basis form more accurate mental models regarding the behavior of automated systems. They are also able to properly judge AI performance and place trust accordingly. Positive learning about Artificial Intelligence can enhance trust using the process of learned trust, while a bad experience with Artificial Intelligence can diminish confidence and lead to suspicion. Hence, trust is not determined only by demographic features but also by users' experiences with technology (Lee & See, 2004). Trust is considered among the key factors in building a successful relationship between Human and AI. The concept of trust of individuals in the use of AI is defined by the willingness of individuals to become vulnerable because of

their expectations of excellent performance of AI in achieving their goals (Lee & See, 2004). Mayer et al. (1995) state that trust arises when people have confidence in other entities' competence, benevolence, and integrity. These criteria have been used in measuring the level of trust in AI systems where users analyze the accuracy, reliability, integrity, and ethics of AI. Lee and See (2004) stated that trust acts as a mediator of the link between perception and reliance behavior in relation to AI. The role of trust becomes crucial in AI systems which work under conditions of uncertainty and complexity. In case people trust AI suggestions, they are ready to act on them in order to make decisions. The research done by Hoff and Bashir (2015) showed that trust can be developed dispositionally, conditionally and through learning process. Moreover, studies have demonstrated that anthropomorphic traits assist in establishing an emotional trust since human-like attributes generate a sense of comfort, familiarity, and social presence (Glikson & Woolley, 2020). Thus, trust functions as a key link between AI perception and HAI relationship building.

The phenomenon of anthropomorphism has been seen to be very important in building trust towards AI. Anthropomorphism is basically the attribution of human-like qualities like intentions, feelings, human traits, and personality to non-human objects. Since AI is getting more social and interactive, people are finding it to have some social actor qualities of a human being. Research has shown that the presence of anthropomorphic features in AI increases the perception of users regarding the social presence, familiarity, and emotional aspects of the machine, which ultimately helps in building trust (Glikson & Woolley, 2020). People feel that when AI looks more human-like, then it will definitely have the qualities that human beings possess when they are reliable and trustworthy. Moreover, Yang and Oshio (2025) stated that people are now looking towards AI in terms of providing comfort, guidance, and reassurance to them, and these are the qualities of their attachment figures. According to the research, it can be suggested that AI can act as a safe haven and secure base for people.

The fact that trust is considered to be the highest influence on reliance of AI is quite common knowledge. According to Lee and See (2004), trust is described as an intention to accept sensitivity on the basis of positive expectations about the agent's actions. With the development of trust towards the AI systems, people are likely to accept the recommendations, task delegation, and usage of the system's output in decision-making processes. It makes it possible to decrease uncertainty and perceived risk, which is why people can trust AI even if they do not understand how the system works. Hoff and Bashir (2015) state that trust is developed due to dispositional, situational and learned factors and makes it possible to develop dependency on the judgements made by AI. As the level of trust increases, users get more comfortable using the AI technology to process information, solve problems, make recommendations and decisions. As a result, dependence becomes an outcome of trust.

Rationale

Artificial Intelligence (AI) has emerged as one of the most important components of contemporary society, which affects how people communicate, learn, work, make decisions and get support. Technologies, such as ChatGPT, virtual assistants, recommendation systems, and intelligent chatbots, are not used by people only for tasks performance anymore; they become companions, consultants and sources of emotional and informational support as well. As AI technologies get more and more advanced and humane, the essence of the interaction between humans and AI changes from using the technology to building Human AI Relationships (Yang & Oshio, 2025). It was proven recently that people tend to view AI systems as social entities rather than machine tools. Since AI systems are getting deeper into the lives of users, people start to trust their recommendations, delegate decision-making to AI, and in some cases form emotional attachment and dependency to AI technologies (Lee & See, 2004; Morales-García et al., 2024; Yang & Oshio, 2025). While previous researchers have looked into constructs such as trust in AI, Human AI relationships. The trust in AI has been found to play an important role in determining the extent to which users trust AI decisions and recommendations (Lee & See, 2004; Hoff & Bashir, 2015). The rise in the use of AI technologies presents a dire need for research on these relationships from the perspective of psychology. Yang and Oshio (2025) postulated that the theories of attachment may be applied in the study of Human AI Relationships since AI systems act as secure base and a safe haven providing comfort, protection, and guidance to individuals.

Thus, knowing what helps to ensure positive and efficient relations between human and artificial intelligence will enable researchers, psychologists, educators, and developers of new technologies to create AI systems which

would be useful for people, but at the same time would not bring about any risks which might arise as a result of dependency. Indeed, according to previous literature review, AI dependency could undermine analytical skills and independent decision making (Morales-García et al., 2024). Previous researches in this field have mostly focused on individual variables without considering their interactions. This current research hopes to shed light on the interconnections between the different variables in order to offer a clearer picture of the dynamics involved in the development of Human AI relationships.

Objective

1. To examine the effect of Trust on AI on Human AI relationship in University Students.
2. To assess gender differences with respect to trust in AI and human-AI relationship.

Hypotheses

- H1: Trust in AI positively predicts Human AI relationship in university students.
 H2: Male university students will score higher on Trust in AI than female university students.
 H3: Male university students will score higher on Human AI Relationship than female university students.

II. METHOD

A cross-sectional survey research design was used in the present study to assess the variables of interest at a single point in time across the sampled population.

Participants

The sample for the present study comprised 300 university students with an equal gender distribution of males ($n = 150$) and females ($n = 150$). All study participants were currently enrolled at the university level and consented voluntarily to participate in the research. The respondents represented a diverse range of academic disciplines and socioeconomic backgrounds thereby enhancing the representativeness of the sample. Data were gathered through convenient sampling technique wherein participants were selected on the basis of their relevance and accessibility to the research objectives.

Measures

[I] Trust in AI. The Short Trust in Automation Scale (S-TIAS), developed by McGrath et al. (2025), is a 3 item self-report measure designed to examine individuals' trust in artificial intelligence systems. It is derived from the original 12-item version of the Trust in Automation Scale (Jian et al., 2000) via psychometric item analysis. The scale evaluates user trust in and their belief in the dependability of the automation system. Respondents are asked to evaluate each item using a 7-point Likert scale where respondents have to give their answers from 1 (Not at all) to 7 (Extremely). Then, the average of the three items is calculated as the trust score, with high trust in AI being reflected by high scores and vice versa. The S-TIAS scale has proven to be extremely consistent in terms of internal validity (Cronbach's $\alpha = .97$), as well as construct, convergent and predictive validity. **[II]** Human AI Relationship. According to Yang and Oshio (2025), a human AI relationship refers to the emotional and psychological bond individuals develop with artificial intelligence systems, characterized by attachment related experiences such as attachment anxiety and attachment avoidance toward AI. Human AI relationships reflect the extent to which individuals seek emotional reassurance, intimacy, support, or maintain emotional distance in their interactions with AI. In the present study, human AI relationship is measured using the Experiences in Human AI Relationships Scale (EHARS) developed by Yang and Oshio (2025). The scale consists of 7 items assessing AI attachment anxiety and AI attachment avoidance.

Procedure

In the current study, data were obtained from university students. Before the data collection process began, formal approval was sought from the relevant authorities at the university. Data collection took place during regular working hours in the university. The participants were informed of the study's objectives and were asked if they were ready to participate. Those who agreed to take part were asked to sign the informed consent form prior to the questionnaire. The participants were told that the data would be used only for research and that their responses would be kept private and anonymous. The researcher was readily available during the data collection process to answer any queries that might arise from the participants before, during, and after the data collection

process. At the end of the data collection process, the researcher thanked all the participants for their invaluable help.

III. RESULTS

Table I: Psychometric Properties for Scales

Scales	<i>M</i>	<i>SD</i>	Range	Cronbach's α
Trust in AI	50.82	12.01	12-107	.87
Human AI Relationship	27.07	8.58	7-48	.83

Table 1 presents the psychometric properties of the scales (N=300). The Cronbach's alpha values of .87(>.80) which indicated high internal consistency. The Cronbach's alpha values of .83(>.80) which indicated high internal consistency.

Table II: Pearson Correlation between Trust in AI and Human AI Relationship

Variable	1	2
1. Trust in AI	-	
2. Human AI Relations	.43***	-

*** $p < .001$

Pearson correlation analysis was conducted to examine the relationship between trust in AI and Human-AI relationship among university students. The results indicated a significant positive correlation between trust in AI and Human-AI relationship ($r = .43$, $p < .001$). This finding suggests that students who reported higher levels of trust in AI also tended to report more positive Human-AI relationships. The significant positive association indicates that trust in AI is an important factor associated with the development of positive Human-AI relationships among university students.

Table III: Regression Coefficients of trust in AI Predicting human AI Relationship

Variables	<i>B</i>	<i>SE</i>	<i>t</i>	<i>p</i>	95% CI
Constant	11.96	4.17	2.87	.005	[3.73, 20.15]
Trust in AI	.19	.04	5.09	.000	[.12, .26]

Simple linear regression analysis was conducted to examine the predictive role of trust in AI on Human-AI relationship among university students. The overall regression model was statistically significant, $F(6, 293) = 29.27$, $p < .000$, explaining 37.5% of the variance in Human-AI relationship ($R^2 = .375$, adjusted $R^2 = .37$). Trust in AI emerged as a significant positive predictor of Human-AI relationship ($\beta = .27$, $p < .000$), indicating that higher levels of trust in AI were associated with stronger Human-AI relationships among university students.

Table IV: Mean Comparison of Male and Female Participants on Study Variables

Variables	Male		Female		<i>t</i> (298)	<i>p</i>	Cohen's <i>d</i>
	<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>			
Human AI relationship	28.42	8.95	25.58	7.93	2.90	.004	0.34
Trust in AI	51.27	13.52	50.33	10.10	.67	.502	0.08

An independent-samples *t*-test was conducted to examine gender differences in trust in AI and Human-AI relationship among university students. The results revealed statistically non-significant gender differences in trust in AI, $t(298) = 0.67$, $p > .05$, with a negligible effect size (Cohen's $d = 0.08$). In contrast, a statistically significant gender difference was found in Human-AI relationship, $t(298) = 2.90$, $p = .004$, with a small effect size (Cohen's $d = 0.34$).

DISCUSSION

The hypothesis, “trust in AI positively predicts human-AI relationship in university students” ($\beta = .27, p < .001$), was supported by the current study. This finding indicates that the more university students trust AI systems as reliable, competent, and trustworthy, the stronger and more positive their relationships with AI are likely to be. Trust is an essential component of interaction between humans and AI, as it encourages users to interact with AI systems, follow their advice, and use them during studying and performing daily routines. When students trust AI, they may consider it a reliable source of information, guidance, and help, which may contribute to more positive relationships with AI technologies. The findings of the current research are consistent with previous studies that highlighted the importance of trust in human-AI interaction. Trust helps develop positive interactions with AI and promotes the acceptance of AI technologies by reducing uncertainty (Gillath et al., 2021). Regarding gender differences, the results revealed no significant difference between male and female university students in trust in AI, $t(298) = 0.67, p = .502$. This suggests that male and female students did not differ significantly in their reported levels of trust in AI. One possible explanation is that both male and female university students may have similar exposure to and familiarity with AI technologies, which could contribute to comparable levels of trust. However, this explanation should be interpreted cautiously, as the present study did not directly examine students’ exposure to or familiarity with AI.

In contrast, a significant gender difference was found in Human-AI relationship, $t(298) = 2.90, p = .004$. This indicates that male and female students differed significantly in their reported Human-AI relationship scores. However, the direction of this difference depends on the respective group means. The final hypothesis, which proposed that male university students would exhibit significantly higher levels of trust in AI and Human-AI relationship than female university students, was therefore not fully supported. The results did not support the predicted gender difference in trust in AI, although a significant gender difference was observed in Human-AI relationship. Previous research has suggested that men tend to be more positive about emerging technologies, demonstrate greater technology acceptance, and report more confidence in using AI-based tools. Sindermann et al. (2021) found that men were more accepting of and trusting toward AI technology, thus increasing their reliance on it. Similarly, studies on technology adoption have frequently shown that males tend to adopt and experiment with new technologies more readily than females (Venkatesh et al., 2003). However, these findings do not necessarily explain the non-significant gender difference in trust in AI observed in the present study, highlighting the possibility that gender differences may vary across populations and research contexts.

CONCLUSION

The present study examined whether trust in AI predicts human AI relationship among university students in Pakistan. The findings revealed that trust in AI was a significant positive predictor of human AI relationship suggesting that students who perceive AI as trustworthy tend to report stronger human AI relationships. Regarding gender differences no significant difference was found in trust in AI whereas a significant difference was observed in human AI relationship. These findings highlight the importance of promoting AI literacy and awareness in educational institutions to encourage informed and responsible interactions with AI technologies. The study also contributes to the limited research on human-AI relationships in the Pakistani context. Future research should examine how human AI relationships relate to students’ academic performance, psychological well-being technology adoption and decision making.

Disclosure Statement

No potential conflict of interest was reported by the authors.

Funding

The author received no funding from any organizations.

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