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The Mediating Effect of AI Trust on AI Self-Efficacy and Attitude Toward AI of College Students

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ABSTRACT

This quantitative study investigated the mediating effect of AI trust on the relationship between AI self-efficacy and attitude toward AI of college students in Region XI, Philippines. Using adapted questionnaires, the data were gathered online via Google Forms, where the respondents were selected using stratified random sampling. Validity and reliability tests were employed on the measurement model, descriptive statistics were also used to describe the constructs in the study, while mediation analysis using the standard algorithm-bootstrapping of SmartPLS 4.0 was performed to assess the hypothesized mediation model. The findings revealed that the constructs of the study are valid and reliable. Moreover, college students also demonstrated moderate levels of AI trust and attitude toward AI and a high level of AI self-efficacy. Finally, the mediation analysis suggests that AI trust is deemed to have a substantial mediating effect on the relationship between AI self-efficacy and attitude toward AI of college students.

INTRODUCTION

Artificial intelligence (AI) is the machines' ability to carry out tasks typically performed by humans (Duan et al., 2019; Dong et al., 2020; Martin & Freeland, 2020; Scotti, 2020; Ahmad et al., 2021; Mota et al, 2023; Sheikh et al.,2023). As artificial intelligence technologies are integrated into digital systems (Duan et al., 2019), they are revolutionizing aspects of life (Makridakis, 2017; Chakraborty, 2020; Sisodia et al., 2020), having a significant influence on how people decide (Duan, 2019; Buiten, 2019; Gualdi & Cordella, 2020). It is fast-growing (Hassani et al., 2020; Olhede & Wolfe, 2018; Beig & Qasim, 2023) and is now perceived to be the most significant and disruptive new technological phenomenon for large businesses (Benbya et al., 2021) that every industry wants to take advantage of these opportunities to save costs and increase efficiency (Hassani et al., 2020). Artificial intelligence has drastically improved the efficacy of various sectors, including manufacturing, services, and education (Verma, 2018; Jiang, 2022). Education is witnessing the emergence of innovative teaching and learning solutions powered by AI (Pedro et al., 2019). AI can function as a beneficial instructional instrument, alleviating the burdens on both instructors and learners while cultivating more efficient learning milieus (Loeckx, 2016; Luckin & Holmes, 2016; Woodruff et al., 2023). Tamir and Knidiri (2023) assert the necessity of adopting these modern technologies (e.g. artificial intelligence, chatbots) in universities to revolutionize learning and to more effectively address the demands and complexities of an ever-evolving educational landscape. However, people's varying acceptance and attitude towards AI continue to be a hurdle (Gaudiello et al., 2016). Even though artificial intelligence is widely employed and is seen as a necessary ability for the future (Jiang, 2022), students get perplexed and frustrated when presented with computer and AI tools (Almaiah et al., 2022) and users struggle to comprehend what artificial intelligence is and how it may benefit them (Kim & Lee, 2023). According to Welding (2023), most college students do not plan to employ AI in the future to finish projects or tests. While some students are prepared to integrate generative AI into their university coursework, many still oppose using the technology (Skeat & Ziebell, 2023). Liehner et al. (2023) assert that attitudes regarding AI have the power to mold beliefs, which in turn affects people's level of trust in AI-based systems and AI itself.

The study of Montag et al. (2023) revealed that attitudes about artificial intelligence (AI) and technology self-efficacy are correlated with the likelihood of trusting automated technology; a stronger inclination for trust is favorably correlated with acceptance of AI and negatively correlated with dread of AI. Similar findings were made by Kraus et al. (2022), who discovered that a greater inclination to trust artificial intelligence should be positively correlated with a higher level of self-efficacy while engaging with AI. In the study of Douali et al. (2022), the majority of participants do not trust artificial intelligence due to their lack of understanding. Correspondingly, students who expressed verbally that the more familiar they are with AI technology, the more comfortable they are in using AI in general. Nonetheless, Fotea et al. (2019) discovered that while respondents view artificial intelligence favorably in their day-to-day, private encounters with technology, they have low trust in its use in an educational environment. Higher levels of general trust are associated with a higher level of acceptance regarding the advantages of AI (Schepman & Rodway, 2023). In the interim, Pan (2020) discovered that students

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who possessed greater technological self-efficacy and a greater sense of familiarity with technology exhibited more positive attitudes about technology-based self-directed learning. Kim and Lee (2023) also assert that a positive attitude toward AI is correlated with a higher level of interest in the field. Nonetheless, even though they do not always grasp the fundamentals of these technologies, the respondents in the study of Yadrovskaia (2023) had a positive attitude about their utilization. As a result, it is crucial, according to Schepman and Rodway (2023), to explore the psychological foundations of views toward AI in particular.

Prior research has examined the impact of social status on individuals' self-efficacy and intentions to utilize artificial intelligence (Hong, 2022). Additionally, Lee (2020) analyzed the AI curricula implemented in elementary and secondary schools, both domestic and foreign. Almaiah et al. (2022) investigated the effects of AI on e-learning students' social and computer anxiety. Lastly, Lee (2020) examined the perceptions and acceptance of AI (Gerlich, 2023). However, research studies incorporating AI trust and self-efficacy towards attitude in tertiary level education is still lacking. The significance of this study is to identify and assess how the university students' belief in their own technology skills can influence their attitude about AI, and how this relationship is affected by their trust in AI as well. The results of this study could add to the body of research in education, technology, and psychology by giving us a better picture of how students' feelings about AI are connected to their confidence and trust in AI. Understanding the things that affect students' attitudes can have real-world effects on how schools work and lead to more research.

LITERATURE REVIEW

As we look into how AI trust affects the relationship between technology self-efficacy and overall attitude toward AI, we need to think carefully about how to fully understand the complex dynamics of how college students feel about AI. The authors of Kraus et al. (2020) say that people who feel more confident in their ability to use new technology are more likely to trust automated systems. Montag et al. (2023) agree and say that there is a positive link between technological self-efficacy and believing in automated technology and having a positive view of AI. So, the tendency to trust technology is linked to technology self-efficacy in a good way. This shows how important self-efficacy is for building trust in AI-related technologies. The depth of trust on AI influences one's attitude and willingness to embrace and engage with AI technologies. The study conducted by Schepman A. & Rodway P. (2022), it shows that people who distrust corporations tended to have a negative attitude towards AI, while those with higher levels of general trust have a more positive attitude towards AI. In addition, the study of Choung et. al (2022), claims that trust plays a significant role in AI attitude. Additionally, it can be concluded that self-efficacy influences attitude as higher levels of technology self-efficacy denotes an impression of more capabilities at creating effective decisions with regards to dealing with automated technology and being able to easily interact with it and control its impacts (Montag et al., 2023). Moreover, it has been discovered that more people intend to adopt AI when they have more positive attitude towards its application (Hong, 2022). Thus, they also tend to trust these technologies more as this reflects their trust with their own capabilities to interact with the technology and it leads a more positive attitude towards artificial intelligence.

This research is grounded in the theoretical framework of the Multicomponent model of attitude, as originally proposed by Eagly and Chaiken (1993) and expanded upon by Zanna and Rempel (1998). This theoretical perspective posits attitudes as intricate evaluations encompassing cognitive, affective, and behavioral dimensions. In accordance with this framework, the study advances the proposition that attitudes towards AI among university students are synthesized evaluations informed by AI trust and technology self-efficacy. With its structured foundation, the Multicomponent model is instrumental in examining the intricate interplay between these pivotal elements—AI trust and self-efficacy—and their cumulative impact on shaping attitudes towards AI. By leveraging this model, the research aspires to make a significant contribution to a nuanced comprehension of the multifaceted nature of attitudes towards AI, discerning the intricate relationships among cognitive assessments, emotional responses, and behavioral tendencies in the evolving landscape of emerging technologies.

From a psychological perspective, the Multicomponent Model of Attitude characterizes an individual's attitude as the expression of their preferences or aversions toward entities like people, places, or objects. In particular, Eagly and Chaiken (1998) define attitude as a psychological tendency involving judgment that is characterized by differing degrees of favor or dislike. Though there is disagreement on the definition of attitude, Eagly and Chaiken's approach is thought to be useful. Individual differences in attitude toward the same thing might result in evaluations of attitudes ranging from extremely favorable to negative (Wood, 2000). Furthermore, Mantle-Bromley (1995) defined attitude as affect and evaluative emotional responses.

According to the Multicomponent model, attitudes have cognitive, behavioral, and affective components (Fishbein & Ajzen, 1975; Kiesler et al., 1969; MantleBromley, 1995; MantleBromley & Miller, 1991). This three-tiered classification implies that attitudes are fundamentally multidimensional, involving information processing, overt acts, and emotional responses. The study of Breckler (1984) emphasizes the synergistic link between cognitive, behavioral, and emotional components, highlighting that favorable attitudes materialize as positive affective and behavioral associations with the object. This complete theoretical framework provides a solid platform for researching university students' attitudes about AI, incorporating cognitive assessments, emotional responses, and behavioral tendencies in the context of developing technologies.

MATERIALS AND METHODS

This study employed a quantitative research design more specifically employing the non-experimental correlational approach in evaluating the relationship between variables and assessing the mediating effect of AI Trust on the relationship between AI self-efficacy and attitude toward AI of college students in Region XI. As defined by Creswell and Creswell (2023), the quantitative research approach involves the systematic gathering, examination, and understanding of data and information, usually acquired through surveys or experimental studies. Additionally, quantitative research design is a systematic approach to experimentally examine the relationships between variables to evaluate objective hypotheses. This form of investigation employs numerical data to quantify the variables under investigation; the resulting data can further undergo statistical and numerical analysis, culminating in the production of quantifiable outcomes. In contrast, mediation analysis in research examines the impact of a mediating variable on the relationship between two other variables by incorporating it into the study. As an approach, mediation analysis has gained considerable traction among psychologists. Furthermore, it typically entails the selection of participants by a random process (MacKinnon, et al., 2007).

The research instruments used to measure the variables were adopted from Choung et al. (2022) for the AI trust variable, Hong (2022) for the AI self-efficacy variable, and Suh and Ahn (2022) for the attitude toward AI. The questionnaires were in the form of a 5-point Likert scale and were primarily utilized in collecting the data through online surveys (Google Forms) among tertiary students enrolled in various programs across different universities and colleges in Region XI, Philippines. Stratified random sampling was used in selecting the respondents. This method uses random selection and categorization to choose groups from a single population. The method involves stratifying the target population and subsequently employing simple random sampling from each stratum. In order to generate a single sample, the selected samples from many strata are combined (Iliyasu & Etikan, 2021).

A priori power analysis using G*Power 3.1.9.6 (Faul et al., 2007) determined that a sample size of N = 89 is required to achieve 80% power for detecting a medium effect (f2 = 0.15) at a significance level of =.05 in testing the hypothesis about the role of AI trust in mediating the relationship between AI self-efficacy and attitude toward AI among college students. The computed noncentrality parameter was 3.6537652 with two predictors in the model, critical t was 1.9879342, and degrees of freedom (Df) were 86. Our actual sample size of N = 408 exceeds this threshold, enhancing the robustness of our study in investigating the complex links between AI trust, AI self-efficacy, and attitude toward AI in the college student community.

Pilot testing and expert validation were performed on these instruments. In addition, Cronbach's alpha was utilized to determine the instruments' validity and reliability, Average Variance Extracted (AVE) was employed to evaluate convergent validity, and the Hetero-Monotrait Ratio (HTMT) was implemented to assess discriminant validity. Additionally, descriptive statistics, including the mean and standard deviation, were utilized in conjunction with Jamovi software version 2.0 to characterize the AI self-efficacy, AI trust, and attitude of college students. SmarPLS 4.0 software was used in assessing the hypothesized mediation model employing the bootstrapping standardized algorithm and taking into account the direct, indirect, and total effects of the model as well as the effect sizes of each path.

Hypotheses

H1: There is a significant relationship between the AI self-efficacy and AI trust of college students.

H2: There is a significant relationship between AI trust and the attitude toward AI of college students.

H3: There is a significant relationship between AI self-efficacy and the attitude toward AI of college students.

H4: There is a significant mediating effect of AI trust on the relationship between AI self-efficacy and attitude toward AI of college students.

RESULTS AND DISCUSSION

Hair et al. (2019) state that prior to performing mediation analysis, it is critical to ascertain the measurement model's validity and reliability. When evaluating the constructs' validity and reliability, a number of items were considered for potential omission. Table 1 displays the construct validity and reliability of the instruments employed in the study. The assessment of the instruments' reliability was conducted utilizing Cronbach's alpha. The internal consistency of the questionnaires was satisfactory, as evidenced by Cronbach's alpha values of 0.875 for AI self-efficacy, 0.904 for AI trust, and 0.941 for attitude towards AI. According to Taber (2018), Cronbach's alpha values equal to or beyond 0.7 signify satisfactory levels of reliability. In general, exploratory studies consider values between 0.60 and 0.70 acceptable, 0.70 and 0.90 tolerable to good, and values greater than 0.95 possibly problematic (Diamantopoulos et al., 2012; Drolet & Morrison, 2001). Since all variables exceeded the threshold of 0.7, the instruments demonstrated acceptable reliability for measuring the constructs of interest. Additionally, none of Cronbach's alpha values exceeded 0.95, indicating that the items are not redundant.

The instruments' convergent validity was evaluated by calculating the average variance retrieved (AVE). The AVE values for AI self-efficacy (0.537), AI-Trust (0.543), and Attitude towards AI (0.587) exceeded the 0.5 threshold. This is deemed acceptable as the minimum allowable AVE is 0.50 or above. An AVE value of 0.50 or above signifies that the construct accounts for 50 percent or more of the variability in the construct's elements (Fornell & Larcker, 1981; Hair et al., 2019). Also utilized to evaluate discriminant validity was the heterotrait-monotrait ratio (HTMT). The HTMT ratios ranged from 0.50 to 0.60 between the following construct pairs: AI-Trust and AI self-efficacy (0.633); Attitude towards AI and AI self-efficacy (0.542); and Attitude towards AI and AI-Trust (0.665). With all ratios below the 0.85 threshold, this indicates a good discriminant validity (Henseler et al., 2015). Therefore, the instruments that were utilized for study are valid and reliable.

Table 2 shows the mean and other valuable statistical scores of the key variables that were collected and analyzed based on the 339 completed responses. AI self-efficacy obtained a mean of 3.47, which describes the university students' high level of AI self-efficacy. This aligns with the findings of Kwak et al. (2022), where nursing students obtained a high level of AI self-efficacy. However, this result contradicts the study of Gatlin (2023) on student teachers' AI self-efficacy. In the study, she found that the respondents generally expressed discomfort and reluctance towards AI, with a majority disagreeing or strongly disagreeing about their comfort levels and readiness to implement AI in future classrooms.

Table 1: Construct Validity and Reliability

Variables	Cronbach's alpha	Average variance extracted (AVE)
AI Self-Efficacy	0.875	0.537
AI-Trust	0.904	0.543
Attitude toward AI	0.941	0.587
Discriminant Validity	**Heterotrait-monotrait ratio (HTMT)**	
AI-Trust <-> AI Self-Efficacy	0.633	
Attitude toward AI <-> AI Self-Efficacy	0.542	
Attitude toward AI <-> AI-Trust	0.665	

AI Trust had a mean of 3.34, which shows that university students have moderate trust in AI. This is consistent with previous studies showing high and low levels of trust in AI. Personen (2021) reported that students in a Finnish vocational education and training organization demonstrated high trust in AI, specifically chatbots providing academic and non-academic support. However, Douali et al. (2022) presented a contradicting view. The majority of participants in their study do not trust artificial intelligence due to their lack of understanding. Additionally, an evaluation of 260 university students in Germany revealed that trust levels were markedly lower for AI essay scoring systems compared to human examiners. Enabling greater human oversight over the AI scoring was found to partially mitigate this distrust. Moreover, when the perceived complexity of essay grading increases, the reliability of the AI-based system diminishes (Harmann et al., 2022).

There are two types of trust in AI: functional trust in AI and human-like trust in AI. Choung and Ross (2022) said that trust in AI means believing that the technology is competent and well-designed, and trust in AI means believing that the algorithms are socially and culturally ethical. These are the values and ethics that guide the design of technology. There was a high level of trust in AI's functionality (x=3.54) and a moderate level of trust in AI acting like a person (x=3.34). This finding is consistent with the results reported by Choung and Ross (2022), which indicated that trust connected to functioning had a more significant overall effect on usage intention compared to trust resembling human trust. This is consistent with the findings of Müller et al. (2019), which indicated that students exhibited a lower degree of trust in AI systems in comparison to humans. When interacting with humans, they were more forthright and frank regarding information than AI. Nevertheless, this contradicts the results reported by Ta et al. (2020), which indicated that social companion chatbots created a "safe zone" where individuals could freely exchange opinions on any subject matter without apprehension of criticism or reprisal. AI may also serve as a potentially valuable resource for providing routine social assistance, including emotional, informational, companionship, and appraisal help. Furthermore, Hoiland et al. (2020) discovered that participants were more inclined to place their trust in an AI designed for mental health purposes when they viewed it to be compassionate and reassuring.

Attitude towards AI obtained a mean of 3.38, which describes that university students hold a moderately positive attitude towards AI. Specifically, students exhibit highly positive attitudes in terms of cognitive components (x=3.62), while expressing moderately positive attitudes in relation to affective (x=3.31) and behavioral (x=3.27) components. This is similar to the findings of Mohammed (2023) who found that teachers showed positive attitude towards integrating AI in education. Multiple studies have indicated that university students utilize AI technologies in their academic pursuits and have an overall good view of AI. In particular, pupils regard AI as a beneficial instrument that facilitates the completion of assignments and aids in individualized learning, writing, and research (Chan & Hu, 2023; Chan & Lee, 2023). This positive attitude carries over into computing education as well. Zastudil et al. (2023) found that computing education students also viewed AI positively, seeing it as beneficial in their studies. For these students, AI reduces effort for coding and finding materials, helps avoid busy work, facilitates focusing on higher levels of abstraction, and provides alternative perspectives and assistance sources. Moreover, across various international studies, medical students expressed positive attitudes towards the integration of artificial intelligence (AI) in healthcare and medical education. Their views highlight the perceived importance of AI in medicine, with the majority advocating for AI training as part of their medical degrees and believing it would benefit their future careers, emphasizing positive outlook on the role of AI in improving medical practices (Al Saad et al., 2022; Bisdas et al., 2021; Mehta et al., 2021; Sit et al., 2020; Stewart et al., 2023; Tung et al., 2023).

Students have, however, voiced reservations regarding the potential negative consequences of AI, according to surveys. Concerns regarding an excessive dependence on artificial intelligence (AI), academic integrity, and reliability were highlighted in the research conducted by Zastudil et al. (2023). Conversely, additional studies have brought forth more extensive apprehensions regarding privacy, ethical implications, accuracy, potential ramifications on personal growth, professional opportunities, and societal values (Chan & Hu, 2023; Ghotbi & Ho, 2021). Notably, in terms of career prospects, UK medical students, with 49% indicating reduced inclination, and Malaysian medical students, with 32.55% expressing similar reservations, reported diminished interest in pursuing careers in radiology due to AI (Sit et al., 2020; Tung et al., 2023). From the perspective of teachers, Mohammed (2023) also revealed that they, too, have varying concerns with the integration of AI into education, such as overreliance on AI, ethical concerns, and misalignment of AI to educational objectives.

Table 2: Status of college students' AI trust, AI self-efficacy, and Attitude toward AI.

Variables	N	Mean	Mode	SD	Description
AI-Trust	408	3.39	3	0.742	Moderate trust
Human-Like trust	408	3.23	3	0.818	Moderate trust
Functionality trust	408	3.54	4	0.796	High trust
AI Self-Efficacy	408	3.47	3	0.678	High level
Attitude towards AI	408	3.40	3	0.794	Moderately positive
Cognitive	408	3.62	3	0.960	Highly positive
Affective	408	3.31	3	0.797	Moderately positive
Behavioral	408	3.27	3	0.886	Moderately positive

The clarification of the complex process of mediation is achieved through the introduction of a third variable, referred to as a mediator, which establishes the relationship between the predictor and criterion variables (Hayes et al., 2011). In the present study, AI trust assumed the role of a mediator, employed to unravel the nuanced connection between AI self-efficacy and the attitude toward AI among college students. Utilizing the standard bootstrapping algorithm within the SmartPLS 4.0 software, our investigation meticulously scrutinized the mediation model.

The outcomes of the mediation analysis, meticulously presented in the accompanying table, unveiled several noteworthy findings. In terms of direct effects, the path from AI self-efficacy to AI trust, illustrated in Figure 1, manifests a substantial and statistically significant relationship ($\beta = 0.570$, f2= 0.482, t= 10.606, p= 0.000). This implies that individuals endowed with higher AI self-efficacy tend to evince heightened trust in artificial intelligence. This observation aligns with the research of Kraus et al. (2020), who posited that individuals possessing a heightened sense of self-efficacy with new technology are more inclined to harbor a positive disposition towards automated technology. Furthermore, Montag et al. (2023) substantiated this claim, asserting a positive correlation between technology self-efficacy and trust in automated technology, along with an augmented affinity towards AI. Similarly, the path from AI trust to attitude toward AI also emerges as both significant and positive ($\beta = 0.491$, f2= 0.283, t= 8.135, p= 0.000). This underscores the notion that trust in AI positively influences one's attitude toward the technology. This finding resonates with Choung and Ross (2022), who asserted that trust serves as a precursor to positive attitudes, subsequently impacting usage intentions. The depth of trust in AI, as noted by Schepman and Rodway (2022), significantly shapes one's attitude and predisposition to embrace and engage with AI technologies. Their study also revealed that individuals harboring distrust towards corporations were more likely to exhibit a negative attitude towards AI, while those with higher levels of general trust demonstrated a more positive attitude.

Furthermore, Choung et al. (2022) confirmed the critical significance of trust in influencing views towards artificial intelligence. The authors, Yang and Wibowo (2022), underscored the complex and diverse aspects of establishing trust, highlighting its importance in promoting favorable modifications in users' cognition, emotions, and conduct.

However, the direct path from AI self-efficacy to attitude toward AI, though statistically significant ($\beta = 0.230$, f2= 0.062, t= 4.017, p=0.000), is comparatively weaker. In conclusion, it can be inferred that self-efficacy exerts an influence on attitude, signifying those higher levels of technology self-efficacy correspond to a perception of enhanced capabilities in making effective decisions related to automated technology, facilitating ease of interaction, and control over its impacts (Montag et al., 2023).

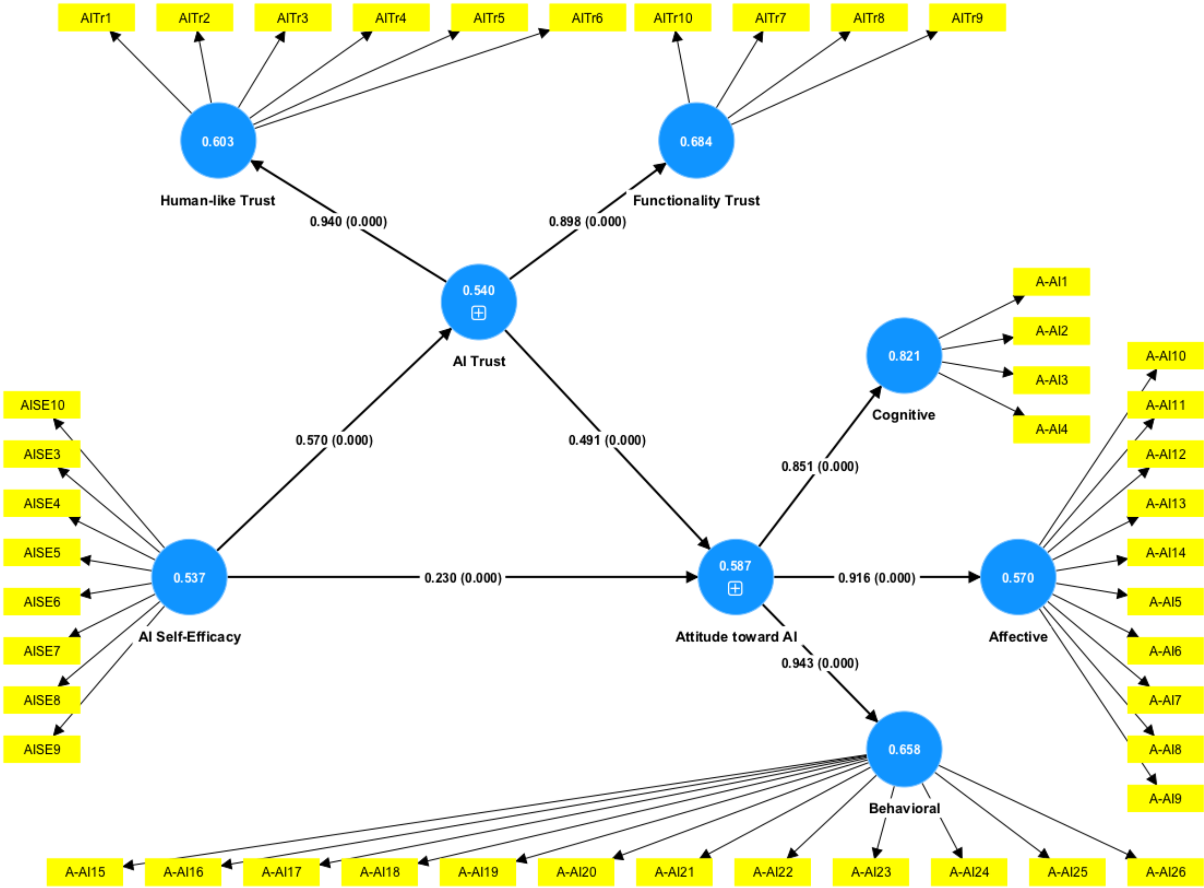

Figure 1: Mediator's Impact - Results using SmartPLS 4.0

Moving to the indirect effects, the pathway from AI self-efficacy to attitude towards AI, mediated through AI trust, reveals a substantial and significant relationship ($\beta = 0.280$, $T = 7.199$, $p < 0.001$). This suggests that part of the influence of AI self-efficacy on attitude towards AI is partially mediated by the trust individuals place in AI. The effect of AI self-efficacy on attitude towards AI is significant when taking into account the total effect, which includes both direct and indirect pathways ($\beta = 0.510$, $T = 9.893$, $p < 0.001$). This suggests that individuals' opinions regarding AI are significantly influenced by AI self-efficacy, both directly and indirectly via AI trust as a

Table 3: The direct effects, indirect effects, and total effects on the relationships between variables- AI self-efficacy, AI trust, and attitude toward AI.

	Original Sample	Sample mean (M)	Standard deviation (stdev)	f^2	T statistics (|0/ Stdev|)	P Values
AI Self-Efficacy -> Al-Trust	0.570	0.573	0.054	0.482	10.606	0.000
Al-Trust -> Attitude toward AI	0.491	0.486	0.060	0.283	8.135	0.000
AI Self-Efficacy -> Attitude toward AI	0.230	0.235	0.057	0.062	4.017	0.000
Indirect Effects						
AI Self-Efficacy -> Attitude toward AI	0.280	0.278	0.039		7.199	0.000
Total Effect						
AI Self-Efficacy-> Attitude toward AI	0.510	0.513	0.052		9.893	0.000
R2=0.423 Adjusted R2=0.420						

Note: .f is the Cohen's (1988) [feet size: 0.02=small, 0.15=medium, 0.35=large.

mediating factor.

Based on the R2 value of 0.423, it can be inferred that the model effectively explains a significant percentage of the variability observed in attitudes towards AI. The adjusted R2 value of 0.420 indicates the robustness of the model when the number of predictors is taken into account. In summary, the results emphasize the significance of direct and indirect mechanisms in comprehending the way in which AI self-efficacy impacts attitudes towards AI. Furthermore, they provide insight into the mediating function of trust in this association.

CONCLUSIONS

In light of the findings of the study, it can be concluded that substantial and significant effects have been found in the relationships between variables, thus supporting hypotheses one to three of the study. Further, hypothesis four was also accepted as a partial significant mediating effect of AI trust was found in the relationship between AI self-efficacy and attitude toward AI. Thus, validating the hypothesized mediation model of attitude toward AI of college students. The utility of the Multicomponent Model is manifest in its efficacy in disentangling the nuanced interplay between AI trust, self-efficacy, and attitudes, thereby elucidating the intricacies inherent in individuals' evaluations of artificial intelligence. Our findings underscore the Model's merit in parsing attitudes into three distinct dimensions, illuminating the cognitive underpinnings through AI trust and self-efficacy. Amidst the ever-evolving landscape of emerging technologies, our study contributes to the expanding comprehension of attitudes toward AI, emphasizing the interconnected and multifaceted nature inherent in cognitive, affective, and behavioral components.

While the findings of the study provide insights into the relationships between variables and support the hypothesized mediation model, several limitations should be considered. The generalizability of results may be constrained by the specific demographic characteristics of the sample and the fast-paced nature of technological advancements, implying that attitudes towards AI may evolve rapidly, which highlights the potential for temporal instability in the observed relationships. Thus, the need for future research across diverse populations and the importance of longitudinal studies to capture the dynamic nature of attitudes towards AI over time is recommended.

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