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AI Trust and Attitude Towards AI of University Students

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Abstract

The quantitative study investigated the relationship between AI trust and attitudes toward AI among university college students. An adapted questionnaire was utilized. Data were gathered through Google Forms, where the respondents were selected using a stratified random sampling technique. Validity and reliability tests were employed using Cronbach's Alpha and Average Variance Extracted. Descriptive statistics were used to describe the variables and subcomponents in the study, while bootstrapping analysis was conducted through SmartPLS 4.0 to assess the hypothesized model. The results demonstrated that college students showed a moderate level of AI trust and attitude toward AI and confirmed the significant relationship between the predictor (AI trust) and outcome (attitude toward AI) constructs.

Keywords

AI Trust, Attitude towards AI, quantitative analysis, SmartPLS 4.0, Artificial Intelligence

Introduction

Artificial intelligence, or AI, refers to machines designed to 'exist' in an environment simulated by the real world (Jackson, 2019). AI possesses human-like decision-making and problem-solving capabilities that are commonly associated with human intelligence (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). These capabilities include perceiving, reasoning, learning, and interacting with the environment to which the machine is exposed (Rai et al., 2019). These factors contribute to the integration of this 60-year-old system into modern society and today's industries (Ertel, 2018), including healthcare and finance (Mikalef et al., 2021).

The education sector has also felt AI's influence, as it has been integrated into the education system, increasing student creativity, enhancing classroom learning experiences, and optimizing teachers' management in classroom settings, which raises efficiency (Huang et al., 2021; Hasibuan et al., 2023; Liu et al., 2022; Colchester et al., 2016). AI also provides immediate feedback to students regarding their inquiries, allowing them to identify and analyze their strengths (Kaledio et al., 2024).

Despite these advancements in artificial intelligence, public opinion regarding AI remains largely unclear (Gerlich, 2023). Higher education institutions vary in their reactions to the usage of AI, ranging from banning AI to providing guides that teach students how to use artificial intelligence effectively and ethically (Clercq, 2023; University College London, n.d.). Trust in AI plays a significant role in determining a student's attitude and intention to use AI (Schiavo, 2024; Choung et al., 2022; Teodorescu et al., 2023). Liehner et al. (2023) provide an even more in-depth analysis, stating that attitudes toward AI help shape users' beliefs and trust in AI-based systems. Montag et al. (2023) further support this by stating that a positive attitude directly correlates with higher trust in AI, while anxiety and fear promote the opposite, having an inverse relationship with trust. This trust is cultivated by familiarity and social attitudes toward AI (Montag et al., 2023).

Developing countries like the Philippines cannot escape the rapid reshaping of the educational landscape and other sectors due to the rapid propagation of artificial intelligence, which addresses specific societal challenges and opportunities (Khanduri & Teotia, 2023; Aderibigbe, 2023). However, AI utilization in the Philippines, specifically among higher education students, has shown significant variation (Lynard et al., 2023). A survey conducted by NYSE showed that 46% of the total respondents had introduced light guidelines, 28% introduced strict guidelines, and the remaining 26% were not introduced to any guidelines (Pascual, 2023). Nonetheless, higher education students showed positive attitudes toward the usage of AI in terms of perceived ease of use and perceived autonomy (Cortez et al., 2024; Bantoto et al., 2024). Obenza et al. (2024b) asserted that higher education students who have relatively higher confidence in their AI self-efficacy positively impact their trust, and therefore their attitudes toward AI.

University students are the focal point of this study due to their pivotal role as early adopters of emerging technologies, particularly in educational contexts where AI has the potential to significantly impact learning experiences and academic practices (Wang et al., 2023). The current generation of students is more exposed to AI-driven tools and platforms, which makes understanding their attitudes crucial for successful integration and acceptance of AI in higher education (Kaledio et al., 2024; Ahmad et al., 2024). Focusing on the relationship between AI trust and their attitudes is essential, as trust is a key determinant of technology adoption and usage intention (Teodorescu et al., 2023; Montag et al., 2023). However, a comprehensive understanding of students' attitudes towards AI requires exploring additional factors beyond trust, such as perceived usefulness, anxiety, and cognitive absorption (Obenza et al., 2024a). By expanding the investigation to include these factors, this study aims to offer a more holistic view of university students' perceptions and acceptance of AI in educational settings, ultimately contributing to more effective policy and curriculum development that supports responsible AI use.

Discovering the relationship between AI trust and attitude toward AI requires one to carefully and fully understand how trust affects attitudes toward AI. Choung et al. (2022) describe trust in AI as a significantly impactful variable that affects perceived usefulness and participants' attitudes toward AI. Dorton et al. (2022) agree, adding that trust in AI is also affected by the interactions of other people with their usage of AI. Authors Schepman & Rodway (2023) showed findings that AI trust also influences the attitudes of consumers and their willingness to engage in AI technologies.

The research study utilized the theoretical framework of the Multicomponent Model of Attitude, initially proposed by Eagly & Chaiken (1993) and later expanded by Zanna & Rempel (1998). The theoretical model views attitudes in three dimensions, namely: cognitive, affective, and behavioral. Utilizing this theoretical framework, the study proposes that university students' attitudes toward AI are evaluated and shaped by a crucial factor: trust in AI technology. This framework serves as the foundation for analyzing how the variable, AI trust, influences attitudes toward AI. It provides a more unbiased understanding of the nature of attitudes toward AI through a thorough investigation of cognitive, emotional, and behavioral responses in the context of the usage of artificial intelligence.

Despite the growth of importance of AI in education, limited understanding of how students' trust in AI shapes their attitude towards its use still remains (Montag et al., 2023; Liehner et al., 2023). Rectifying this issue is essential as higher education institutions are challenged to introduce AI in an ethical and effective manner (Palmer et al., 2023). This becomes an increasingly urgent issue to investigate given its potential to influence educational practices and policies (Vincent-Lacrin et al., 2020; Conijn et al., 2023).

Given the growing integration of AI in higher education, university students are a critical group to investigate due to their unique position as digital natives who regularly engage with emerging technologies (Tóth et al., 2022). As future professionals, these students will likely encounter practical projects about AI applications in various industries to prepare them for technical positions, making it essential to understand their trust in AI and how it shapes their attitudes toward its usage (Cortez et al., 2024; Yang et al., 2019). Studying the relationship between AI trust and their attitude towards AI specifically allows for a focused analysis of how perceptions of trust can influence students' acceptance, adoption, and interaction with AI-based educational tools. This emphasis is crucial, as trust has been identified as a primary determinant in technology acceptance models and a predictor of user engagement (Liehner et al., 2023).

Although studies regarding the relationship between AI trust and attitudes toward AI are slowly gaining traction in the research community, there remains a lack of such studies particularly within the context of developing countries such as the Philippines. Prior studies placed a large emphasis on other sectors such as healthcare and finance (Mikalef et al., 2021; Mota et al., 2023) overlooking the challenges and perceptions present in higher education (Gerlich, 2023). This study aims to fill in this gap through the gathering empirical data regarding the relationship between AI trust and attitude, leading to a deeper understanding of how students' perceptions impact acceptance and utilization of AI in educational settings.

Materials and Methods

This study used a quantitative research method, employing a non-experimental correlational approach to analyze the relationship between the independent and dependent variables, namely AI trust and attitude toward AI of university students. The quantitative research approach relied on a given set of quantitative or numerical data, focusing on validating hypotheses with empirical data to determine if they were supported (Antwi & Hamza, 2015). Quantitative research methods, unlike qualitative research designs, involved a larger sample size and required a relatively short time to gather data compared to qualitative approaches, which made quantitative research more suitable in the context of language testing and assessment research (Rahman, 2017).

The research instruments used in this study were adopted from Choung et al. (2022), focusing on AI trust. The medium of choice for the questionnaire was online Google Forms, where the link was distributed through Messenger and/or email. A 5-point Likert scale was primarily used to quantify the data collected from the respondents. 423 university students from Region XI, Philippines were chosen as respondents. Stratified random sampling was the method used to select the respondents. This method stratified a random target population, distributing the respondents from a single group to a collection of strata. Random sampling was then employed from each stratum afterward.

Cronbach's Alpha and Average Variance Extracted were employed to evaluate convergent validity and determine the questionnaire's validity and reliability. Descriptive statistics, including mean and standard deviation, were calculated through Jamovi software version 2.0 to characterize university students' AI trust and attitude. During the assessment of the hypothesized mediation model, SmartPLS 4.0 software was utilized to apply the bootstrapping algorithm to calculate standardized estimates, taking into account the model's direct, indirect, and total effects and the effect sizes of each path. Aside from more complex models to be used, mediation analysis also allowed organized causal pathways from their respective outcomes, contributing to a more systematic understanding of how certain effects occur and ensuring the versatility of the tool (Valeri et al., 2013; Lange et al., 2017; Mackinnon et al., 2019; Blum et al., 2020; Montoya et al., 2017).

Results and Discussion

Ensuring the validity and reliability of a measurement model is crucial, according to Hair et al. (2019), and should be done before performing mediation analysis. Table 1.1 displays the model's validity and reliability measurements used throughout the entire study. The reliability of the instruments was measured using Cronbach's Alpha. Based on the given Cronbach's alpha values (AI Trust = 0.904; Affective Component = 0.916; Attitude Toward AI = 0.963; Behavioral Component = 0.953; Cognitive Component = 0.927; Functionality Trust = 0.846; Human-like Trust = 0.867), a satisfactory level of reliability was signified, wherein most of the values were lower than 0.7, with the exceptions of Attitude Toward AI and the Behavioral Component, which had values higher than 0.95, indicating possible redundancy (Taber, 2018; Diamantopoulos et al., 2001; Drolet & Morrison, 2001).

The instruments' convergent validity measurement was evaluated by calculating the average variance extracted (AVE). The AVE values (AI Trust = 0.540; Affective Component = 0.570; Attitude Toward AI = 0.587; Behavioral Component = 0.658; Cognitive Component = 0.821; Functionality Trust = 0.684; Human-like Trust = 0.603) all exceeded the minimum allowable value of 0.50 and were therefore deemed acceptable, denoting that the construct explains at least 50% of the variance of the construct's elements (Fornell & Larcker, 1981; Hair et al., 2019).

Table 1.1: Cronbach's Alpha / Average Variance Extracted

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
AI Trust	0.904	0.907	0.921	0.540
Affective Component	0.916	0.919	0.930	0.570
Attitude toward AI	0.963	0.963	0.966	0.587

Behavioral Component	0.953	0.954	0.959	0.658
Cognitive Component	0.927	0.929	0.948	0.821
Functionality Trust	0.846	0.847	0.896	0.684
Human-like Trust	0.867	0.873	0.901	0.603

Investigating collinearity before evaluating structural relationships is imperative to guarantee the non-introduction of biased regression results. Variance Inflation Factor (VIF) values exceeding 5 indicate collinearity or overlapping information among the predictor constructs (Hair et al., 2019). Possible collinearity can occur with VIF values between three and five (Mason & Perreault, 1991; Becker et al., 2014). Ideal VIF values should approach three or lower. Collinearity problems can be resolved by utilizing higher-order models supported by theory (Hair et al., 2017a).

The Variance Inflation Factor (VIF) values, as shown in Table 1.2, indicate 1.000 for all predictor and outcome relationships. These values suggest that each of the predictor variables has no existing redundancy regarding their information, which explains the variance of the outcome variables. This also supports the notion that AI Trust is an independent predictor of university students' attitudes toward AI and all of its subcomponents, namely: Affective, Behavioral, and Cognitive Components. This absence of overlapping information ensures the reliability of the model's findings.

Table 1.2: Variance Inflation Factor

	VIF
AI Trust -> Attitude toward AI	1.000
AI Trust -> Functionality Trust	1.000
AI Trust -> Human-like Trust	1.000
Attitude toward AI -> Affective	1.000
Attitude toward AI -> Behavioral	1.000
Attitude toward AI -> Cognitive	1.000

Table 2.1: Factor Loading

	AI Self-Efficacy	**AI Trust**
AISE10	0.717	
AISE3	0.76	
AISE5	0.755	
AISE6	0.806	
AISE7	0.814	
AISE8	0.804	
AISE9	0.711	
AITr10		0.732
AITr3		0.723
AITr4		0.783
AITr5		0.799
AITr6		0.725
AITr7		0.791
AITr8		0.772
AITr9		0.794

Factor loadings shown in Table 2.1 assess the correlation between observed indicators and their underlying latent constructs (Schmitt et al., 2011; Jackman et al., 2020). This tool also allows for the examination of the existence of common underlying factors across populations (Please et al., 1973). High factor loadings suggest that the observed variables effectively represent their constructs. In this study, the factor loadings for AI Self-Efficacy range from 0.711 to 0.814, and for AI Trust, they range from 0.723 to 0.799. Since all values exceed the commonly accepted threshold of 0.7, the items reliably measure their respective constructs, confirming indicator reliability (Peterson et al., 2000). This test is necessary to ensure that each item contributes meaningfully to the measurement of its latent construct, providing internal consistency within the model.

Table 2.2: Heterotrait-Monotrait Ratio

	AI Self-Efficacy	AI Trust
AI Self-Efficacy		
AI Trust	0.63	

Table 2.2 presents values for the Heterotrait-Monotrait Ratio (HTMT). HTMT ratio is used to assess discriminant validity, which checks whether two different constructs (AI Self-Efficacy and AI Trust) are truly distinct (Benitez et al., 2020; Henseler et al., 2017; Henseler et al., 2016). A lower HTMT value indicates that the constructs do not overlap. The HTMT value between AI Self-Efficacy and AI Trust is 0.630, well below the threshold of 0.85, confirming that the two constructs are distinct from each other (Benitez et al., 2020). Discriminant validity is essential to demonstrate that each construct captures a unique dimension, preventing the results from being confused by overlapping meanings. Without discriminant validity, it would be difficult to distinguish whether each construct is contributing independently to the model.

Table 2.3: Fornell and Larcker Criterion

	AI Self-Efficacy	AI Trust
AI Self-Efficacy	0.754	
AI Trust	0.573	0.765

Fornell and Larcker Criterion shown in Table 2.3, further assesses discriminant validity by comparing the average variance extracted (AVE) for each construct with the squared correlations between constructs where discriminant validity is established if the AVE is greater than the squared correlations (Hamid et al., 2017; Shiu et al., 2011; Afthanorhan et al., 2021). It could also be determined by comparing the square root of the AVE and the correlations between constructs with the same condition of determining discriminant validity. The AVE indicates the proportion of variance in a construct explained by its indicators. In this study, the square root of the AVE for AI Self-Efficacy is 0.754, and for AI Trust, it is 0.765, both of which are greater than their inter-construct correlation of 0.573. This suggests that each construct explains more variance in its own indicators than it shares with other constructs, further confirming their distinctiveness.

Table 3 displays the descriptive statistics for the key variables that were collected and analyzed throughout the study. AI Trust is moderate overall, obtaining a mean of 3.37 and a relatively low standard deviation of 0.745, indicating that AI trust among the university student respondents does not fluctuate widely, with most responses clustered near the mean. The obtained level of trust coincides with the results from the study by Samonte et al. (2023), where students' general AI trust was measured to be at a neutral level.

Functionality trust, one of the sub-components of AI Trust, scored a mean of 3.51 and a standard deviation of 0.807. Analyzing these descriptive statistics for functionality trust shows that university students generally trust the practical and functional aspects of AI, with moderate variability in this dimension of trust. This aligns with a study from China, where students' trust in the AI-based educational system is influenced by technology-related factors, one of which is the functionality of AI (Qin et al., 2020). However, Tossell et al. (2024) presented a contradictory view. In their study, students required to use ChatGPT within an undergraduate engineering course did not trust ChatGPT to grade their assignments by itself, preferring instructors to oversee the use of this generative AI.

Human-like Trust, the second sub-component of AI Trust, had a mean of 3.22 and a standard deviation of 0.822. This indicates the level of student trust in AI's human-like qualities, which, according to the mean, is lower than that of functionality trust, reflecting a lower level of trust. This finding coincides with the study conducted by Choung et al. (2022), which highlighted the difference in the total impact on AI usage retention compared to functionality-related trust in AI. The standard deviation shows a diverse set of opinions among the respondents regarding this level of trust, with a higher degree of variability compared to the previously mentioned sub-component of AI Trust.

The university students showed a moderate level of attitude toward AI (x = 3.38) with minimal fluctuation, and responses fell near the middle of the scale in terms of their attitude (SD = 0.809). This coincides with the study findings of Obenza et al. (2023b), wherein positive reception and utilization of AI technologies. The behavioral aspect of attitude also remained at a relatively neutral level (x = 3.25). A standard deviation of 0.892 suggests fluctuating opinions across the respondents, indicating a wider range of behaviors.

The Affective Component, which measures the emotional response to AI, had a mean of 3.29 with high consistency among the respondents' answers (SD = 0.810), indicating little variation in responses. This reflects a moderate level of emotional response toward AI among the respondents of this study. The cognitive component refers to university students' beliefs and knowledge about AI. The measured mean was 3.69, with a standard deviation of 0.972. The descriptive statistics indicate that students generally have more positive cognitive beliefs regarding AI, with the highest variability among the attitude sub-components. This finding does not align with Yüzbaşıoğlu's (2020) study, which concluded that when 1,103 students participated, they showed insufficient knowledge of AI overall. However, the students did express an optimistic view regarding AI and its potential positive impact on future practices.

Table 3: Fornell and Larcker Criterion

	N	Mean	Median	Mode	SD
AI Trust	423	3.37	3.38	3	0.745
AI Trust- Functionality Trust	423	3.51	3.5	4	0.807
AI Trust- Human-Like	423	3.22	3.17	3	0.822
Attitude towards AI	423	3.38	3.36	3	0.809
Behavioral Component	423	3.25	3.17	3	0.892
Affective Component	423	3.29	3.3	3	0.81
Cognitive Component	423	3.6	3.5	3	0.972

Assumption checks are important in statistical analysis, as they are crucial for maintaining the internal validity of a study. Failing to conduct these checks may compromise the reliability of the results and findings (Hu et al., 2019; Nielsen et al., 2019; Ernst & Albers, 2017). The lack of assumption checks may also lead to unreliable statistical assumptions, resulting in inappropriate use of statistical methods (Ernst & Albers, 2017; Schmidt et al., 2017). Table 1.2 shows the Collinearity Statistics and Normality test conducted in this study. The collinearity statistics displayed a Variance Inflation Factor (VIF) and Tolerance value of 1.00, indicating that there were no issues regarding multicollinearity in the model.

Table 4: Assumption Checks/Collinearity Statistics

	VIF	Tolerance
AI Trust	1	1

A particularly useful way of analyzing sparse information with unclear distributional assumptions is through the bootstrapping analysis technique, wherein the accuracy of the estimator is taken into account (Henderson et al., 2005; Zoubir et al., 1998; Wasserman et al., 1989). The accuracy and precision of this analytical method, while maintaining its ability to retain data, make it a theoretically efficient and effective method for acquiring more knowledge (Wu et al., 2017).

Table 4: Bootstrapping Model Fit

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	f-square	T statistics (|O/STDEV|)	P values
AI Trust -> Attitude toward AI	0.622	0.621	0.044	0.631	14.273	0
R^2 = 0.387 Adjusted R^2 =0.385						

The bootstrapping analysis shown in Table 4.1 displayed data that demonstrate a significant and positive relationship between AI trust and students' attitudes toward AI. The coefficient of 0.622 signifies a direct relationship between AI trust and the level of attitude, wherein a higher level of trust correlates with a higher level of positive attitude toward AI. The validity of this relationship was further supported by the low standard deviation (0.044), indicating consistency across samples, along with a high T-value (14.273) that confirms statistical significance at the 95% confidence level. Moreover, a 0.631 f-square value suggests a substantial effect size, adding to the strong influence of AI trust on university students' attitudes. An R^2 value of 0.387 indicates that 38.7% of the variance in attitude toward AI is explained by AI trust. This suggests that AI trust, particularly its functionality and human-like attributes, has a significant influence on student attitudes toward AI.

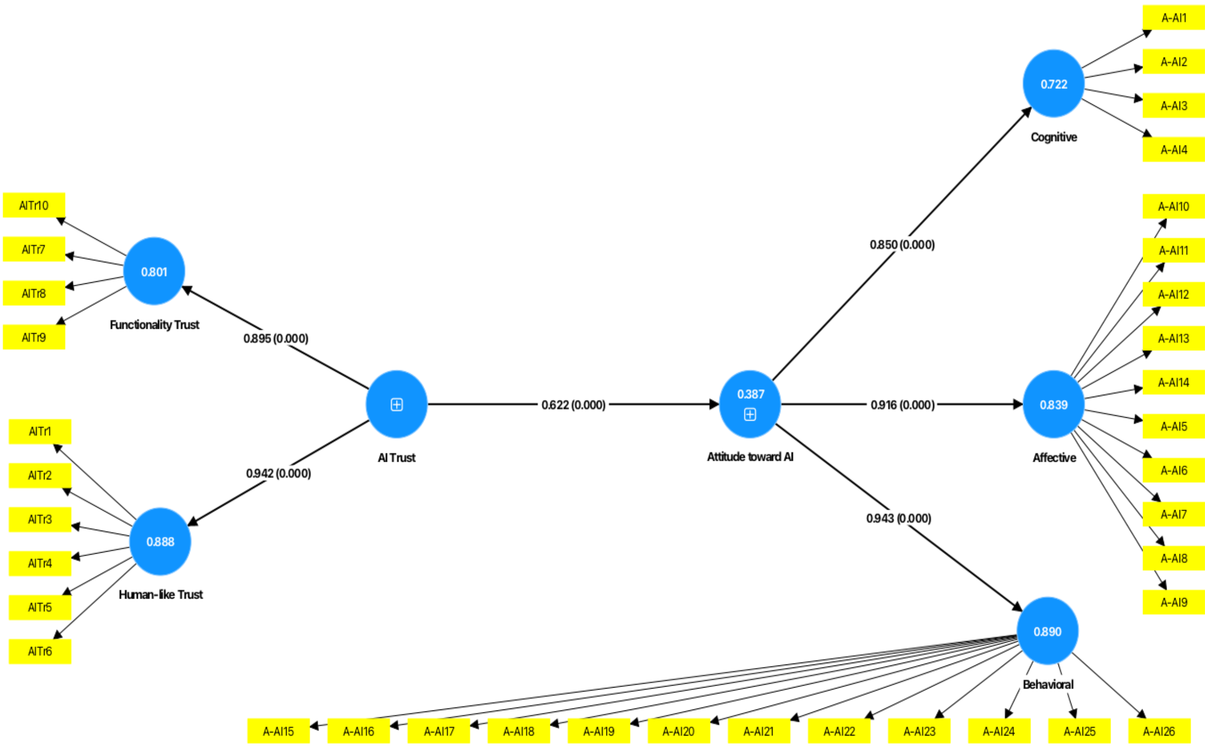

Figure 1: Predictor's impact on the outcome variable results using SmartPLS 4.0

The results and findings of this study strongly suggest that AI trust has a significant influence and is a significant predictor of student attitudes toward AI. This finding coincides with the recent findings where significant impact of AI trust is found to influence both attitude and behavioral intention to use AI (Obenza et al., 2024a, Obenza et al., 2023a). The model indicates that AI trust accounts for the majority of the variance affecting attitudes. This suggests that instilling and building AI trust within university students can have a profound impact on how they perceive and improve their attitudes toward the use of artificial intelligence. As AI continues to permeate various vital sectors of the community, the data gathered in this study highlight the importance of fostering trust in AI to form a moderate to strong positive relationship between users and technology, which can translate to responsible use of AI in society.

The results of this study can be further enriched by considering the Multicomponent Model of Attitude (Eagly & Chaiken, 1993), which provides a comprehensive lens to examine how AI trust influences students' attitudes toward AI. The model suggests that attitudes are shaped by three components: affective (emotions), cognitive (beliefs and knowledge), and behavioral (actions or intentions). In the context of this study, AI trust plays a crucial role in shaping all three components, thereby offering a deeper understanding of the findings.

The affective component, which pertains to students' emotional responses to AI, reveals a moderate level of comfort or unease toward AI technology. Building trust in AI could enhance positive emotional responses, fostering a more welcoming and less anxious attitude toward its use. The cognitive component, on the other hand, reflects students' understanding and beliefs about AI. As seen in the study, the moderate level of cognitive trust suggests that students with greater knowledge and familiarity with AI exhibit stronger trust and, consequently, more positive attitudes. Finally, the behavioral component, which is tied to students' actions and intentions, shows how trust in AI influences their willingness to interact with AI systems. This finding is similar to the results found by Obenza et al. (2023a), which concluded the mediating effect of AI trust in attitude towards AI thereby validating the mediation model. By fostering trust, educational institutions can encourage more proactive engagement with AI technologies, leading to greater integration and utility in educational settings.

Thus, the Multicomponent Model underscores the importance of addressing all dimensions of attitudes when seeking to build trust in AI among university students. Enhancing emotional comfort, increasing knowledge, and promoting positive behavioral intentions will likely result in stronger, more favorable attitudes toward AI. Future research should continue to explore how these components interact across different cultural and institutional contexts to provide a more nuanced understanding of AI trust and attitudes.

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