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The Relationship Between AI Self-Efficacy and AI Trust of College Students

John Patrick T. Aliño[1], Albert Jose B. Rebato[1], Arah Nova V. Abrenica[1], Julian M. Baguio[1], Matthew U. Villanueva[1], Dianne Mariz Nacua Obenza[2], Kenneth Sumatra[1]

[1] The University of Mindanao
[2] Department of Education, Cotabato Division, Philippines

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Abstract

This study investigates the relationship between AI self-efficacy and AI trust among college students, employing a quantitative research strategy with a non-experimental correlational approach. Data were collected from 372 participants using a Google Forms questionnaire designed with modified items assessing AI self-efficacy and AI trust, structured on a 5-point Likert scale. The analysis utilized various statistical techniques to ensure the validity and reliability of measurement models, including Average Variance Extracted (AVE) for convergent validity, the Heterotrait-Monotrait Ratio (HTMT) for discriminant validity, and Cronbach's alpha for internal consistency. Results indicated an R-square value of 0.329, suggesting that AI self-efficacy explains 32.9% of the variance in AI trust, thereby demonstrating a moderate explanatory power. The adjusted R-square value of 0.327 further confirms the absence of overfitting in the model. These findings highlight the significance of AI self-efficacy in fostering trust in AI among students, while suggesting the potential influence of other unexamined factors.

Keywords

AI Self-Efficacy, AI Trust, Unified Theory of Acceptance and Use of Technology (UTAUT), SmartPLS, Philippines

Introduction

Trust in artificial intelligence (AI) is a multifaceted concept that includes the firm belief on the reliability of the tool regarding the AI systems' behavior. Trust in AI not only alleviates uncertainty but also fosters user engagement and acceptance of AI technologies across various applications (Taddeo & Floridi, 2018; Obenza & Obenza, 2024). Furthermore, it has been observed that trust relies heavily on the system's transparency, interpretability, and ethical considerations, which are essential for users to feel secure in their interactions with AI (Mittelstadt, 2019). This trust is built on users' expectations regarding the AI's functionality and its ability to act in their best interests, which parallels interpersonal trust concepts found in sociology (Jacovi et al., 2021).

A recent study in the United States by Kreps et al. (2023) uncovered an interesting pattern called the AI Trust Paradox. This is where people's willingness to use AI-powered technologies often surpasses the trust they actually place in these systems. The paradox is particularly striking in high-stakes areas, such as police surveillance, where often public support for adopting AI exceeds the measured confidence in AI reliability. The study identifies a host of factors at work creating this gap. Many believe that AI has enough competence to give credible answers, while 'fear of missing out' (FOMO) pressures even those who do not trust AI entirely into purchasing it. At the same time, core beliefs-like optimism about AI's early advancements and the view that benefits outweigh risks-have a bearing on the decision. To address public concerns about trust in AI, it's not enough to focus solely on making the technology more transparent. It's also important to understand the social dynamics that shape how people perceive and react to AI, including their fears and hopes. Engaging with these human factors can help build stronger acceptance and encourage more responsible use of AI in the future.

Regionally, a survey conducted in parts of Asia by Gillespie et al. (2023) revealed that three out of five people (61%) are wary about trusting AI systems, reporting either ambivalence or an unwillingness to trust. Trust is particularly low in Finland and Japan, where less than a quarter of people report trusting AI. Populations in developing nations such as Brazil, India, and South Africa, as well as developed countries with increasing technological reliance like China attain the highest level of Artificial Intelligence trust with the majority of this fraction relying on AI systems for their day-to-day residential and commercial functions. This faith and trust in the technology stems from its ability to produce reliable and accurate results consistently in providing human services such as safety, security, and fairness of AI systems and structures and the degree in which they prioritize the privacy rights of the parties involved in the usage of the technology. Of the applications we examined, people are generally less trusting and accepting of AI use in human resources (i.e. for aiding hiring and promotion decisions), and more trusting of AI use in healthcare (i.e. for aiding medical diagnosis and treatment) where there is a direct benefit to them. People are generally more willing to rely on, than share information with AI systems, particularly recommender systems (i.e. for personalizing news, social media, and product recommendations) and security applications (i.e. for aiding public safety and security decisions). Many people feel ambivalent about the use of AI, reporting optimism or excitement on the one hand, while simultaneously reporting worry or fear.

Overall, two-thirds of people feel optimistic about the use of AI, while about half feel worried. While optimism and excitement are dominant emotions in many countries, particularly the BICS countries, fear and worry are dominant emotions for people in Australia, Canada, France, and Japan, with people in France the most fearful, worried, and outraged about AI. In the study created by Obenza et. al. (2023), among the college students in Region XI, Philippines, the mediating effect between the variables – AI self-efficacy and attitude towards AI – emphasizes the significant role of trust in shaping a user's (in this case, college students') perceived notions and confidence in effectively utilizing AI tools and technologies. In the study, it has been found that with a higher level of AI trust from the students, their level of self-efficacy in using the technology, in turn, also increased proportional to the previously mentioned variable. Meanwhile the opposite can also be said to be true as a lower level of AI trust leads the students' to be more skeptical and find it hard to accept – and in turn, use – these technologies which limits their exposure to AI and the benefits it provides for their academic performance. The interactions of these variables are becoming more prevalent in the Philippines where educational establishments and institutions are investing more into the integration of Artificial Intelligence into their curricula.

The results and findings of the study suggest that creating systems and programs that nurture and foster trust in AI can promote its effective use and lead to a more effective and efficient learning environment in an ever-digitizing era of academics. The relationship between AI trust and self-efficacy is an important aspect of understanding user engagement with artificial intelligence technologies, as demonstrated by Obenza's (2023) research, which focuses on the mediating effect of AI trust on AI self-efficacy, specifically attitudes toward AI among university college students. The study found that college students had a high level of AI self-efficacy, meaning that their good experiences, learnings, and predictions from interacting with AI add to their overall confidence in these systems. This demonstrates that AI trust primarily functions as a link between AI self-efficacy and attitudes toward AI. With this in mind, it is clear that students' faith in AI systems, coding, and other tools has a significant impact on how they perceive and use these technologies. Trust in AI can strengthen and enhance self-efficacy by giving users the confidence that AI systems will operate as expected. When students believe they can trust AI, their confidence in their own ability to successfully react to and coordinate with these technologies grows, thereby improving their skills and knowledge. AI self-efficacy is critical because people who regard themselves as tech-savvy, technologically adept, and AI users are more likely to adapt more efficiently, particularly to its key features and efficient uses. This concept extends beyond AI to other technologies, as demonstrated by Mallari et al. (2024), who found that students with strong technological expertise held positive perceptions of technology-enabled learning. Similarly, the study by Alayacyac et al. (2024) revealed that higher levels of computer self-efficacy significantly enhanced the effectiveness of learning management systems, further emphasizing the importance of technological efficacy in educational settings. Additionally, AI self-efficacy fosters a positive attitude and behavior toward AI tools. Students confident in their ability to use AI are less likely to feel intimidated or doubtful about these technologies. Instead, they view AI as a valuable resource, increasing their trust and engagement with it. Mediation analysis from the study further indicates that as students' self-efficacy improves, so does their trust in AI. This, in turn, cultivates a more positive attitude toward integrating AI into their academic pursuits.

From the research conducted by Montag et. al. (2023) suggests strong positive correlations between the propensity of trust in automated technology, self-efficacy, and attitude towards Artificial Intelligence (ATAI), and particularly the acceptance of the component of ATAI. Conclusively, this reveals that users who attain higher self-efficacy and confidence in using technologies beforehand are also capable to trust Artificial Intelligence technologies more as they feel more in tune and connected to use and manipulate these technologies to their needs and tailor their experiences to whatever is appropriate for their environment and work. This relationship between the variables is significant due to the nature of a person's self-efficacy that encompasses one's ability and confidence in their usage of tools and technologies. The results of this study show that technological self-efficacy has a positive and proportional impact on the acceptance of the integration of AI in different environments in a person's life, be it academical, commercial, or simply for recreational and residential use, when they have a deeper understanding and are confident with their skills in the technology. Conversely, the inverse is also true where users who have a lower level of self-efficacy are often prone to the skepticism and distrust towards automated technologies and, in turn, negatively affect their level of trust towards the technology. Self-efficacy is emphasized as having an important role in the level of AI trust as both a facilitator and a mitigator of the adverse personal attributes to its users. The investigation also points out that while a degree of overlap exists between the constructs of trust in automated technology and attitudes towards AI, significant unique variance remains. This is pertaining to the understanding that there are psychological structures and there is the idea that behind trust and self-efficacy, when related to AI, it would require further study and research. Mainly, student's trust in AI mainly has a large impact on their willingness to basically use and dedicate the time to learn on how to fully use the functions that these technologies have. In doing so, enhancing self-efficacy through the specific teaching, training, and learning/support could be a very useful method on fostering greater acceptance, which ultimately aims to improve the integration of AI in various methods and domains.

Materials and Methods

This study influences the handling of the quantitative research approach, which specifically targets a non-experimental correlational approach. This is to look and dive into the correlation between AI self-efficacy and AI Trust among university college students. From a study conducted by Cresswell and Cresswell (2022), quantitative research provides a systematic examination of the relationships among variables which also allows for the objective measurement of constructs and their interconnections. The methodological approach is crucial in assessing and analyzing the significance of the two aforementioned variables in shaping students' interactions with automated Artificial Intelligence technologies. The research instruments utilized for measuring the variables were carefully adopted from established sources: the AI trust variable was based on Choung et al. (2022), while the AI self-efficacy variable drew from Hong (2022). The data collection involved questionnaires structured using a 5-point Likert scale, distributed primarily through online surveys via Google Forms to tertiary students enrolled in various programs across different universities and colleges in Region XI, Philippines. Closed-ended questions permitted respondents to convey their levels of agreement and/or disagreement, concerning distinct statements that are relevant to student's self-efficacy in utilizing AI technologies – and their trust in matching and similar systems. Before data collection, a power analysis was regulated which mainly used G*Power 3.1.9.6 (Faul et al., 2007), which exposed that a sample size of $N = 89$ was required to achieve 80% power in the detection of a medium effect size ($f^2 = 0.15$) at a significance level of $\alpha = 0.05$. The concluding sample size of $N = 372$, not only surpassed this threshold, but enhanced as well the study's competency to comprehensively investigate the complex relationship between AI Self-Efficacy and AI trust among university college students. The SmartPLS 3.0 software was used to analyze the data of structural equation modeling (SEM). This was done in order to obtain appropriate data analyses of the measurement and structural models. The researcher used several other statistical procedures in order to establish the validity and reliability of the models concerned with trust in AI and self-efficacy. Average Variance Extracted (AVE) was used for assessing convergent validity of the measurement models on AI self-efficacy and AI trust, while the Heterotrait-Monotrait Ratio (HTMT) was used for evaluating discriminant validity. Cronbach's alpha was calculated to measure the internal consistency of the constructs.

Results

The foundational work of Ab Hamid et al. (2017) establishes strict guidelines for indicator loadings in the context of structural equation modeling, particularly emphasizing that acceptable loadings must exceed the threshold of 0.70. This benchmark signifies that a construct accounts for over 50% of the variance in each respective indicator, thus ensuring a meaningful representation of the underlying theoretical framework. Indicators with loadings between 0.40 and 0.70 can be kept, but if they fall below 0.40, they should be removed because they don't contribute enough to the overall validity of the construct.

This analysis provides a clear look at the standardized loadings for the indicators tied to AI Self-Efficacy and AI Trust. For AI Self-Efficacy, the loadings range from 0.717 to 0.814, which shows that the indicators—namely AISE10, AISE3, AISE5, AISE6, AISE7, AISE8, and AISE9—are closely related to the construct. Notably, the indicator AISE7 stands out with the highest loading of 0.814, thereby indicating that it explains a greater proportion of variance in AI Self-Efficacy compared to its counterparts.

Similarly, the standardized loadings for AI Trust span from 0.723 to 0.799, indicating that the items AITr10, AITr3, AITr4, AITr5, AITr6, AITr7, AITr8, and AITr9 adequately encapsulate the AI Trust construct. Among these, AITr5 demonstrates the strongest loading at 0.799, reinforcing its effective representation of AI Trust. The consistently high loadings above 0.70 across both constructs not only affirm their convergent validity but also enhance the reliability of the overall measurement model. Such strong indicator loadings are indicative of a well-structured conceptual framework, thereby providing compelling evidence for the effectiveness of the measurements utilized in the assessment of AI Self-Efficacy and AI Trust.

Table 1: Indicator Loading

	AI Self-Efficacy	AI Trust
AISE10	0.717	
AISE3	0.760	
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

Reliability and Validity Measures (Cronbach's Alpha, Composite Reliability, and AVE) This study used Cronbach's alpha and composite reliability among one of its methods. A criterion utilized for the evaluation of the model includes Cronbach's alpha and composite reliability, which ensure internal consistency. According to Hair et al. (2021), composite reliability values above 0.70 and Average Variance Extracted (AVE) values above 0.50 indicate adequate reliability and validity. Specifically, an AVE value should exceed 0.50 to be considered sufficient, as this indicates that the construct explains at least 50% of the variance of its indicators (Ab Hamid et al., 2017). Both AI Self-Efficacy and AI Trust demonstrate strong internal consistency, with Cronbach's alpha values of 0.873 and 0.899, respectively. The composite reliability values, which assess the overall reliability of the constructs, are high for AI Self-Efficacy (0.902) and AI Trust (0.919), both exceeding the recommended threshold of 0.70. Furthermore, the AVE values are 0.569 for AI Self-Efficacy and 0.586 for AI Trust, indicating that both constructs are well above the minimum acceptable level of 0.50, thereby confirming adequate convergent validity. These results collectively demonstrate that the measurement model exhibits both reliability and validity.

Table 2: Reliability and Validity Measures

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
AI Self-Efficacy	0.873	0.882	0.902	0.569
AI Trust	0.899	0.903	0.919	0.586

The HTMT (Heterotrait-Monotrait Ratio) between AI Self-Efficacy and AI Trust is 0.630. This value is below the conservative threshold of 0.85, indicating sufficient discriminant validity between the two constructs. This means that AI Self-Efficacy and AI Trust are distinct and separate constructs, allowing respondents to differentiate between them effectively. This finding aligns with the research by Hair et al. (2021), which states that discriminant validity is indicated by HTMT values falling below the conservative threshold of 0.85. A value below this threshold confirms that the constructs in question are sufficiently distinct from one another, thereby mitigating concerns about overlapping measurements.

In the current study, the HTMT ratio between AI Self-Efficacy and AI Trust was found to be 0.630. This value is well below the established threshold, suggesting adequate discriminant validity between these constructs. Thus, respondents are indeed capable of effectively differentiating between AI Self-Efficacy and AI Trust. Additionally, Henseler et al. (2015) argue that the HTMT method is significantly superior in terms of sensitivity and specificity, achieving impressive rates of 97% to 99% compared to traditional methods such as the Fornell-Larcker criterion. This superiority emphasizes HTMT's capacity to detect potential overlaps between constructs more reliably, thereby strengthening the robustness of the measurement model. In summary, the use of HTMT in this analysis supports the conclusion that AI Self-Efficacy and AI Trust are distinct constructs, enhancing the overall validity of the research findings.

Table 3: Heterotrait-Monotrait Ratio (HTMT)

	AI Self-Efficacy	AI Trust
AI Self-Efficacy		
AI Trust	0.630	

The model previewed shows a notably positive relationship between AI Self-Efficacy and AI Trust ($\beta = 0.573$, $p < 0.001$). The T-statistic of 10.905, which far exceeds the critical value of 1.96, shows that the relationship is highly significant. The f-square value of 0.490 suggests that AI Self-Efficacy has a considerable effect size in predicting AI Trust, further stating the importance of AI Self-Efficacy in this model.

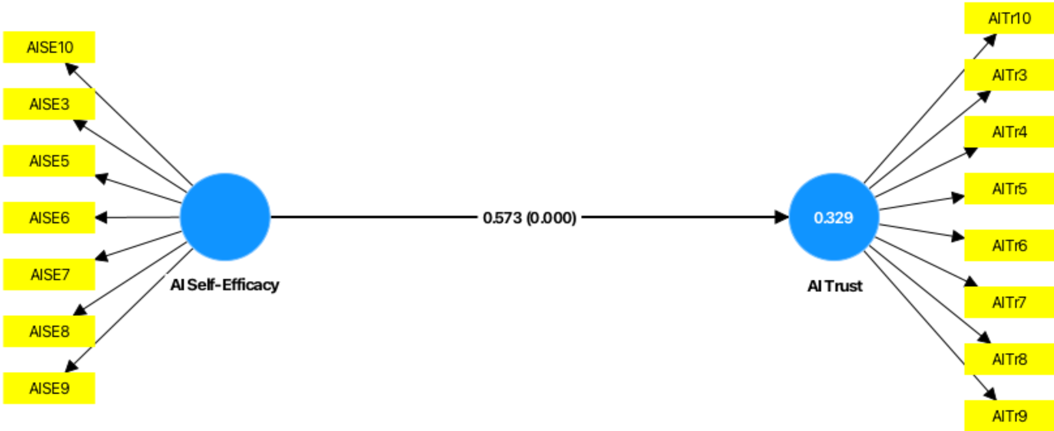

Figure 1: Structural Model Results

The findings covered indicate that individuals with higher levels of AI Self-Efficacy are more likely to trust AI technologies. This result is supported by the study of Hair et al. (2021), which emphasizes the relationship between Self-Efficacy and AI Trust as best analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). According to Hair et al., this method is particularly effective for assessing structural models, including complex models with latent constructs such as AI Self-Efficacy and AI Trust. PLS-SEM provides robust parameter estimates even with diverse sample sizes. The data derived from this modeling approach is well-suited for exploratory studies aiming to maximize explained variance, making it significantly effective when considering both predictive accuracy and model complexity.

The mean value is commonly utilized in Partial Least Squares Structural Equation Modeling (PLS-SEM) as a method for addressing missing data and summarizing the central tendency of indicator scores. Specifically, mean value replacement is a widely accepted practice when the proportion of missing values is less than 5% for each indicator. This technique involves substituting missing entries with the mean value of the respective indicator, which helps to preserve the integrity of the dataset and allows for more accurate modeling outcomes (Hair et al., 2021). Furthermore, the graphical representation of the structural model effectively illustrates the standardized path coefficient from AI Self-Efficacy to AI Trust, which is valued at 0.573. This result is statistically significant, as indicated by a p-value of 0.000. Such a visual representation underscores the strength and significance of the direct effect of AI Self-Efficacy on AI Trust. Additionally, the R-square value associated with AI Trust indicates the model's ability to explain the variance observed in AI Trust. Overall, this visualization facilitates a clearer understanding of the model's structure and highlights the essential role that AI Self-Efficacy plays in fostering trust in AI technologies.

Table 4: Structural Model Results - Interpretation

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	f-square	T statistics (|O/STDEV|)	P values
AI Self-Efficacy -> AI Trust	0.573	0.578	0.053	0.490	10.905	0.000

The R-square (R^2) value implies that the share of the differences resulted from the independent variables in a regression model, with values of 0.75, 0.50, and 0.25 considered significant, average, and weak, respectively. Nevertheless, R^2 can still increase with the addition of more descriptive variables, potentially leading to overfitting (Hair et al., 2021). These outcomes exhibits to us that there is a durable and well-validated measurement model, with emphasis on resilient construct, validity, reliability, and significant predictive abilities.

Table 5: R-Square Model

	R-square	R-square adjusted
AI Trust	0.329	0.327

Discussion

These outcomes exhibit to us that there is a durable and well-validated measurement model, with emphasis on resilient construct, validity, reliability, and significant predictive abilities. The outcomes discovered pertain that AI Self-Efficacy is a pivotal determining factor of AI Trust – indicating its important ideas for designing interference that aim to uplift trust in AI, by means of enhancing self-efficacy in the usage of AI systems. The structured model showcases a particularly positive relationship between AI Self-Efficacy and AI Trust ($\beta = 0.573$, $p < 0.001$). Future studies could explore additional factors influencing AI Trust and examine how contextual variables may moderate this relationship.

Conclusion and Recommendation

The study investigates the relationship between AI self-efficacy and level of AI trust, as well as how these variables interact with each other and the findings of the methods used indicate a strong link. The results suggest that AI self-efficacy is a key determinant that dictates the level of trust that a college student attains with the aforementioned technology. Schools and universities are encouraged to create programs that help students build their confidence in using AI technologies, as this can greatly increase their trust in these tools. A practical method to achieve this is by including interactive AI training sessions and workshops in the curriculum, which allow students to gain real-world experience with AI systems. Further investigation should focus on the different characteristics that influence the capacity of students to effectively use and trust AI, with an emphasis on practical techniques to improve these aspects even more. Additionally, institutions are encouraged to design targeted programs that consider the unique needs of different demographic groups and specific circumstances. This strategy will guarantee that AI education programs will remain inclusive and relevant in addressing the different backgrounds and experiences among the students.

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