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The Nexus Between AI Self-Efficacy and Attitude Towards AI of University Students in Davao City as Moderated by Sex

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ABSTRACT

This study quantitatively explores how sex moderates the relationship between AI self-efficacy and attitudes toward AI among university students in Davao City, Philippines. Data were obtained online via google forms using tailored questionnaires, with respondents chosen using stratified random sampling. The measurement model was tested for validity and reliability, and the constructs were defined using descriptive statistics. To evaluate the suggested moderation model, a moderation analysis was conducted using smartpls 4.0's standard bootstrapping technique. The results showed that the constructs were valid and reliable, with university students exhibiting modest levels of ai self-efficacy and attitude toward ai. Furthermore, the study found that sex had a significant moderating role in the relationship between AI self-efficacy and attitude toward AI.

INTRODUCTION

Artificial Intelligence (AI) is a fast developing field that has become prevalent in modern life, impacting many facets of society, including education. AI has improved learning outcomes and enhanced educational experiences through intelligent tutoring, automated assessments, and adaptive learning systems that offer customized feedback (Zawacki-Richter *et al.*, 2019; Ahmad *et al.*, 2021). Similar results from a research by Obenza *et al.* (2023) show that students are more likely to utilize ChatGPT as an educational supplement, particularly when they are enhancing their reading and writing skills. AI may modify curriculum to student performance, enhancing effectiveness and engagement. One example of this is China's Squirrel AI (Bourne, 2019). These findings suggest that generative AI is frequently seen positively in educational environments (Obenza *et al.*, 2023). However, personal beliefs about AI and self-efficacy play a major role in the effective implementation and use of AI in education. Students who think favorably of AI are more likely to use it, according to the strong behavioral intention association (Obenza *et al.*, 2024). This study demonstrates that how students engage with AI may be influenced by their opinions about the technology. The degree of confidence students have in their ability to interact with AI technology is determined by their AI self-efficacy, even though their attitudes toward AI in this context reflect their perceptions generally and their willingness to integrate AI into their learning activities (Chen *et al.*, 2020; Dogan *et al.*, 2023; Gligorea *et al.*, 2023; Zawacki-Richter *et al.*, 2019; Tang *et al.*, 2021; Harry, 2023; Hashim *et al.*, 2022; Hamal *et al.*, 2022). Higher technical self-efficacy individuals feel they can discriminatively impact the results of interactions by asserting control over automated technology use (Montag *et al.*, 2023; Obenza-Tanudtanud & Obenza, 2024). Considering this, it is vital to investigate how such dynamics change between sexes. There may be minor differences between male and female students' views regarding AI and self-efficacy, which are influenced by their upbringing. Studies indicate that females are less accepting as compared to males in the consideration of AI. It is an explicit and implicit disparity, and specific interventions have been sought to help improve this area as well (Fietta *et al.*, 2022).

Obenza *et al.* (2023) found that the concepts of AI self-efficacy, AI trust, and attitude toward AI are related to one another since they can all be used to predict one another quite well. All the hypotheses were confirmed, including the mediating hypothesis, which assumed a partial mediation to be performed by trust in AI between attitudes toward AI and self-efficacy on user acceptance to use AI. However, more research is needed because the previous study did not look at how sex could act as a moderating element in the relationship between AI self-efficacy and views about AI. Moreover, recognizing these distinctions offers important context for understanding how AI technologies are being adjusted to better meet the individual requirements of every student and enhance their involvement in educational environments. Therefore, this study aimed to assess university students' views toward AI and their self-efficacy while accounting for the possible influence of sex in Davao City.

Theoretical Framework

The Technology Acceptance Model (TAM), the Theory of Planned Behavior (TPB), and self-efficacy are the three main theories that support this study and shed light on how college students view the application of AI. The

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Bandura 1977 self-efficacy theory was used to explore the extent of student confidence in using AI tools (Gallagher, 2012). Greater confidence means more AI engagement, which results in being more familiar with and skilled at any given technology and consequently more open to exploring AI applications. This is supplemented by the Technology Acceptance Model (TAM) proposed in 1989 by Davis, which looks at two key concepts: the usefulness of AI to students and its ease of use (Charness & Boot, 2016). The more people view AI as a helpful tool for their profession or studies and as something that is simple to use, the more positive their overall perception of the technology is. Students are more likely to begin integrating AI technologies into their daily activities if they are less complicated. Ajzen's (1991) Theory of Planned Behavior (TPB) takes one step further, describing how these attitudes, combined with impacts from self-efficacy and TAM, influence students' actual usage of AI, whether personally or professionally. TPB implies that if students have AI efficacy and social considerations, they are more likely to use it. This refers to attitudes, ideas, and societal pressures that interact throughout the AI adoption process, according to this theory.

In summary, this study combines self-efficacy theory, the acceptance of technology model, and the theory of planned behavior to provide a holistic understanding of how university students perceive and interact with AI. Thereby, these theories explain how confidence, perceived usefulness, ease of use, and social influences all come together to shape the attitudes of a student toward AI. Educators and decision-makers may facilitate students' adoption of AI technology and ensure they possess the necessary knowledge and outlook to thrive in an increasingly AI-dependent world by being aware of these factors.

MATERIALS AND METHODS

This study employed the quantitative approach, that is, by using the non-experimental approach of correlation in analyzing how sex impacts the relationship between AI self-efficacy and attitudes toward AI among university students in Davao City. According to Creswell and Creswell (2022), quantitative research is a systematic study that employs numerical data to answer research questions through statistical analysis of the correlations between variables. This approach measures variables using tools, hence allowing the application of statistical methods for data analysis. A moderating variable by Ramayah *et al.* (2017) was used to explain how the criterion affects the predictor's effect. This element is essential when doing a detailed analysis of the correlation between criteria and predictor variables. Even if the MV does not affect the predictor, it may influence the strength and direction of relationships among the components.

The research instruments that were utilized and modified were the AI self-efficacy scale developed by Hong (2022) and the attitude toward the AI scale created by Suh and Ahn (2022). These variables were measured using 5-point Likert scales (5 - Strongly Agree, 4 - Agree, 3 - Neutral, 2 - Disagree, and 1 - Strongly Disagree). An online survey through Google Forms was conducted among the college students of various programs across universities in Davao City, Philippines. The participants were 423 selected at random from each subdivision using stratified random sampling—the division of populations into subgroups—to ensure that every section or subgroup is represented. By implementing it into the study framework, mediation analysis was utilized to investigate how a mediating variable affects the connection between two other variables. Psychologists are using this method more and more, and it usually includes selecting participants at random (MacKinnon *et al.*, 2007).

Average Variance Extracted (AVE) was applied to verify convergent validity, and Heterotrait-Monotrait Ratio (HTMT) confirmed discriminant validity as well as Cronbach's alpha for internal consistency assurance of the measurement models. The self-efficacy and attitude toward AI descriptive statistics, such as mean and standard deviation, were calculated using Jamovi version 2.0. As a final step, the bootstrapping results through SmartPLS 4.0 software verified the moderation effect of sex in this path between self-efficacy and attitude toward AI.

Hypotheses

H_0: There is no significant relationship between AI self-efficacy and attitude towards AI among university students in Davao City, and sex does not moderate this relationship.

H_1: There is a significant relationship between AI self-efficacy and attitude towards AI among university students in Davao City, and this relationship is moderated by sex.

RESULTS AND DISCUSSION

For establishing internal consistency of the variables, Cronbach's alpha and composite reliability have been selected as major measures to be used in evaluating the data, as the reliability of variables is determined by the interrelationship shown between the items, according to (Hamid *et al.*, 2017). Table 1 shows the reliability of the study's instruments.

The artificial intelligence self-efficacy construct shows great internal consistency with Cronbach's alpha value of 0.875, considerably above the threshold of 0.70 (Wilson *et al.*, 2018; Dzin and Lay, 2021; Kukul and Karatas, 2019). Besides, its rho_c value was 0.902, further proving reliability, as the items possessed consistency in measuring the same underlying concept (Dzin and Lay, 2021; Kukul and Karatas, 2019). AVE = 0.536, which means that this construct explains more than 50% of the variance in its indicators and thus strengthens the good convergent validity. Compared to this, the construct attitude towards AI shows more reliability with Cronbach's alpha of 0.961 and rho_c = 0.964. The AVE for this construct is 0.589, which shows high convergent validity as it explains a huge portion of the variance in its indicators. Overall, both constructs show very high internal consistency and reliability.

To further evaluate discriminant validity between the constructs under research, the heterotrait-monotrait ratio (HTMT), was used. The HTMT is useful in determining if two latent constructs are sufficiently different from each other by comparing relationships between variables across different scales (Hamid *et al*., 2017). Henseler *et al*. (2015) also state the use of HTMT since it is straightforward, performs robustly, and therefore assists in this case. This test was selected because, given the provided data, it provides a strong tool for assessing how well different constructs, or scales, differ from one another. According to Ringle *et al*. (2024), if the value for HTMT is below the threshold limit of 0.85, strong discriminant validity exists. Achieving this threshold proves to be a critical issue because it reflects discriminant validity between constructs (Henseler *et al*., 2015). In the case of the studied research, the HTMT value of AI self-efficacy toward attitude toward AI is 0.534. The value is remarkably below 0. threshold, which suggests an important difference between the two constructs.

This finding suggests that AI self-efficacy—which is defined as belief or confidence in using AI appropriately—is not the same as an individual's general attitude or feelings regarding AI. Because of this, different aspects of students' interactions with and views toward AI can be captured by these factors individually. By ensuring that AI self-efficacy and attitude towards AI measure different cognitive and affective aspects of how students perceive and interact with AI-related technologies, this distinction strengthens the study and provides a more thorough understanding of the students' varied perspectives and competencies about AI.

Table 1: Construct Validity and Reliability.

Variables	**Cronbach's alpha**	**Composite reliabi lity (rho_a)**	**Composite reliabi lity (rho_c)**	**Average variaance extracted (AVE)**
AI Self-Efficacy	0.875	0.889	0.902	0.536
Attitude towards AI	0.961	0.964	0.964	0.589
Discriminant Variable			**Heterotrait -Monotrait Ratio(HTML)**	
AI Self -Efficacy <-> Attitude Towards AI			0.534	

Table 2 shows that university students, with an average self-efficacy score of 3.47 (SD = 0.683), are fairly confident in their abilities to work with AI. With a score of 3.38 (SD = 0.809), they also have a moderate overall attitude toward AI, leaning slightly toward neutrality. As such, this finding resonates well with what Obenza *et al*. (2023) found because this would amount to an overlap of opinions on how students feel towards AI. As pointed out by Chen *et al*. (2022), the study shows how AI programming self-efficacy and AI literacy are vital regarding wanting to teach students about delving into AI software development. This finding is in line with the moderate levels of self-efficacy displayed in Table 2, suggesting that university courses and AI training programs significantly boost students' self-confidence. Similarly, Fryer *et al*. (2020) highlight the role that curiosity and self-efficacy play in academic performance, stressing the impact that past experiences and passions have on students' future success. This theory is consistent with the moderate levels of self-efficacy that was observed, demonstrating the importance of students' prior experiences and excitement for AI in fostering their present confidence. In contrast to their emotional reactions (mean = 3.29, SD = 0.810) or cognitive views (mean = 3.60, SD = 0.972), students' behaviors toward AI are more neutral (mean = 3.25, SD = 0.892) when the specific components of attitude are examined.

This finding is consistent with multiple research examining students' diverse perspectives on artificial intelligence. For example, a study on Chinese secondary school students' impressions of AI revealed that their opinions are influenced by their beliefs about the technology's benefits to society and how useful they believe it to be. Thus, what matters is exactly what students believe concerning the benefits of AI (Chai *et al*., 2020). Another study with college students proved to be similar to the earlier discussion, where it established that the amount of success those higher-education students were expecting to have with AI as well as their feeling of support had significantly influenced their attitudes and intentions towards AI. This goes a long way in showing that cognitive factors are crucial in determining their overall perception (Alzahrani, 2023).

The role is also significant with emotional responses to AI among the students. It has been indicated through research that improved learning experiences as well as attitudes in students come with positive engagement of the students with AI tools. For example, in the research into AI writing tools, it has been observed that students who have had interactions with the mentioned AI tools had emotional engagements and could still view AI positively (Nazari *et al*., 2021). While emotional reactions to AI are more consistent, cognitive attitudes—reflecting their views and beliefs—lean somewhat more positively but exhibit a larger range of perspectives.

Table 2: Descriptive Statistics

Variable	N	Mean	Median	Mode	SD
AI Seld-Efficacy	423	3.47	3.40	3.00	0.683
Attitude towards AI	423	3.38	3.36	3.00	0.809
Behavioral	423	3.25	3.17	3.00	0.892
Affective	423	3.29	3.30	3.00	0.810
Cognitive	423	3.60	3.50	3.00	0.972

Table 3 demonstrates how an individual's attitudes toward the application of AI are strongly correlated with their level of self-efficacy in using it. Specifically, for each one-unit increase in self-efficacy, attitudes toward AI go up by 0.519 units. This positive connection indicates that people who feel capable of using AI are likely to view it more favorably. Furthermore, with a standardized coefficient of 0.519 and a mean of 0.526, Figure 1 demonstrates that there is a substantial ($p < 0.001$) direct association between views toward AI and AI self-efficacy. These results are in line with what has been seen in the travel and hospitality industry, where attitudes and desire to use AI services are significantly influenced by self-efficacy (Ho *et al.*, 2022).

Table 3: Direct effect

Hypothesis	Original sample(O)	Sample Mean(M)	Standard Deviatiion (STDEV)	F-square	T-statistics	P-values
AI Seld-Efficacy<-> Attitude towards AI	0.519	0.526	0.048	0.368	10.869	0.000
R^2= 0.269 Adjusted R^2=0.267						

This also shows that fostering self-efficacy can lead to more positive attitudes toward AI, which is crucial for effective integration into learning environments. Research indicates that early development of self-efficacy and interest can have lasting benefits (Fryer *et al*, 2020). However, it's worth noting that while many express positive attitudes, their subconscious feelings may not align; one study found that participants often showed negative implicit responses despite positive explicit attitudes, indicating that self-efficacy alone might not capture all concerns about AI (Fietta *et al.*, 2022).

The substantial t-statistic of 10.869 indicates that self-efficacy plays a significant role in influencing attitudes, and data that are consistent in various circumstances support this conclusion (Grassini, 2023; Fryer *et al.*, 2020; Livinũi *et al.*, 2021). The impact of human contact in learning, however, does not always translate to other domains-where AI is the focal point because the outcomes are context-dependent (Fryer *et al.* 2020).

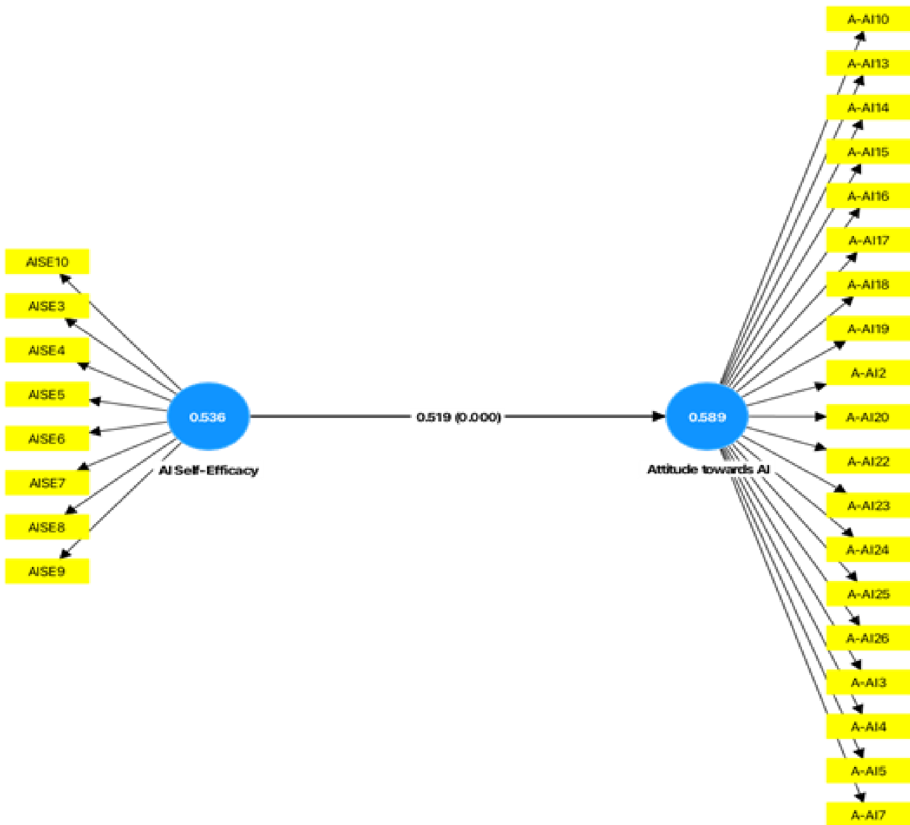

Figure 1: The Correlation Between AI Attitude and Self Efficacy

The effect size of 0.368, as indicated by Table 3, suggests that students' attitudes toward AI are influenced in a moderate to strong way by their level of AI self-efficacy. This points out that attitudes toward the employment of AI increase dramatically for students who are becoming more confident in their capacity to use it (Chen *et al*., 2022; Ayanwale, 2023; Park, 2023). This therefore implies that there is a need to boost self-efficacy as a step to achieve more positive views of AI among the students. Programs that involve enhanced AI self-efficacy through hands-on, interactive, and supportive learning settings work well in enhancing positive attitudes toward AI (Chai *et al*., 2022; Nazari *et al*., 2021; Alzahrani, 2023). Both helpful and enjoyable courses enhance literacy concerning AI and self-efficacy, which leads to more positive attitudes and higher intentions to engage with AI (Chen *et al*., 2022; Chai *et al*., 2022).

The R^2 for attitudes toward AI in Table 3 is 0.269 with an adjusted R^2 of 0.267. This means about 26.9% of the differences in students' attitudes can be accounted for by their self-efficacy in AI. A very minor change in this R^2 means that although self-efficacy is a significant predictor of attitudes toward AI, other factors are also involved in forming these perceptions. Therefore, whereas self-efficacy contributes, clearly other influences remain.

CONCLUSION

This study provides highly compelling evidence concerning the positive relationship that AI self-efficacy bears with attitudes toward AI among university students. These results suggest that AI self-efficacy has a strong relationship with attitudes toward AI among university students in Davao City. It implies that individuals who believe that they are better equipped to use AI possess more favorable attitudes toward AI, which would explain much of the variance in those attitudes. The results are strengthened with strong construct reliability and validity, which increase the confidence in them. Improving AI self-efficacy may also significantly strengthen the attitudes students have toward AI technologies. As a result, educational institutions could then conduct practice and training activities that would give students a feeling of confidence in using AI and increase their acceptance and use of the tools in their respective careers. Although the data presented in this study does not reveal whether sex acts as a mediator in the relation between AI self-efficacy and attitudes toward AI, further closer examination would be required to shed further light on this dimension. Furthermore, given the strong direct effect that self-efficacy has on attitudes, a moderated mediation analysis might provide light on the ways in which sex moderates or even reverses this effect. It should be noted that this study is limited to Davao City university students, and hence cannot be generalized to a larger student population. Future research would help to broaden this sample demographically across locations or types of study. In addition, while sex has been considered as an essential moderator in this association, other demographic factors that were not taken into account in this study may possibly influence attitudes regarding AI. Studying such implications of gender difference on perceiving AI may therefore provide direct avenues for developing targeted educational interventions that boost AI literacy and acceptance. Overall, this study emphasizes the significance of AI self-efficacy in education which in fact promotes more positive attitudes and higher acceptance of AI in both academic and professional settings.

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