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Research Article

Artificial Intelligence Anxiety, Self-Efficacy, and Self-Competence among Students: Implications to Higher Education Institutions

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Abstract

Artificial intelligence (AI) has become a trending topic of study, especially in education. However, due to its unknown potential, students are adamant about it. The objective of this study is to investigate college students' perceptions of artificial intelligence (AI) anxiety, AI self-efficacy, and AI self-competence in a tertiary education institution. The study used a correlational research design with the help of an online survey to determine the variances and relationships among 1,030 purposively chosen students. This study adopted and modified measures that underwent reliability testing to gather data. The collected data were subjected to descriptive and inferential analysis using SPSS 23 for data computation. Results show that students have a moderate level of AI anxiety and AI self-efficacy; however, in terms of AI self-competency, they have a high level of it. Inferential analysis also revealed significant differences when the three variables were grouped according to demographic characteristics. At the same time, the study also found significant associations between AI anxiety, AI self-efficacy, and AI self-competence. The regression analysis confirmed that learning, job replacement, sociotechnical blindness, and AI configuration significantly influenced AI self-efficacy. On the other hand, job replacement, sociotechnical blindness, and AI configuration also predict AI self-competence. The study concludes that variances and relationships exist among AI anxiety, self-efficacy, and self-competence among college students.

Keywords *Artificial Intelligence (AI), AI anxiety, AI self-efficacy, AI self-competence, Higher Education Institutions (HEIs)*

INTRODUCTION

In the past few years, the rapid development of artificial intelligence (AI) has brought about substantial changes in a variety of sectors of human life, including education. Throughout the last half-century, there has been a proliferation of research on artificial intelligence education, which has produced some intriguing viewpoints (Bozkurt et al., 2021). Artificial intelligence (AI) has attained sufficient traction in recent years, particularly in higher education (Huang et al., 2021; Yang et al., 2020). Additionally, AI has succeeded in all three areas of college operations (Hannan & Liu, 2023). However, some obstacles arise from the incorrect application of AI approaches (Zhai et al., 2021). Artificial intelligence (AI) has the capability to generate learning experiences; nevertheless, AI also brings forth new obstacles and concerns. In their previous work, Alam and Mohanty (2023) mentioned that the use of artificial intelligence (AI) in education calls for a more in-depth assessment of ethical and pedagogical methods. In addition, Fitria (2021) emphasized that the technology operates based on human orders and that teachers impart new information. In a similar vein, Orhani (2023) claimed that although technology like robotics can be useful as a teaching tool in schools, it will only partially replace teachers.

Researchers, academicians, and policymakers must understand the relationship between worry about artificial intelligence (AI), self-efficacy, and self-competence. If we investigate these links, we will be able to establish techniques to alleviate worries about artificial intelligence and promote positive psychological outcomes for students. In their earlier research, Carolus et al.

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(2023) demonstrated several fascinating connections that lend weight to the theory presented in this study. Enhancing students' self-efficacy and self-competence allows them to embrace AI technologies as learning and personal growth tools rather than sources of fear and self-doubt. Both Carolus et al. (2023) and Carolus et al. (2023) highlighted the strong connection that exists between self-efficacy and self-competence.

The review of relevant literature revealed a knowledge gap regarding the three variables discussed in this study. Further research is necessary, especially to understand the perceived levels of variation and the underlying interrelationships among the three variables. Specifically, this is the primary reason why the authors of this research wished to fill this gap.

This study analyzes the unique dynamics between AI anxiety, self-efficacy, and self-competence among students. By examining the factors influencing these variables and identifying potential interventions, we can foster a more supportive educational environment that prepares students to navigate an AI-driven future with confidence. To answer the main aim, the study intends to investigate the following research questions:

- What are the levels of AI anxiety, self-efficacy, and self-competence in the participants?
- Is there a significant difference in the participants' AI anxiety, self-efficacy, and self-competence when grouped according to their demographic characteristics?
- Is there a significant relationship between AI anxiety, self-competence, and self-competence in the participants?
- What factor(s) predicted the AI self-efficacy and AI self-competence among the participants?

The results of this investigation will benefit the institution, especially the administrator, in facilitating the appropriate use of technology (i.e., Artificial Intelligence) to enhance the teaching-learning process in colleges. The results can serve as a basis for policy development and implementation to regulate proper usage among students and faculty in the institution.

LITERATURE REVIEW

Artificial Intelligence (AI) Anxiety among Students

Students should pay close attention to their anxiety around artificial intelligence (AI). There are various ways in which this setting can be manifest (Almaiah et al., 2022). Students often seek clarification and guidance when confronted with computer and artificial intelligence tools. In a recent paper, Hopcan et al. (2024) found that students expressed concern regarding the influence of artificial intelligence. Some people expressed concern that AI could replace human teachers, or that AI-driven assessments could evaluate students' abilities alone. Wang et al. (2022) highlighted in their previous research that artificial intelligence learning anxiety affects learning motivation. Research by Ayanwale et al., (2022) and Jatileni et al., (2023), has demonstrated the impact of AI learning anxiety on learning motivation. Research has revealed that teachers' fear of AI does not accurately reflect their intent and willingness to use AI in their classrooms. Anxiety can negatively impact a person's sense of self-efficacy and self-competence, two critically important psychological variables that influence academic success and personal growth.

Students' Self-Efficacy in Artificial Intelligence (AI)

Self-efficacy relates to individuals' belief in their ability to complete specific tasks and achieve desired outcomes successfully. Based on the article by Wang et al. (2023), the artificial intelligence capabilities of higher education institutions are affected by students' creativity and self-efficacy. Another study showed that the use of artificial intelligence apps in the review process greatly boosts students' sense of self-efficacy—precisely (Lee et al., 2022). In an alternative way of looking at things, Ayanwale (2023) found that most students have a high level of self-efficacy and believe that they can learn AI. Increased levels of concern about artificial intelligence (AI) can negatively impact students' sense of self-efficacy. In their previous research, Wang et al. (2022) highlighted the role of self-efficacy in online learning as a mediator between interaction and learning engagement among students. They may doubt their abilities and overuse AI systems, thus lowering their confidence. Wang et al. (2021) found that self-efficacy predicted instructors' application of AI in their classrooms. By highlighting the mutually beneficial relationship that exists between self-efficacy and student engagement, Wu et al. (2023) highlighted the revolutionary potential of artificial intelligence.

Self-Competence of Students on Artificial Intelligence (AI)

In a similar vein, self-competence refers to an individual's view of his or her overall capabilities and performance in various disciplines. Sabordino et al. (2024) indicated in their research that although students have a high level of confidence in their ability to use artificial intelligence effectively, their self-efficacy appears to be lower. Anxiety about AI may cause students to mistrust their capabilities and feel inferior to technology that uses AI. Specifically, Sanusi et al. (2022) emphasized the significance of AI competencies in their research article. Additionally, the results highlighted that self-efficacy was a reflection of an individual's self-evaluation of their capabilities to participate in activities. This perceived lack of expertise can negatively affect participants' motivation, engagement, and willingness to undertake challenging tasks.

The study's conceptual framework used an IV (Independent Variable) – DV (Dependent Variable) model to determine the underlying relationships between AI anxiety, AI self-efficacy, and self-competence. To illustrate, the independent variable (IV) is AI anxiety. Then, for the dependent variable (DV), we indicate students' AI self-efficacies and self-competence. The study conducted inferential analysis (i.e., linear regression) to analyze the relationship.

The study then proposed the following research hypotheses to be tested at the.05 alpha significance level:

1. Is there a significant relationship between AI anxiety and students' AI self-efficacies?
2. Is there a significant relationship between AI anxiety and AI self-competency among students?
3. What factors influence AI anxiety and self-efficacy among students?

RESEARCH METHOD

Research Design

This paper employed a descriptive-correlational research design, with an online survey as the main data collection instrument. This study determines the anxiety levels of artificial intelligence (AI), self-efficacy, and self-competence. At the same time, the goal is to discover the underlying associations and effects of AI anxiety on AI self-efficacy and self-competence.

Participants

The study's participants included 1,030 students from a tertiary educational institution located in Olongapo City, Philippines. The study also employed a purposive sampling technique to obtain the necessary number of samples. Purposive sampling is a strategy that ensures that specific types of cases are included in the final research sample. Therefore, based on the study's assumption, particular people may hold different and important views about ideas (e.g., Artificial Intelligence) and issues. In order to be part of the study, a participant should be: a) a bona fide student of the participating tertiary institution for the study; b) currently enrolled in the current semester; c) a regular student; d) must have a smartphone/device; e) have internet connectivity; and f) willing to participate voluntarily. The criteria that make a participant excluded from the study include a) students from another institution; b) not enrolled in the current semester; c) part-time/unregular student; d) no gadgets/ smartphone; e) no internet connection; and e) not willing to take the online survey.

Prior to data gathering, the study ensured that all participants were informed and well-acknowledged regarding their rights and privileges in the survey. No participants were injured during the data gathering process. If the participants refused to participate, the researcher would not hold them liable for any damages.

Measures

This study adopted and used previous papers by Wang et al. (2022) to determine the students' four dimensions of the AI anxiety scale. These four dimensions include learning, job replacement, sociotechnical blindness, and AI configuration. Their initial reliability coefficients were .974 for learning, .917 for job replacement, .917 for sociotechnical blindness, and .961 for AI configuration, all higher than the benchmark score of .07 for reliability.

For the second measure, the study modified the instrument used by Carolus et al. (2023) for the Meta AI literacy scale. In this study, AI self-efficacy and AI self-competency were the only variables that were considered. The Cronbach Alpha reliability coefficients ranged from .70 to .90, which is also reliable.

The study also included some essential demographic characteristics of the participants, such as college, year level, age, gender, GPA, and use of AI.

The validity and reliability of the two instruments were meticulously evaluated before data gathering. A panel of experts critiqued the tailored research tool, each bringing their unique expertise to the table. They include a research director, seasoned researcher, data analyst, and faculty member. Their insightful comments and suggestions influenced the design of the research tool. The instrument then underwent a pilot test for reliability with students who did not participate in the survey. The alpha Cronbach coefficient, a measure of reliability, yielded an impressive overall result of more than .90 indicating a remarkably high level of reliability.

The author then secured permission from the college deans of the participating tertiary institutions. After their approval, data gathering was conducted, and an online survey form link was opened for the students to answer. The data gathering period was from September to August 2023 during the first academic year.

Statistical Analysis

After collecting sufficient data, the research employed both descriptive and inferential statistical processes. We also used Microsoft Excel and SPSS 23 software for the research. The data was computed using frequency, percentage, and mean distribution for descriptive statistics. During this process, the inferential statistics employed included the independent t-test, analysis of variance (ANOVA), the Pearson-R moment of correlation, and linear regression analysis.

This research report formatted the students' responses using a five-point Likert scale, ranging from (1) very low, (2) low, (3) moderate, (4) high, and (5) very high. The responses were intended to evaluate the students' levels of anxiety regarding artificial intelligence (AI), self-efficacy regarding AI, and self-competence regarding AI.

FINDINGS AND DISCUSSION

The primary purpose of this study was to determine the perceived levels of AI anxiety, self-efficacy, and self-competence of tertiary education students. It also intends to determine the degrees of variance and associations of the variables. The following tables represent the study results.

Table 1. Demographic Characteristics of the Respondents

Characteristics	Frequency	Percentage
College		
CAHS	256	24.9
CBA	49	4.8
CCS	289	28.1
CEAS	354	34.4
CHTM	82	8.0
Year Level		
First Year	385	37.4
Second Year	287	27.9
Third Year	173	16.8
Fourth Year	185	18.0
Age		
Less than 20 years old	605	58.5
21–25 years old	387	37.4
26–30 years old	19	1.8
31 years old and above	19	1.8
Gender		
Female	567	55.0
Male	439	42.6
Prefer Not to Say	24	2.3
GPA from the Previous Year		
75 – 79%	24	2.3
80 – 84%	183	17.8
85 – 89%	449	43.6
90 – 94%	344	33.4
95% and above	30	2.9
Used Artificial Intelligence (AI) in Study		
No	173	16.8
Yes	857	83.2
Total	**1030**	**100.0**

An exhaustive investigation revealed some significant discoveries, as shown in Table 1, which details the demographic features of the respondents. The College of Computer Studies (CCS, n = 354, 34.4%), the College of Education, Arts, and Sciences (CEAS, n = 289, 28.1%), and the College of Business and Accountancy (CBA, n = 289, 28.1%) accounted for the majority of respondents. The largest group consisted of students who were in their first year (n = 385, 37.4%), followed by students who were in their second year (n = 287, 27.9%), students who were in their fourth year (n = 185, 18.0%), and students in their third year (n = 173, 16.8%). The age distribution of respondents revealed that the majority were younger than 20 years old (n = 605, 58.5%), with smaller proportions falling into the categories of being between the ages of 21 and 25 (n = 387, 37.4%), 26 to 30 (n = 19, 1.8%), and 31 years old and older (n = 19, 1.8%). In addition, the distribution of respondents based on gender revealed that the majority of respondents were female (n = 567, 55.0%), whereas a smaller minority identified as male (n = 439, 42.6%), and a few respondents did not identify their gender (n = 24, 2.3%). The highest proportion of respondents had a grade point average from the previous year that ranged from 85-89% (n = 449, 43.6%), followed by the range of 90-94% (n = 344, 33.4%), the range of 80-84% (n = 183, 17.8%), the range of 95% and above (n = 30, 2.9%), and the range of 75-79% (n = 24, 2.3%). Last but not least, most respondents (n = 857, 83.2%) stated that they had used artificial intelligence (AI) in their research.

Table 2. Level of Perceived Artificial Intelligence (AI) Anxiety, Self-Efficacy, and Self-Competence

Variables	Composite Mean	Description Interpretation
1. AI Learning	2.77	Moderate
2. Job Replacement	3.58	High
3. Sociotechnical Blindness	3.62	High
4. AI Configuration	3.13	Moderate
5. AI Anxiety Level	3.27	Moderate
6. AI Self-Efficacy Level	3.05	Moderate
7. AI Self-Competency Level	3.53	High

Note: 1.00-1.79=Very low; 1.80-2.59=Low; 2.60-3.39=Moderate; 3.40-4.19= High; 4.20-5.00=Very high

Table 2 presents the respondents' levels of self-efficacy, self-competence, and anxiety regarding artificial intelligence (AI). We use the means of the variables to represent them, and the descriptions of the variables illustrate appropriate interpretations at each level. The respondents perceived a moderate level of AI learning (M = 2.77), indicating a reasonable comprehension of AI concepts and applications. With a mean value of 3.58, the variable "job replacement" earned a high value, indicating that respondents expressed high levels of anxiety about the possibility of artificial intelligence replacing human occupations. Similar to the previous measure, the "Sociotechnical Blindness" variable yielded a high mean score of 3.62, indicating a high level of unawareness or ignorance among respondents regarding artificial intelligence's social and ethical consequences. The mean score for the variable "AI Configuration" was 3.13, indicating that respondents had a modest level of comfort or knowledge when configuring AI systems. The respondents expressed moderate anxiety about AI (M = 3.27), indicating a moderate level of worry or dread regarding the influence of AI. While the variables "AI Self-Efficacy Level" (M = 3.05) and "AI Self-Competency Level" (M = 3.53) both had moderate and high mean values, respectively, in terms of self-efficacy and self-competence. The mean values for both variables were moderate and high, respectively. These results suggest that respondents had a moderate level of confidence in their ability to interact with AI systems and a high level of perceived proficiency in using AI effectively. It is possible to gain some understanding of the respondents' feelings about AI anxiety, self-efficacy, and self-competence by observing the table. In terms of dealing with artificial intelligence technologies, it demonstrates care, comprehension, and confidence.

Table 3. Variations in AI Anxiety, Self-Efficacy, and Self-Competency

Characteristics	AI Anxiety	AI Self-Efficacy	AI Self-Competency
College	2.133	6.106*	2.824*
Year Level	2.060	3.969*	2.202
Age	2.031	2.474	0.739
Sex at Birth	8.145*	15.602*	1.585
GPA	1.934	1.251	6.445*
Usage of AI in Study	0.578	-4.286*	-3.110*

*Note: *p < .05*

Table 3 presents the results of the computation for the analysis of variance, which categorizes respondents based on their demographic features. We conducted this experiment to ascertain the anxiety, self-efficacy, and self-competence levels associated with artificial intelligence. To begin with, regarding the anxiety caused by artificial intelligence, the sole factor that produced a significant result was the individual's sexual orientation at birth [$F(2, 1027) = 8.145$, p=.000]. Because the p-value obtained is lower than the.05 significance level, it is safe to assume that there is a significant difference in AI anxiety among respondents when grouped according to sex at birth. Other characteristics (like college, year level, age, GPA, and usage of AI in the study) did not yield sufficient results to reach the threshold of a significance level of.05; thus, no significant differences were observed. Regarding the self-efficacy of AI, the following demographic characteristics produced significant results: in terms of college, F(4. 1025)= 6.106, p=.000; in terms of year level, $F(3, 1026)$= 3.969, p=.008; in the case of sex at birth, $F(2, 1027)$= 15.602, p=.000; and finally, in terms of the utilization of AI in the study, $t(1028)$= -4.286, p=.000. Based on the calculation's probability values (p-values) generated, the study rejects the null hypothesis because the obtained p-values were all significant at the 0.05 significance level. Age and GPA did not generate sufficient results for consideration; hence, we accept the null hypothesis. The study also revealed the following significant findings on AI self-competency: in terms of college, $F(4, 1025) = 2.824$, p=.024, for GPA, $F(4, 1025) = 6.445$, p=.000, and for AI usage in the study, $t(1028) = -3.110$, p=.002. We found these findings were significant. These probability values are all lower than the alpha significance level of .05. Thus, we reject the study's null hypothesis. It is also safe to assume that there were significant differences in the AI self-competency of the students when they were grouped according to college, GPA, and AI usage. Other characteristics such as year level, age, and sex at birth did not yield significant differences.

Table 4. Relationships between AI Anxiety, Self-Efficacy, and Self-Competency

Variables	AI Self-Efficacy	AI Self-Competency
Learning	.174*	.080*
	.000	.010
Job Replacement	.056	.298*
	.071	.000
Sociotechnical Blindness	.088*	.307*
	.005	.000
AI Configuration	.049	.112*
	.119	.000

*Note: *p < .05*

Table 4 depicts the association between AI anxiety's subvariables, AI self-efficacy, and AI self-competency, with the help of the Pearson r-moment of correlation. One can decipher that in the case of AI self-efficacy, there were significant findings for learning (r= .174, p= .000) and sociotechnical blindness (r= .088, p= .005). Regarding AI self-competency, significant results were also obtained from learning (r= .080, p= .010), job replacement (r= .298, p= .000), sociotechnical blindness (r= .307, p= .000), and AI configuration (r= .112, p= .000). Based on the preceding results, all p-values were considered significant at a .05 alpha significance level. Therefore, we reject the null hypothesis of this study. For AI self-efficacy, learning and sociotechnical blindness had a weak positive relationship. Then, AI self-competency, learning, job replacement, sociotechnical blindness, and AI configuration also generated a weak positive relationship.

Table 5. Regression Analysis of the Predictors of AI Self-Efficacy and Self-Competency

Variable	AI Self-Efficacy			AI Self-Competency		
	B	**β**	***t***	**B**	**β**	***t***
Learning	.210	.241	6.300*	.021	.023	0.619
Job Replacement	- .126	- .162	-2.382*	.138	.167	2.542*
Sociotechnical	.187	.244	3.517*	.237	.291	4.352*

Variable	AI Self-Efficacy			AI Self-Competency		
	B	β	*t*	B	β	*t*
Blindness						
AI Configuration	- .112	- .153	-3.198*	- .163	- .208	-4.522*

Note: AI Self-Efficacy- Constant=2.598; F(4, 1025)= 12.647, p= .000; R^2*= .047*
AI Self-Competency- Constant=2.629; F(4, 1025)= 34.141, p= .000; R^2*= .118*
**p< .05*

Table 5 presents the results of the linear regression analysis for AI self-efficacy and AI self-competency. The table reveals that the four characteristics of AI anxiety influence AI self-efficacy. Job replacement (β= -.162), sociotechnical blindness (β=.244), and AI configuration (β= -.153) were the three factors considered relevant. Upon closer examination, we discovered that the t-values for learning (*t*= 6.300), job replacement (*t*= -2.382), sociotechnical blindness (*t*= 3.517), and AI configuration (t= -3.198) all met the.05 Alpha significance threshold. Furthermore, we demonstrated the statistical significance of the AI self-efficacy regression model (F(4, 1025) = 12.647, p=.000). R^2 explains 4.7% of the variance among the variables.

In the case of artificial intelligence (AI) self-competence, we identified three situations in which AI anxiety had a meaningful impact on AI self-competence. Job replacement (β=.167), sociotechnical blindness (β=.291), and artificial intelligence configuration (β= -.208) are all included in this category. Because job replacement received a *t*-value of 2.542, sociotechnical blindness received a *t*-value of 4.352, and AI configuration received a *t*-value of -4.522, the *t*-values for each scenario were similarly significant at a significance level of 0.05. On the alpha significance scale. The regression model for AI self-competency also produces significant results, as evidenced by the fact that F(4, 1025)= 34.141, p=.000, and 11.8% of the R^2 explain the variance among the variables.

The study provides interesting attributes and ideas that future researchers can consider. The present paper explores the relevant associations between the study's three variables: AI anxiety, self-efficacy, and self-competence. As proposed in the previous section of this paper, no particular paper is needed to investigate the context of the three variables in a single study. Moreover, this research also sought answers to the variances and relationships among these variables. Based on these premises, we presume the novelty and originality of this study.

The fundamental objective of this research is to investigate the connections between students' artificial intelligence (AI) fear, self-efficacy, and self-competency, as well as the differences that exist between these three factors. For higher education institutions to map out and create proper rules to control the use of AI in colleges, they must conduct baseline data collection.

Based on the acquired data and statistical analysis, the study yields significant findings that serve as baseline information for the institution's decision-making body. According to the findings of this study, the demographic characteristics indicate that a greater number of students come from the College of Education, Arts, and Sciences (CEAS). At the same time, the College of Business and Accountancy (CBA) received the lowest number of students. Additionally, there were a greater number of students in their first year of study, with the third-year having the lowest number of participants. The findings indicate that students under the age of 20 were enrolled at a higher rate than those aged 26 and above. There was also a greater number of females than males and individuals who chose not to participate. In addition, a greater number of pupils had an average grade that fell between 85% and 89%. In conclusion, most students use AI in their academic pursuits.

The findings indicated that the level of concern regarding AI was moderate, which is similar to the level of self-efficacy with AI. Hopcan et al.'s (2024) study in which students expressed their concerns about artificial intelligence's effects, aligns with this conclusion. Lérias et al.'s (2024) most recent research also found a low average score for AI self-efficacy, which is consistent with the current report's findings. On the other hand, the research revealed a high level of self-competency among AI. Additionally, respondents in a recent study by Sabordino et al. (2024) expressed a high level of agreement with AI self-competence. Ayanwale's (2023) study echoed these findings, revealing that over 74% of students had confidence in their ability to learn AI. Chiu et al. (2022) concluded that students formed a favorable attitude toward learning artificial intelligence and perceived themselves to be more competent because of their experience.

There were notable differences observed in the levels of anxiety regarding artificial intelligence (AI) based on gender, self-efficacy regarding AI (in terms of college, year level, gender, and usage of AI in study), and self-competency regarding AI (in terms of college, grade point average, and usage of AI in study). However, Hopcan et al. (2024) found no significant factors related to gender, age, or department when learning about artificial intelligence. Park (2023) conducted an experiment that revealed a substantial disparity in the level of self-efficacy regarding artificial intelligence among students.

The calculation also revealed a marginally positive correlation between AI self-efficacy, learning, and sociotechnical blindness. The study's attempt to determine the association between the variables led to this discovery. On the other hand, the calculation revealed a weakly positive relationship with each of the four AI characteristics, particularly regarding the self-competency of AI. According to Ayanwale (2023), students' self-efficacies in learning artificial intelligence affects their intentions to learn it. Additionally, Carolus et al. (2023) discovered a significant connection between AI self-competence and AI self-efficacy. On the other hand, concern over artificial intelligence (AI) plays a crucial role in determining how individuals interact with technology that uses AI.

In addition, the regression analysis for AI self-efficacy found that learning, sociotechnical blindness, AI configuration, and job replacement were important predictors of AI self-efficacy. Regarding AI self-competency, significant predictors include AI configuration, sociotechnical blindness, and job replacement skills. These discoveries are highly pertinent and timely, especially for the engaged educational establishment, as they will serve as a solid foundation for formulating acceptable policies to control the use of artificial intelligence (AI) in the educational process among students.

CONCLUSIONS

Based on the proceeding results and discussion of the study, the study concluded that the students had moderate AI anxiety levels. Similarly, they demonstrated moderate AI self-efficacy. However, they achieved high levels of AI self-competence. The study also observed variations in AI anxiety, self-efficacy, and self-competency when the students were grouped according to their demographic characteristics. However, there was also a weak association between the subvariables AI anxiety, AI self-efficacy, and AI self-competency. Regression analysis also revealed that learning and job replacement, sociotechnical blindness, and AI configuration were significant predictors of AI self-efficacy. Regarding AI self-competency, job replacement, sociotechnical blindness, and AI configuration were the predictors.

The findings of this study are vital, especially in higher education learning, where the academic use of Artificial Intelligence in education is already extensive. Since the main focus of the study was students, exploring the manifolds of AI anxiety, self-efficacy, and self-competency is essential for promoting a better understanding of AI phenomena. In this way, appropriate measures and policies can be implemented to implement more adaptable measures to deal with the challenges AI technology brings to the institution. Institutions must plan and uphold standard operating procedures and flexible classroom teaching and management regulations where AI technology is prominent. Therefore, the academic integrity of students and faculty will not be violated or exposed to public scrutiny or media spotlight.

LIMITATION & FURTHER RESEARCH

The current study's limitations are related to the fact that the researchers only employed one college institution in the study. Future research can maximize other institutions. At the same time, since the study was conducted at the tertiary level of education, a similar investigation could be conducted on senior high school students or even junior high school students. Future researchers are also encouraged to use mixed research design methods or structural equation modeling (SEM) to better understand variables' interrelationships.

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